IMT-RIKEN　Workshop @Brest France
Feb.11, 2020

AI Approach for Advanced Weather Forecasting

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Disaster Prevention Science Team
Center for AIP, RIKEN

Center for AIP, RIKEN (2016-2026)

1. Developing Next-Generation AI Technologies
2. Accelerate scientific research with AI technologies
3. Solve Socially Critical Problems by AI

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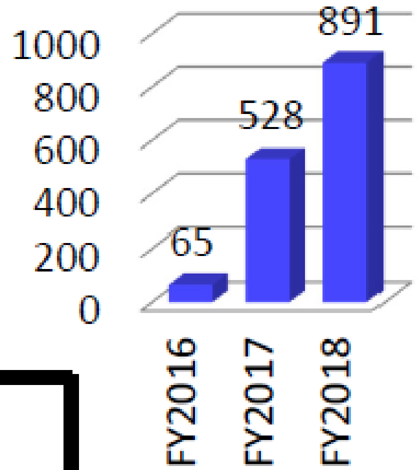
Personnel (incl. students & visitors)



Generic Technology Research Group	Goal - Oriented Technology Research Group	Artificial Intelligence in Society Research Group
(21 teams/units)	(24 teams/units)	(7 teams/units)

Research Project

- ✓ The Japan's Big Data Assimilation (BDA) Project
  JST CREST, 2013-2019, Leader : Dr. Miyoshi (RIKEN, R-CCS)

- ✓ AIP (Advanced Intelligence Project) Acceleration Research, 2019-2022,
  Integration of DA and AI with high-performance computation (HPC).

JST: Japan Science and Technology Agency
CREST: Core Research for Evolutional Science and Technology
Funding program for team-oriented research with the aim of achieving the strategic goals set forth by the government

Disaster Resilience Science Team 2016.9 ~

Our challenge is to develop novel AI approaches to accelerate disaster prevention research.

Researcher & PostDoc: 4
Visiting Researcher: 5

Research collaboration with

- National Research Institute Earth Science and Disaster Resilience
- Earthquake Research Institute, University of Tokyo
- Japan Meteorological Agency

Research Topics

1. Earthquake damage evaluation

- Evaluate how much damage will occur by a megaquake

2. Earthquake occurrence forecasting

- Reproduce the Nankai Trough historical sequence

3. Landslide susceptibility mapping

- Create a map for the potential for landslide

4. Weather forecasting 2019.10~

- Develop “Integrated Guidance” to optimally combine multiple numerical forecast results

Today’s　Topics

- ✓ **Forecasting Rapidly Developing Typhoon**

  Kurora, Hachiya, Shimada, and Ueda

  Japan Meteorological Society 2019

- ✓ **Integrated Guidance**

  Just started …

Collaboration with Japan Meteorological Agency

Research Topics

- ✓ **Forecasting Rapidly Developing Typhoon**
- ✓ **Integrated Guidance**

Collaboration with JMA

Background

- Severe damage by rapidly developing typhoons

damage in Japan by Jebi, 2018

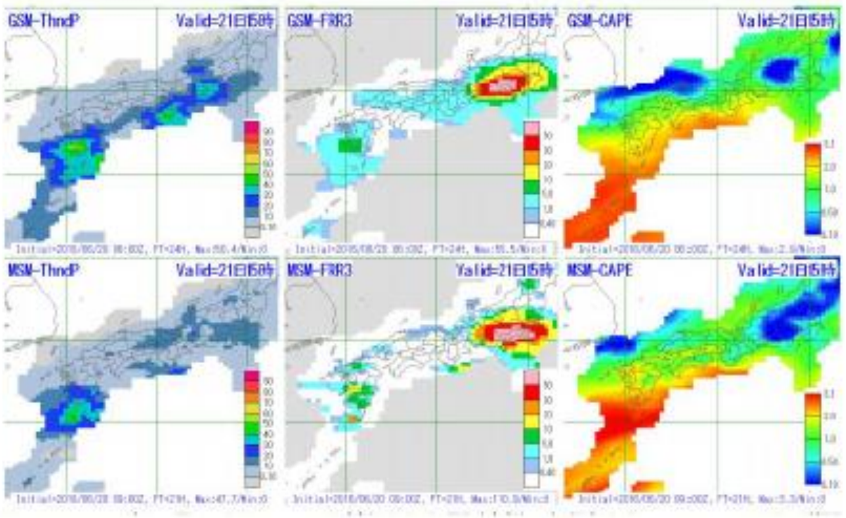
- Accurate forecasting of rapidly development is required
- However, # of rapidly developing typhoons is very limited

Related works: SHIPS

SHIPS: Statistical Hurricane Intensity Prediction System

- Predicting the central pressure change y_t^i from environmental features $\boldsymbol{x}_t^i$ generated from models

