



[Topic I: Artificial intelligence for tropical cyclones related applications]
**DEVELOPMENT OF NEW RAINFALL
PRODUCTS BY ADAPTING AI
TECHNOLOGY TO HIMAWARI-8**



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Professor

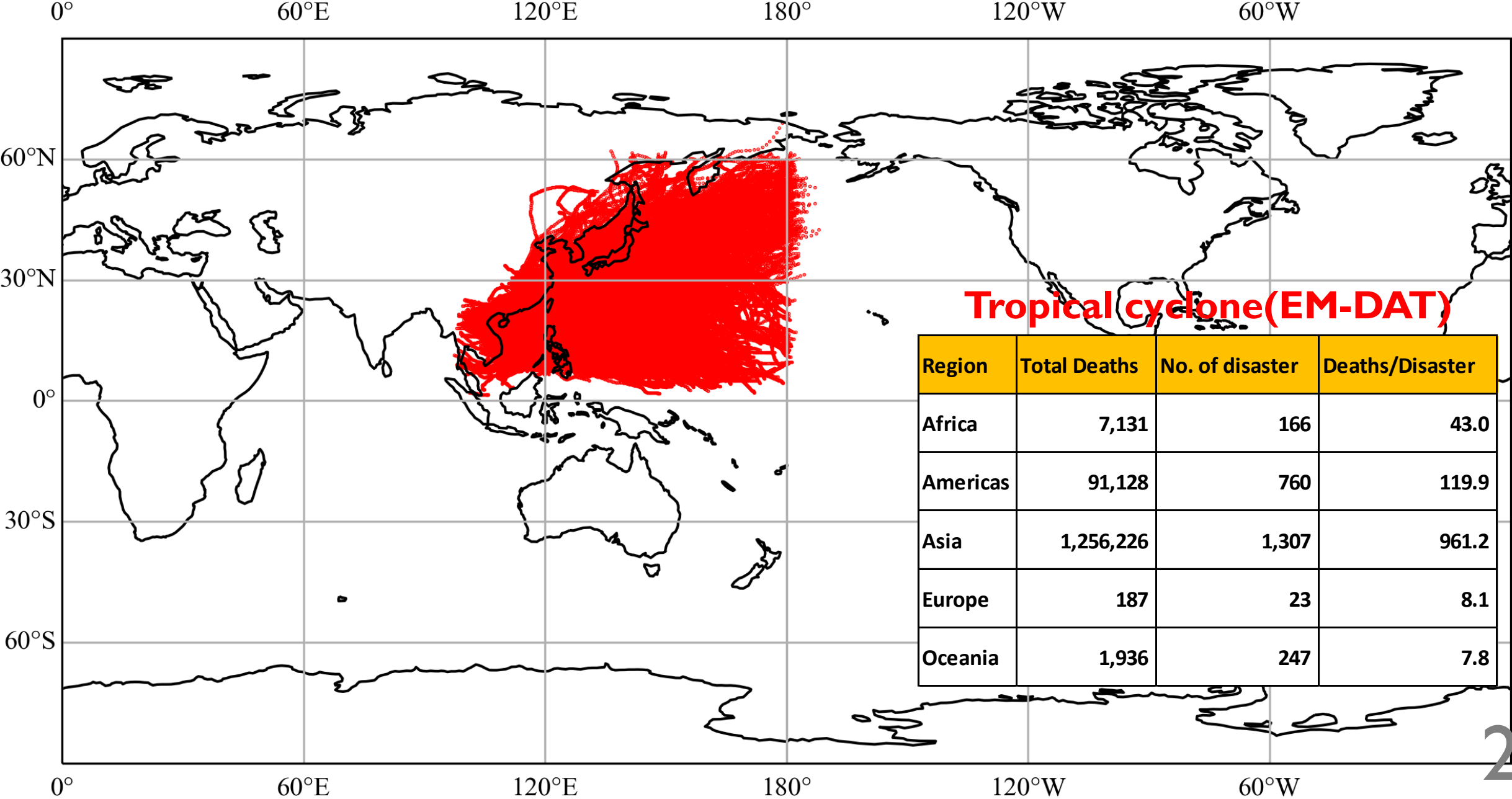
Department of Civil and Environmental Engineering