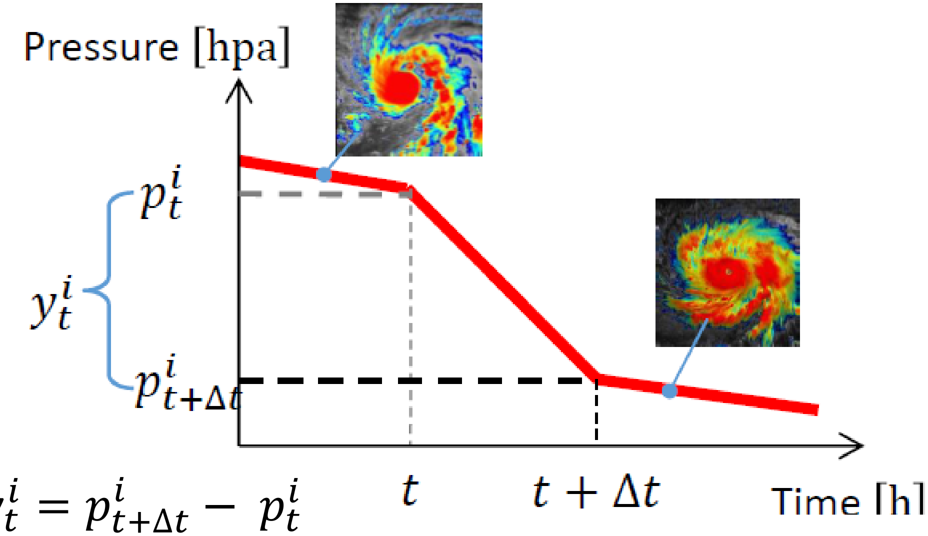
MSM, GSM guidance



Feature extraction

$$\boldsymbol{x}_t^i = \begin{pmatrix} x_{t1}^i \\ x_{t2}^i \\ \vdots \\ x_{t24}^i \end{pmatrix}^T$$

Observation



$y_t^i = p_{t+\Delta t}^i - p_t^i$

- Linear regression model is used in SHIPS

$$\hat{y}_t^i = f(\boldsymbol{x}_t^i) = \boldsymbol{x}_t^i \boldsymbol{w} \qquad \boldsymbol{w} = (w_1, w_2, \cdots w_{24})$$

Catalog data (SHIPS)

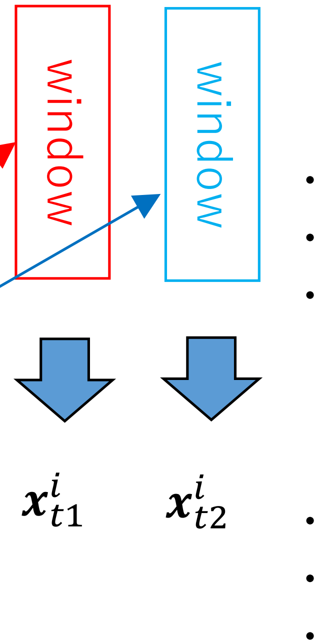
- Environmental conditions
  - Sea temperature, wind strength over sky etc.
  - Time-series data from birth to death of a typhoon

Extracting features for every 6 hours sliding window

time

conditions

TIME	0	6	12	18	24	30	36	42	48	54
VMAX	30	30	30	30	30	30	35	40	40	50
MSLP	1006	1006	1004	1004	1004	1004	1002	1002	998	990
⋮					⋮					
T000	254	256	259	258	257	257	259	258	254	252
E000	3527	3524	3538	3533	3529	3522	3532	3533	3521	3512

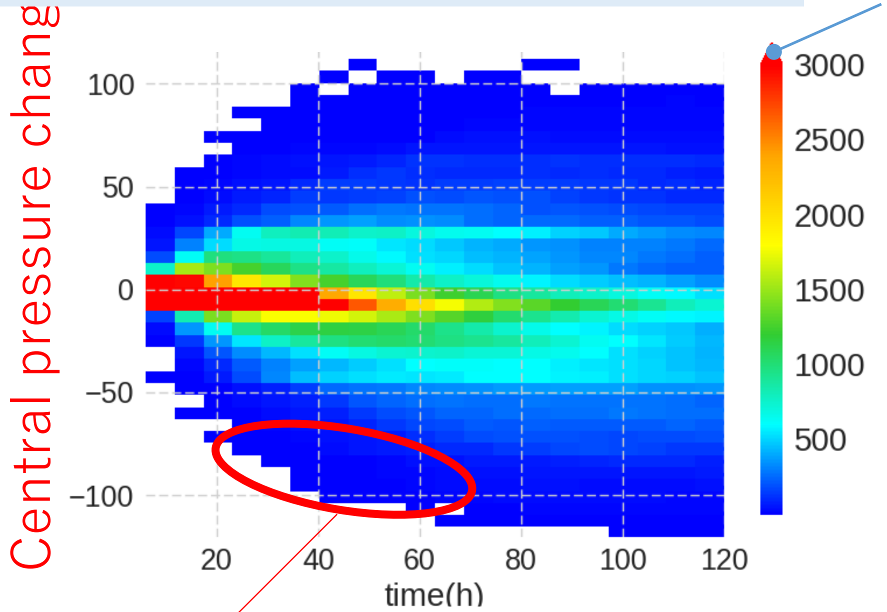


Problem of SHIPS

- Linear regression tends to influenced by the majority of data and it is difficult to predict rapid intensification

Histogram of training sliding-window data

# of window data



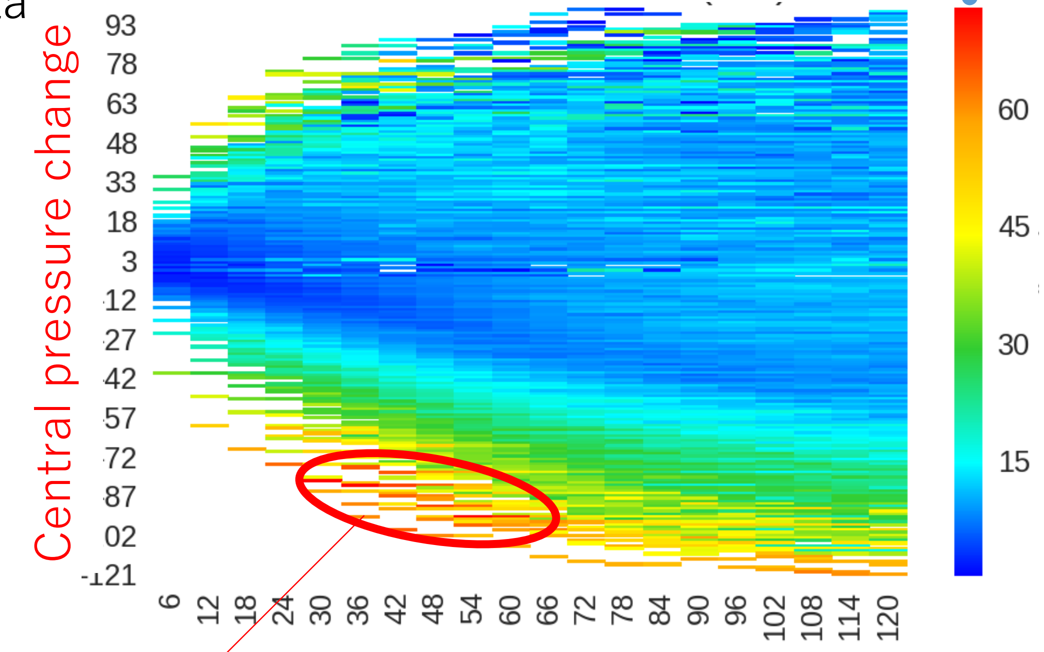
Time Δt [hour]

# of data of is very limited

Training linear regression model

Histogram of error in test data

Absolute error



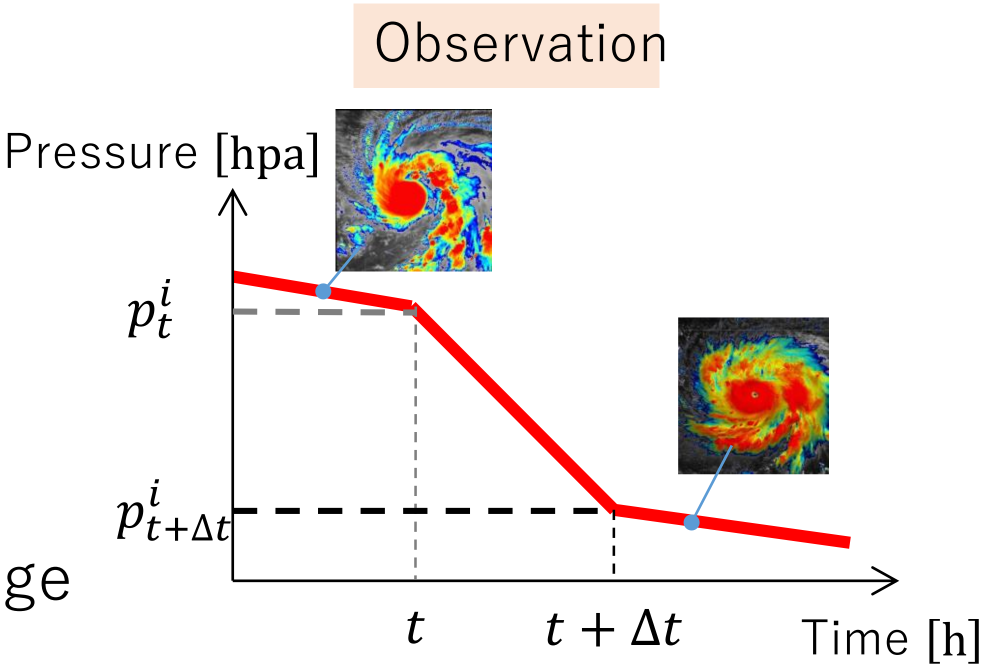
Large error

Time Δt [hour]

Intensification forecast as classification task

- We define rapid intensification forecasting as binary classification task

$$y_t^i = \begin{cases} 1 & p_{t+\Delta t}^i - p_t^i < \tau \\ 0 & p_{t+\Delta t}^i - p_t^i \geq \tau \end{cases}$$



τ:threshold of central pressure change

$y_t^i = 0$: normal typhoon

$y_t^i = 1$: rapidly developing typhoon

Setting threshold

- Calculate the amount of change in the central pressure between the forecast time and the initial time for each window

  Ex: the forecast time is 48 hours after the initial time

time

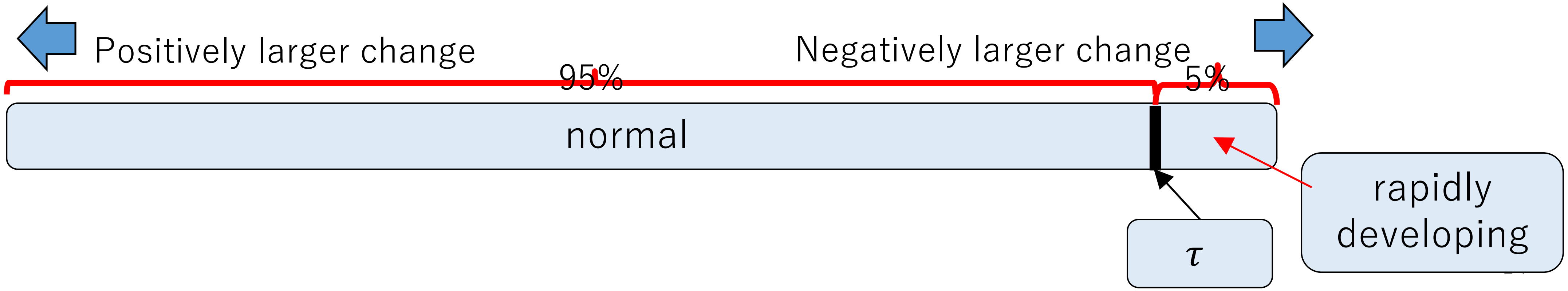
Central pressure	0	6	12	18	24	30	36	42	48	54
SLP	1006	1006	1004	1004	1004	1004	1002	1002	998	990