Director

Asia Water Science Research Center

Chuo University

Typhoon Track, 1978-2022, N. Pacific



Region	Total Deaths	No. of disaster	Deaths/Disaster
Africa	7,131	166	43.0
Americas	91,128	760	119.9
Asia	1,256,226	1,307	961.2
Europe	187	23	8.1
Oceania	1,936	247	7.8

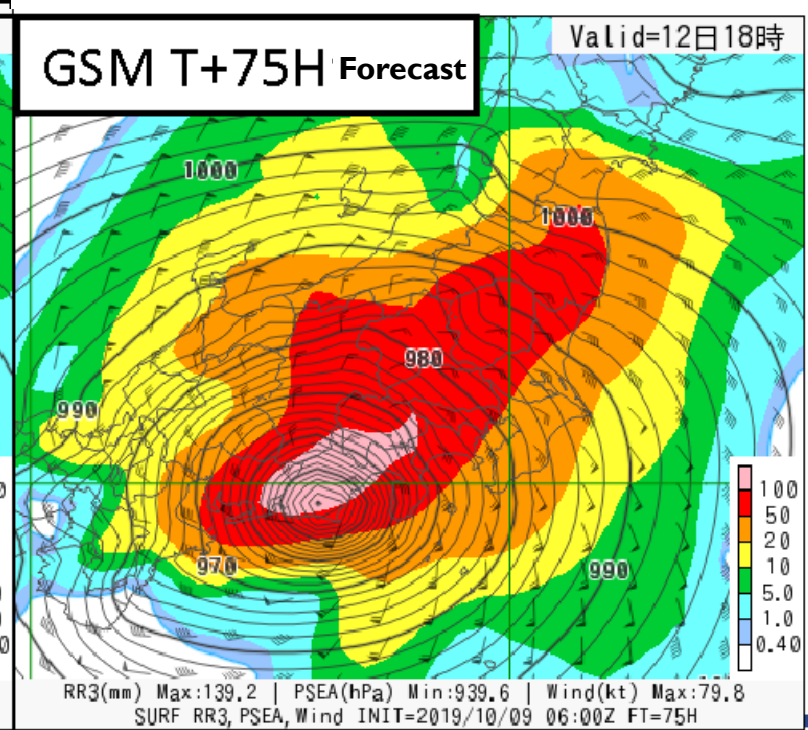
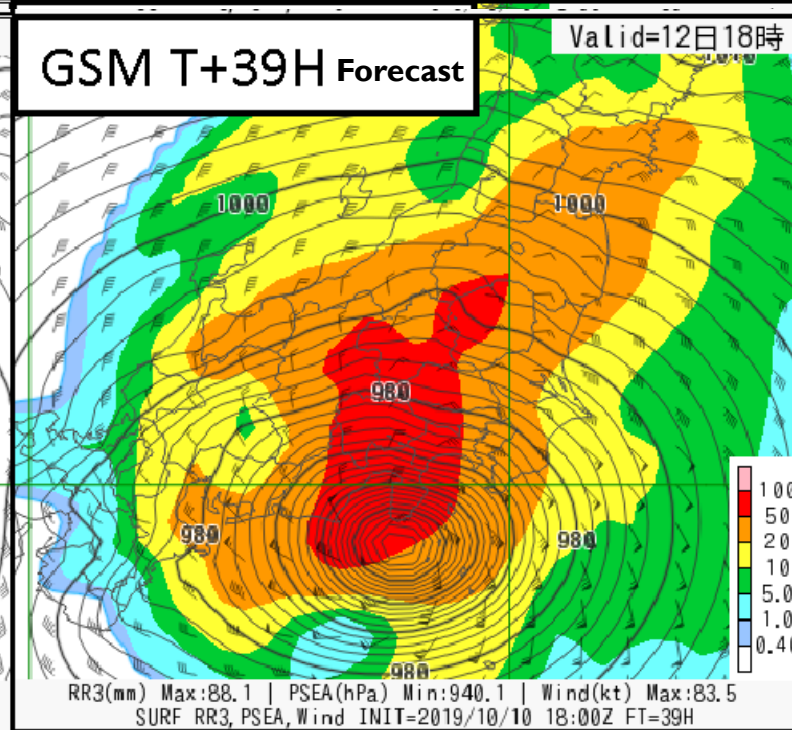
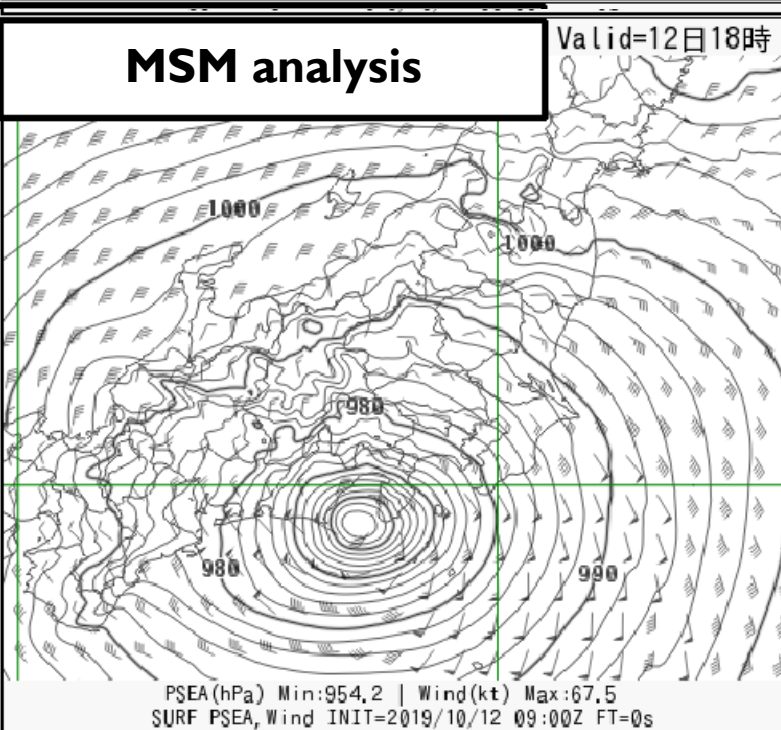
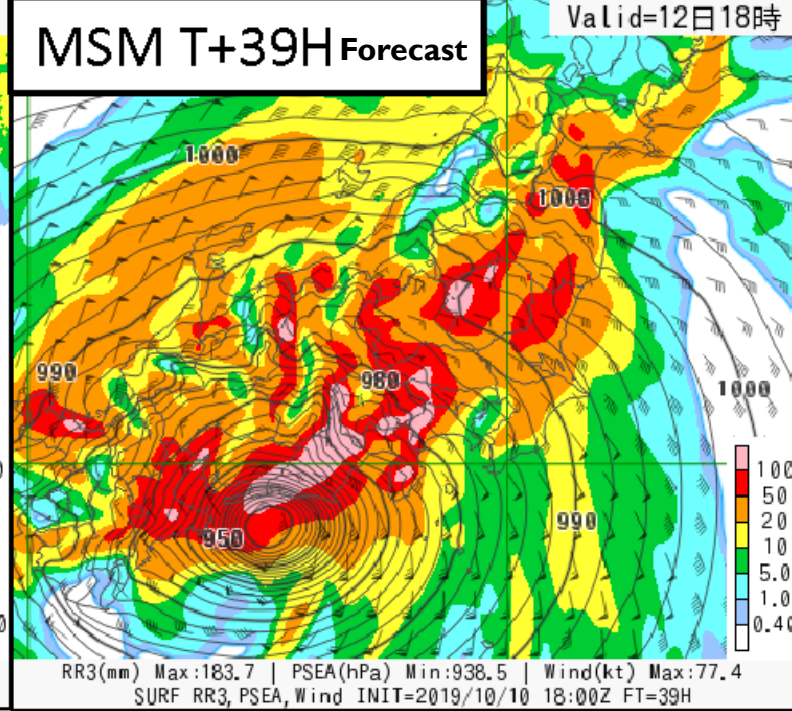
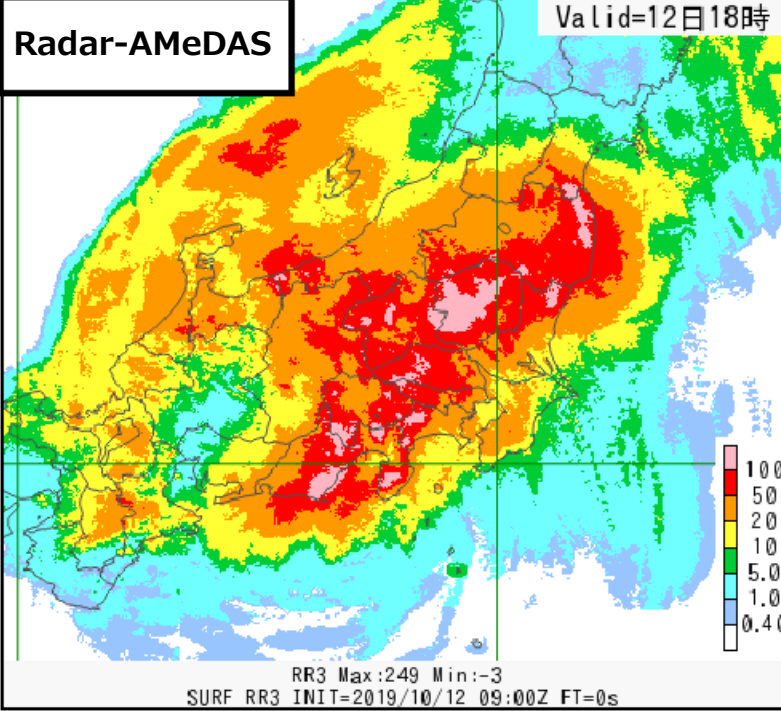
Current status of typhoon forecasting/a review

What is required to develop a global model

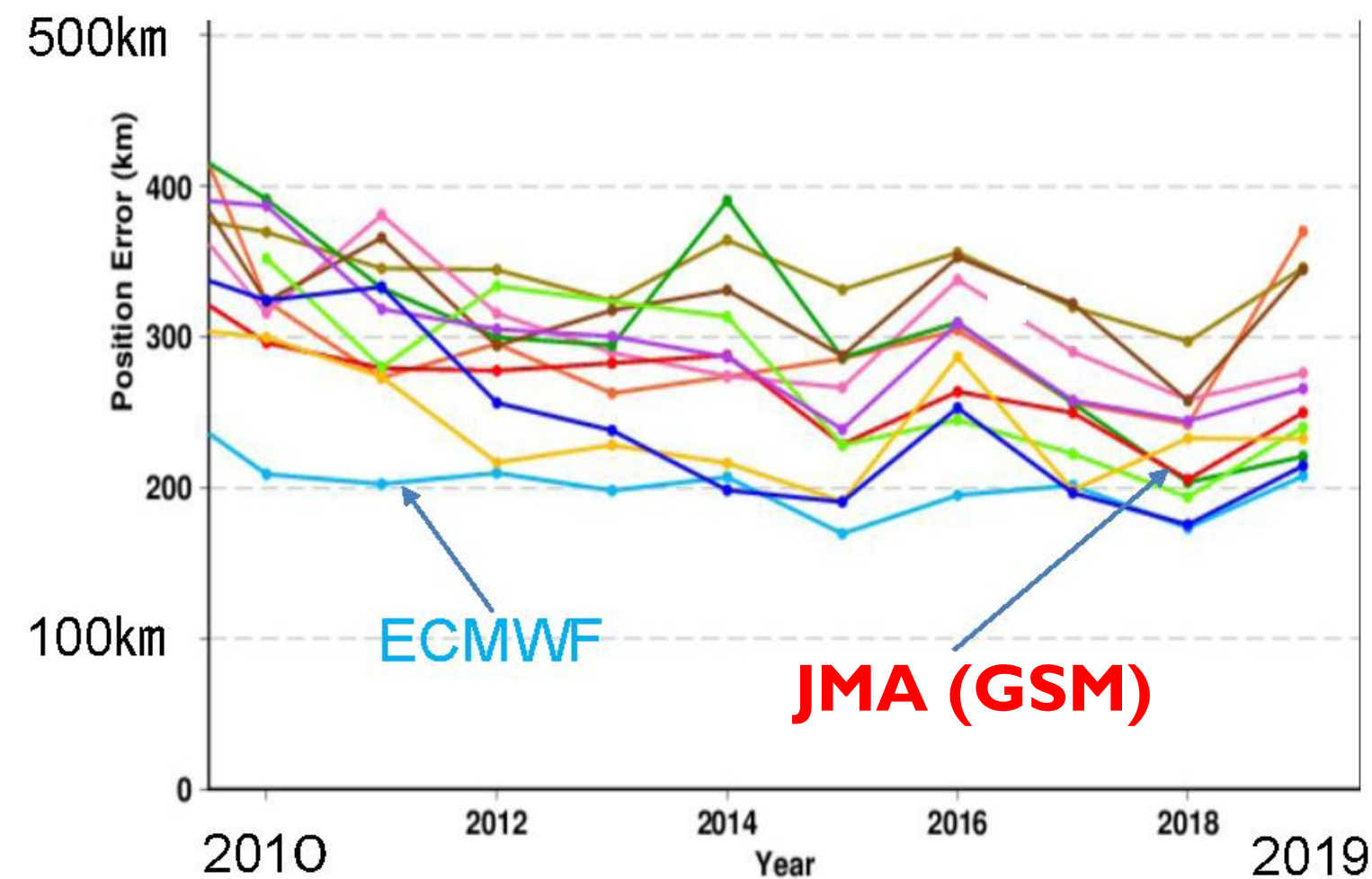
- Improved accuracy in forecasting the path of typhoons **three days ahead**
 - ✓ Timelines for large-scale flooding in municipalities, etc., require precise wide-area evacuation, etc., with a narrowing of the area about three days in advance.
 - ✓ Improved typhoon forecast error of about 100 km for the next 3 days (currently over 200 km)
 - ✓ Rain and storm surge forecasts associated with typhoons lose value when path forecasts are off, so the first and most important step is to improve the accuracy of path forecasts
- Provide "more appropriate boundary values" for meso-models
- Prerequisites: Ensuring stable operations, cost of proper operation and development, reliability of daily forecasts.