$998 - 1006 = -8$ $\quad y^i_{t1}$

$990 - 1006 = -16$ $\quad y^i_{t2}$

$\vdots \quad \vdots$

- 95% point of the result of sorting the central pressure change in descending order is set as threshold τ



Usual Binary Classification Scheme

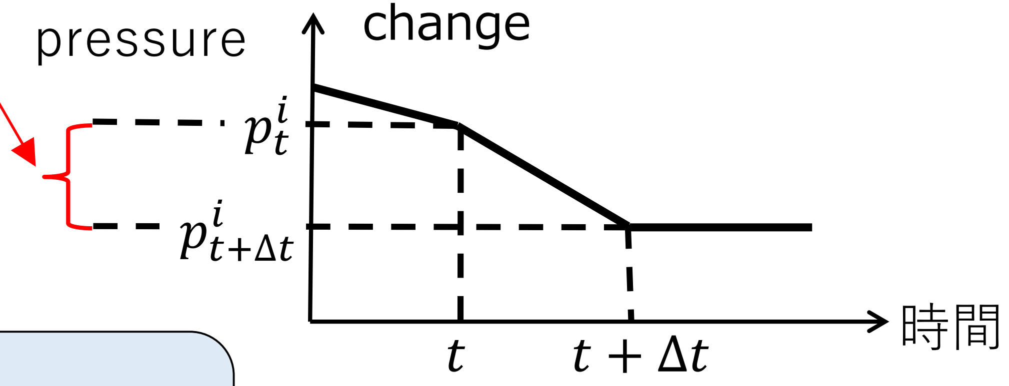
- Binary (rapid or normal) classification formulation

$$y_t^i = \begin{cases} 1 & y_t^i < \tau \\ 0 & y_t^i \geq \tau \end{cases}$$

1 : rapid
0 : normal

$$y_t^i = p_{t+\Delta t}^i - p_t^i$$

the ith typhoon's pressure change



Cross-Entropy loss function

$$\mathrm{CE} = \sum_{k=1}^{N} -y_k \log \hat{y}_k - (1 - y_k)\log(1 - \hat{y}_k)$$

y_k : true
$\hat{y}_k$: prediction

➡ The loss CE decreases as the predicted value approaches the true value

Cross-entropy minimization cannot handle imbalances between rapidly developing (small) and normal (many) data

Direct AUC maximization using neural network

Ueda & Fujino, 2018

- In binary classification tasks, accuracy is the most commonly used as a measure of classifier performance.
- In some applications such as anomaly detection and diagnostic testing, accuracy is not an appropriate measure since prior probabilities are often greatly biased.
- Although in such cases, the AUC has been utilized as a performance measure, few methods have been proposed for directly maximizing the AUC.
- The conventional approach utilizes a linear function as the scoring function.
- In contrast, we newly introduce nonlinear scoring functions for this purpose.

TPR , FPR

		Truth: positive	Truth: negative
Prediction	positive	TP	FP
	negative	FN	TN
		n_+ # of positives	n_- % of negatives

True Positive Rate（TPR）：

Prob. that true positives are correctly predicted as positive:

$$TPR = \frac{TP}{TP + FN} = \frac{TP}{n_+}$$

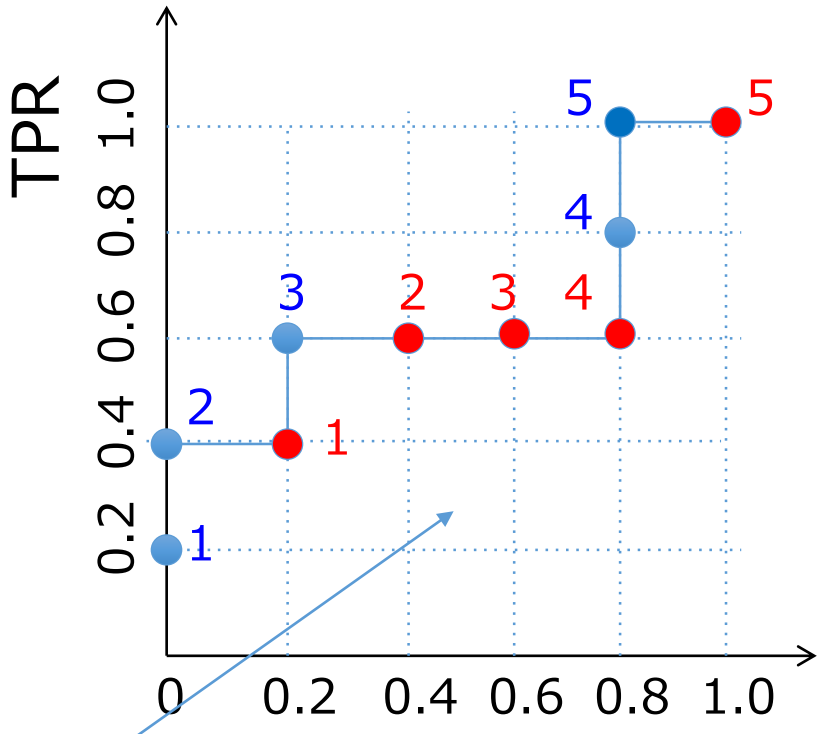
False Positive Rate（FPR）：

Prob. that true negatives are incorrectly predicted as positive:

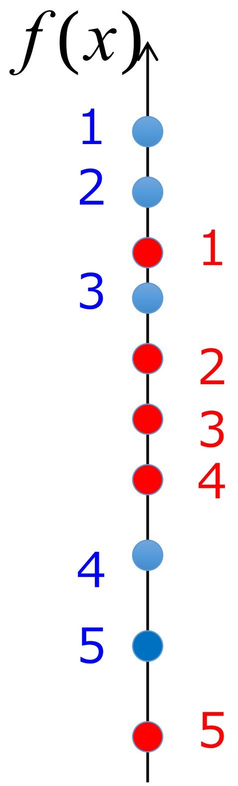
$$FPR = \frac{FP}{FP + TN} = \frac{FP}{n_-}$$

ROC (Receiver Operating Characteristic)

Binary classification (positive or negative)
should be evaluated by ROC-AUC



Scoring function: f: x -> R



$$FPR_f(t) = \Pr\{f(x^-) > t\}$$

$$TPR_f(t) = \Pr\{f(x^+) > t\}$$

AUC is the probability of
$f(x^+)$ being larger than $f(x^-)$

AUC (Area Under the ROC Curve)

$$\mathrm{AUC} = \mathrm{Prob}\big(f(\boldsymbol{x}^+) > f(\boldsymbol{x}^-)\big)$$

Direct AUC maximization using neural network

$$\mathrm{AUC} = \mathrm{Prob}\big(f(\boldsymbol{x}^+) > f(\boldsymbol{x}^-)\big) \approx \frac{1}{n^+n^-}\sum_{i=1}^{n^+}\sum_{j=1}^{n^-} I\big(f(\boldsymbol{x}^+) > f(\boldsymbol{x}^+)\big)$$

$\boldsymbol{x}^+$:input feature of intensifying window
$\boldsymbol{x}^-$:input feature of normal window

n^+:number of intensifying windows
n^-:number of normal windows

$$I(x) = \begin{cases} 1 & x = True \\ 0 & x = False \end{cases}$$

- AUC is the probability of $f(x^+)$ being larger than $f(x^-)$
- We maximize smoothed version of AUC

$f(x;\theta) = \theta^t x$ **:conventional**

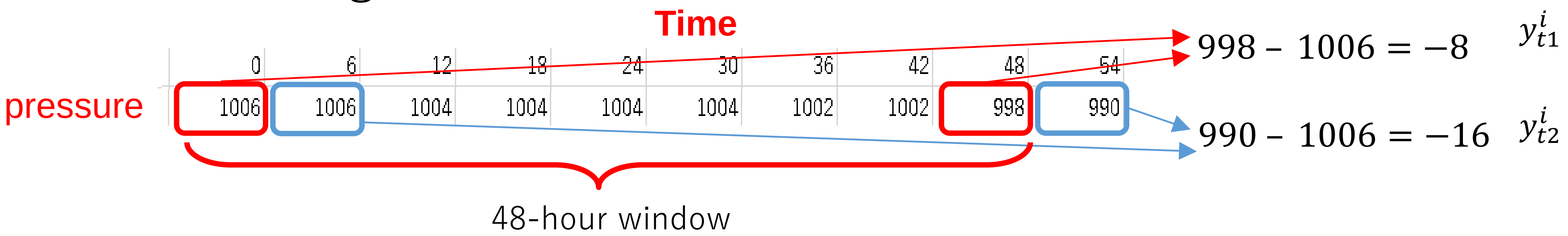
$$\mathrm{AUC}_{\mathrm{smooth}} = \frac{1}{n^+n^-}\sum_{i=1}^{n^+}\sum_{j=1}^{n^-} s(\boldsymbol{x}^+, \boldsymbol{x}^-; \theta)$$

$$s(x^+, x^-; \theta) = \frac{1}{1 + \exp[-\{f(\boldsymbol{x}^+;\theta) - f(\boldsymbol{x}^-;\theta)\}]}$$

- We design function $f(\boldsymbol{x})$ with fully connected neural network

Experimental setting

- Window length: 48-hour



- Intensifying threshold: 95 percentile pressure change in windows

- Training data: typhoons occurred in 1987-2012 year

- Test data: typhoons occurred in 2013-2017 year

Result

NN-CE: neural network with cross-entropy loss

NN-AUC: neural network with AUC maximization (proposed)

Precision: Percentage of data that is predicted positive and that is actually positive

Recall: The percentage of real positives that were predicted positive

14-17 point improved

method	Precision	Recall	F1 score
SHIPS	0.272/0.096	0.166/1.0	0.206/0.175
NN-CE	0.450/0.426	0.159/0.180	0.235/0.253
NN-AUC	0.325/0.327	0.361/0.368	**0.342/0.346**