Typhoon Hagibis, 2019

- Caused extensive flooding over a wide area of Japan
- MSM accurately represents topographic precipitation
- The center position is good for GSM



Changes in the Accuracy of Typhoon Track Prediction over the Past Decade (International comparison)



- The accuracy of typhoon path prediction by numerical forecast centers in various countries continues to improve (Yamaguchi, 2017), while the improvement trend has slowed in recent years.
- Top center accuracy has been stagnant for the past decade, and **breakthroughs are needed**.

- ✓ Northwest Pacific Region
- ✓ 72-hour forecast
- ✓ Noncommon sample

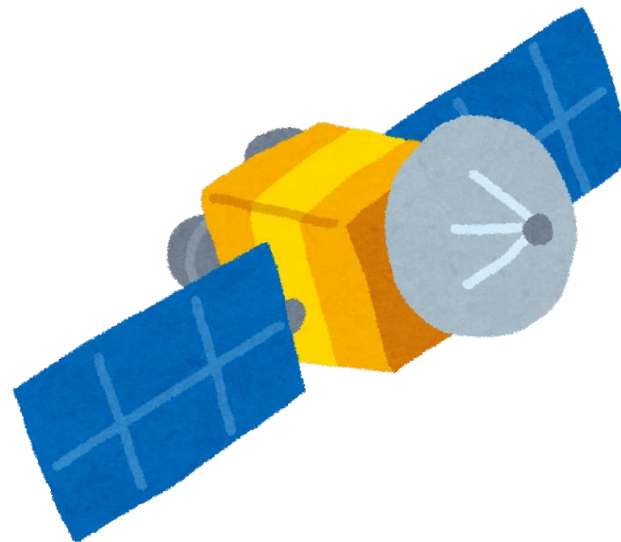
Key Issues in Forecast Model Development

1. Improved parameterization
 - ✓ Various previous studies suggest that the impact is significant.
 - ✓ First estimate to further exploit the potential of the observed data (performance in representing the phenomenon)
 - ✓ Addressing various problems (gray zone issues) caused by higher resolution
2. Upgrading to higher resolution
 - ✓ TYMIP (Nakano et al., 2017, GMD) suggests the effect of higher resolution (7 km)
 - ✓ Horizontal grid spacing of 10 km or less by 2030 (JMA)
3. Evaluation and verification methods, progress in understanding error generation mechanisms, etc.
 - ✓ Establishment of a method for verifying typhoon structure and winds over the ocean flowing through the typhoon
 - ✓ Analysis of causes of path prediction errors
 - ✓ Predictability studies (shift to probabilistic forecasting once the limitations of deterministic forecasting are understood)

Issues in the Use of Satellite Data for Numerical Forecasting

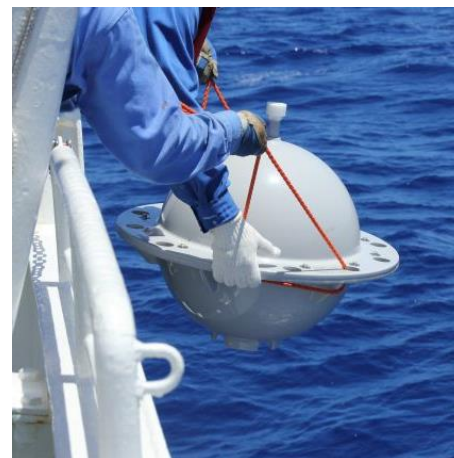
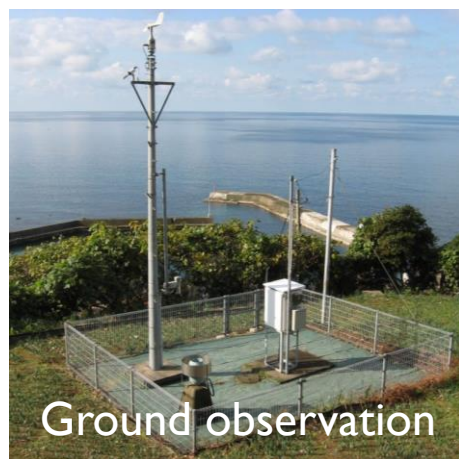
Satellite data for numerical forecasting

- ◆ Creation of initial condition for numerical forecast (data assimilation)
 - ✓ Objective: To improve the accuracy of initial condition
 - ✓ Brightness temperature, atmospheric tracking wind, GNSS signal delay, etc. are used for assimilation.
- ◆ Creation of boundary condition for numerical forecast
 - ✓ Sea surface temperature, sea ice, snow cover, ground albedo, aerosols, etc.
- ◆ Model validation