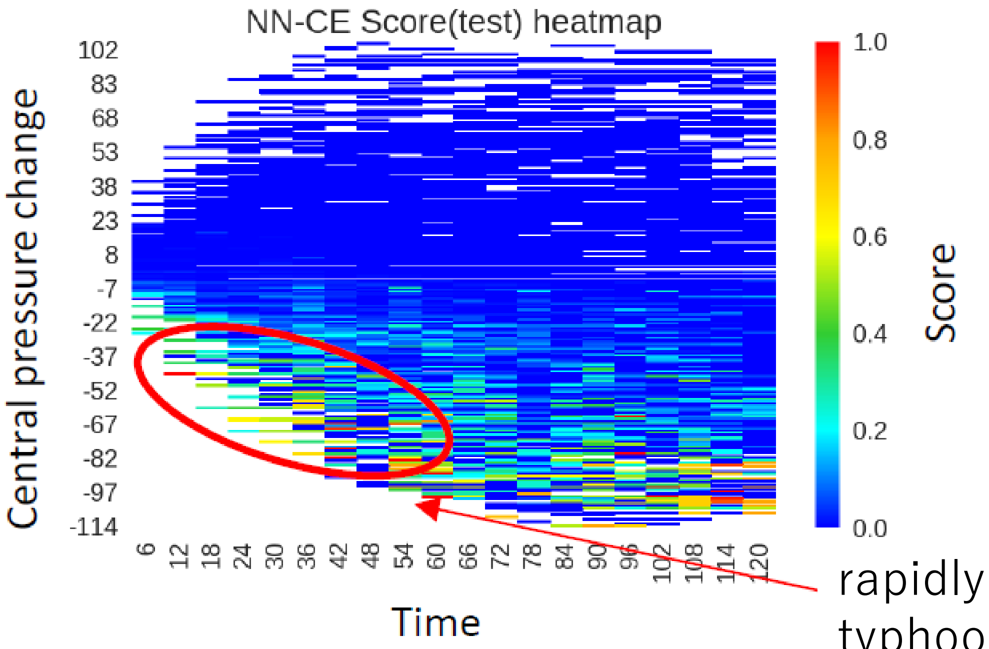
8-9 point improved

Classification threshold is set to 10/50 percentile

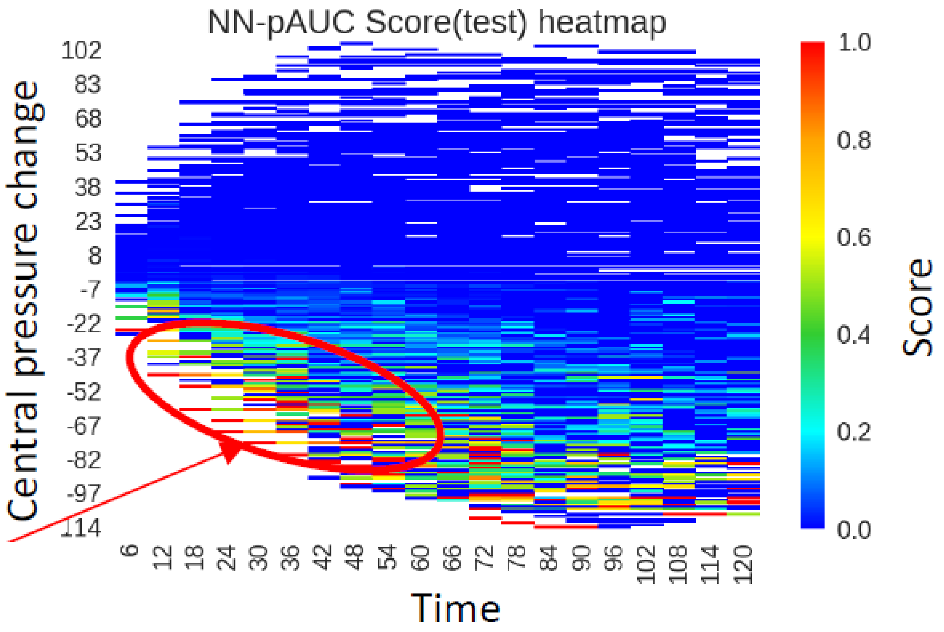
Evaluation (score distribution)

- Intensifying score predicted by NN-CE and NN-AUC

NN-CE



NN-AUC



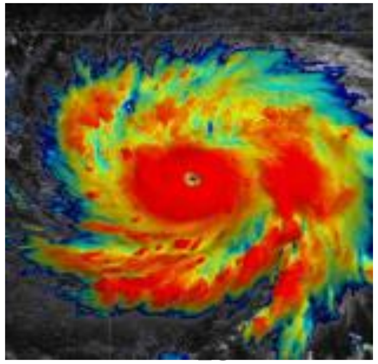
rapidly developing typhoons

- Proposed method can provide high score for rapidly developing typhoons

Summary

- Goal： improve the forecasting performance for intensifying typhoons with limited training data
- Existing methods: affected by the majority of normal typhoons
- Proposed method: directly maximizing AUC by introducing smoothed variant of with neural network
- Results:
  - Proposed method improved the performance for forecasting intensifying typhoons
  - However, recall is as low as 0.68
- Future works:
  - Combine satellite images with SHIPS features

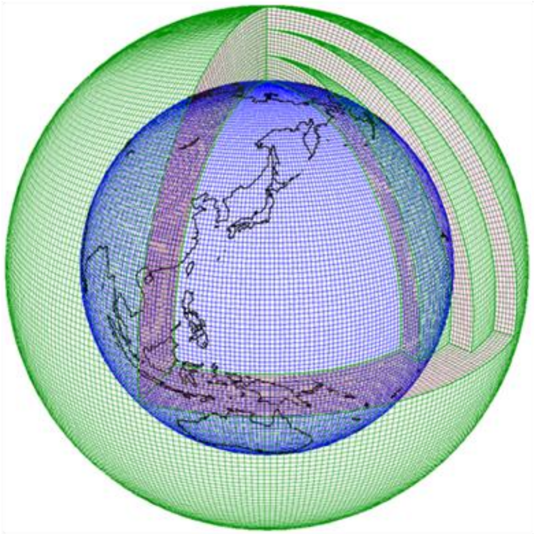
SHIPS +



Integrated Guidance

Collaboration with Japan Meteorological Agency

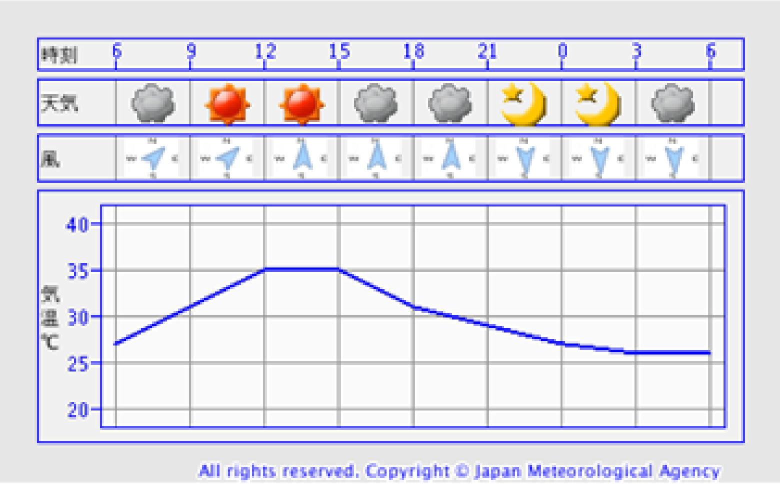
Guidance: Bridging Numerical Model and Forecast



Numerical Model

Interpretation
&
Correction

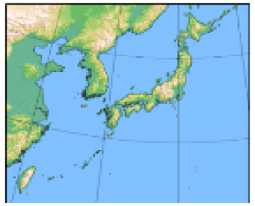
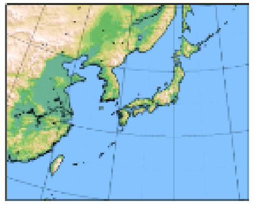
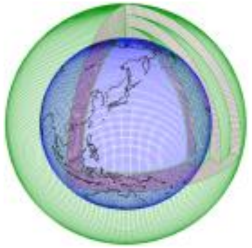
Regression, NN,
Karman Filter etc..



Guidance

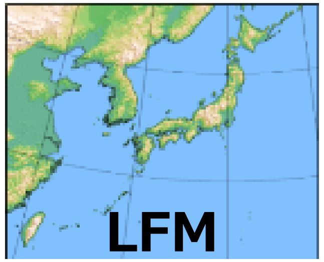
- **Interpretation of Numerical Model**
  - Model values to weather properties.
    e.g., What’s the weather like tomorrow?
- **Forecast Correction**
  Adjusting model biases associated with…
  - e.g., topography, cloud models, etc…

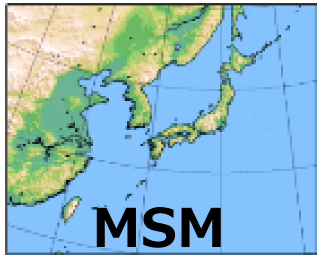
Pros and Cons among Numerical Models

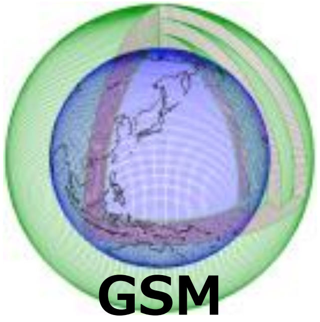
		Topography	Spatial Resolution	Temporal Resolution	Length of Forecast
	LFM	Detailed	2 km	1 Hours	9 Hours
	MSM		5 km	3 Hours	39 Hours
	GSM	Coarse	20 km	6 Hours	132 Hours

Fine but Short vs. Coarse but Long (or Stable)

Our Current Issue







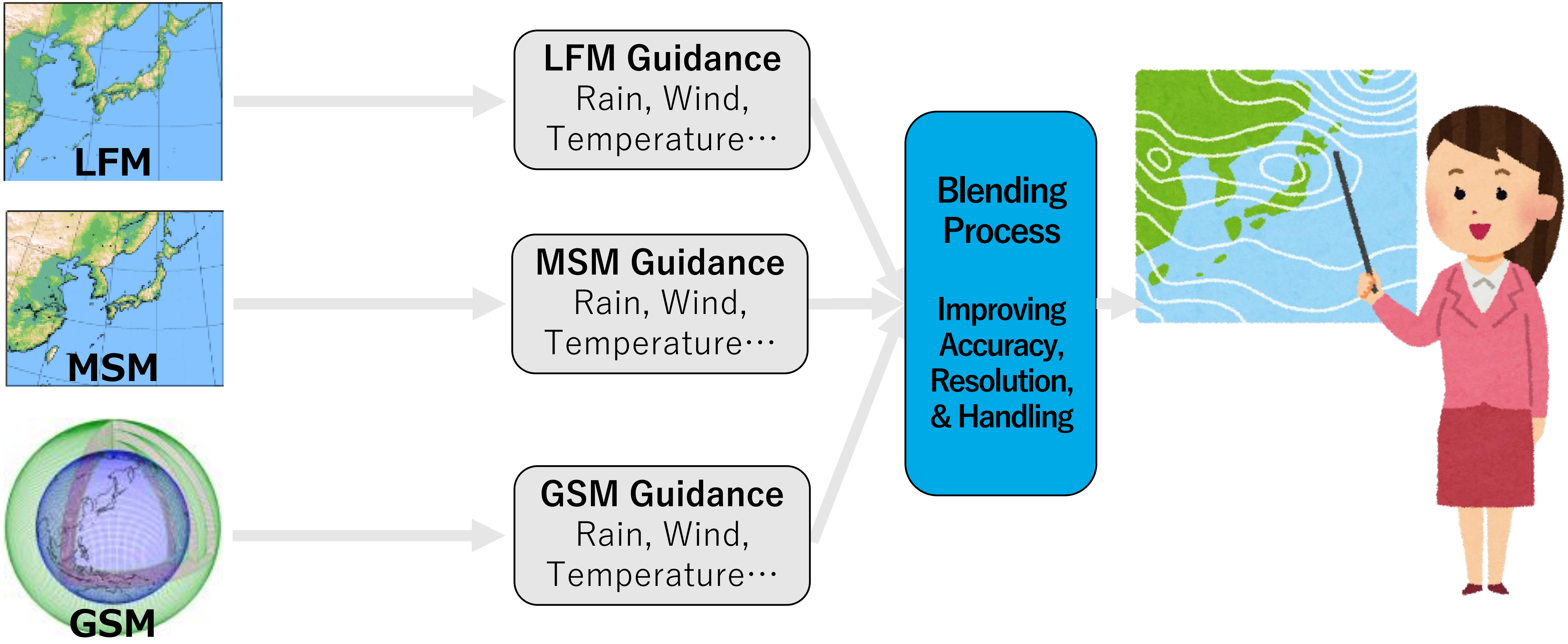
LFM Guidance
Rain, Wind,
Temperature…

MSM Guidance
Rain, Wind,
Temperature…

GSM Guidance
Rain, Wind,
Temperature…

- Officer has to integrate three forecasts based on past experience

Aim of Our Study: Integrated Guidance

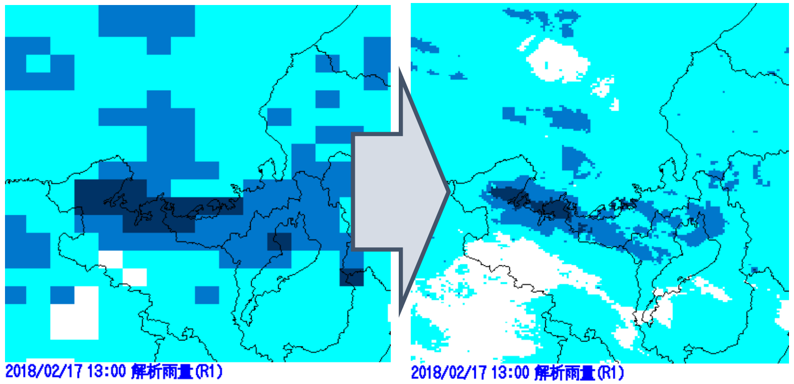


- Integrating models based on data in past
- Enabling Smart Forecast Operation !

Current Projects

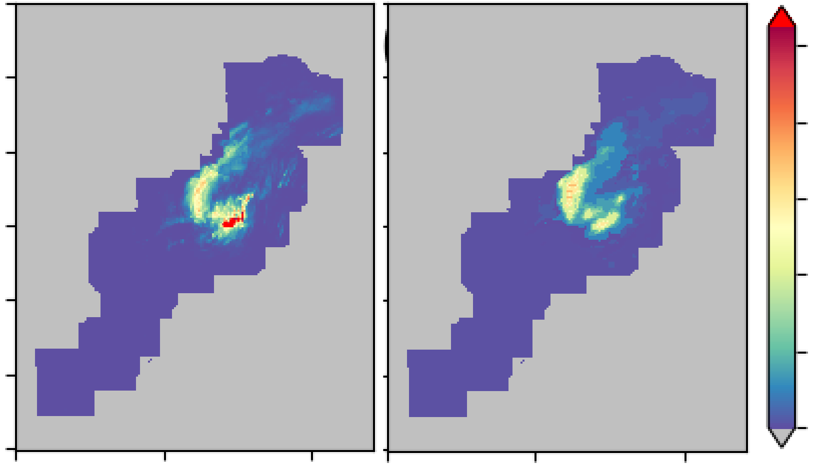
Unifying Model Resolution	Developing Integration Model	Examining Nature of Data

DNN



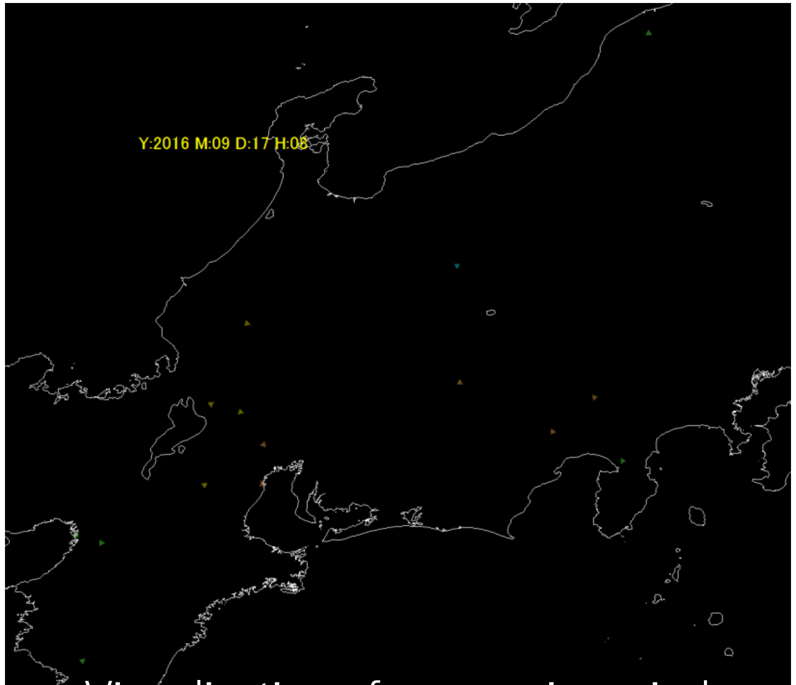
GSM to finer resolution using Deep Neural Network (JMA, 2019)

GAN
Auto Encoder



Precipitation observation (left) and mixed model (right), (Kawanishi and Hachiya).

Geostatistics



Visualization of converging wind associated with a stationary front

Simulation-Based Machine Learning

Prediction

Deductive inference ⟸ process model

Simulation Science (3rd science)

Inductive inference ⟸ experience, observation

Data-driven Science (4th science)

⇩

Deductive + Inductive = SBML