Observations used for numerical forecasting

Direct Observation



Unattended buoy for marine meteorological observation



Remote sensing and remote observation



WIND PROFILER

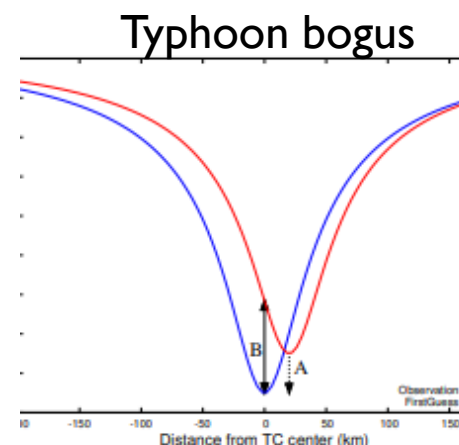


Doppler radar



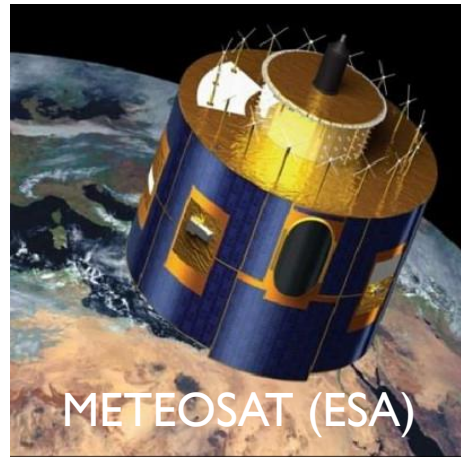
GNSS

Quasi-observation

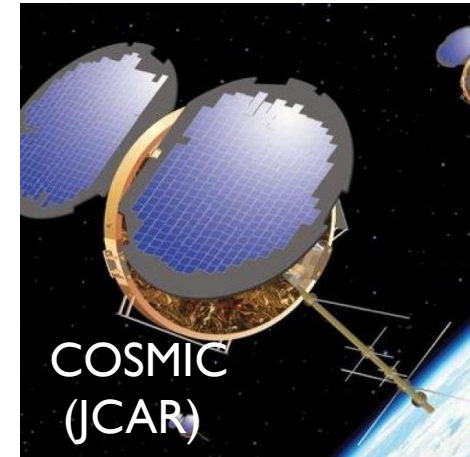


Observations used for numerical forecasting

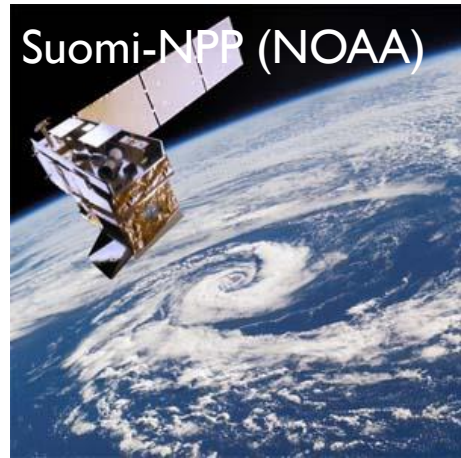
Geostationary Orbit Satellite



GNSS Radio Occultation

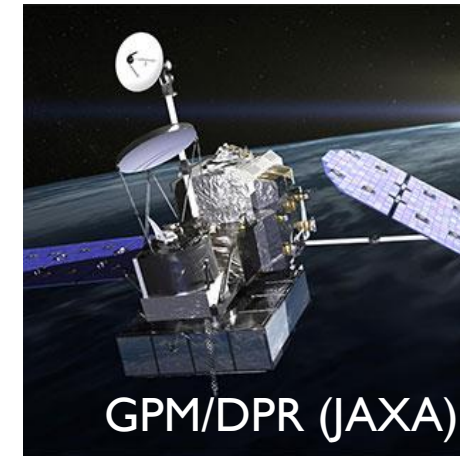
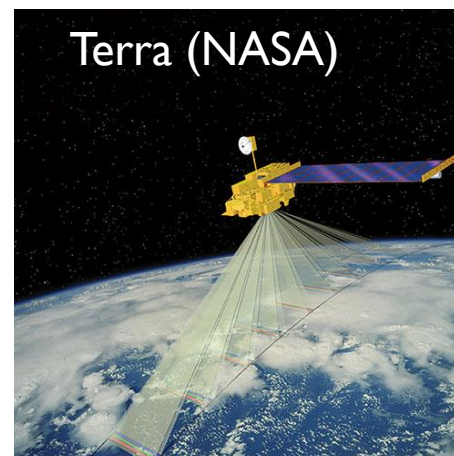
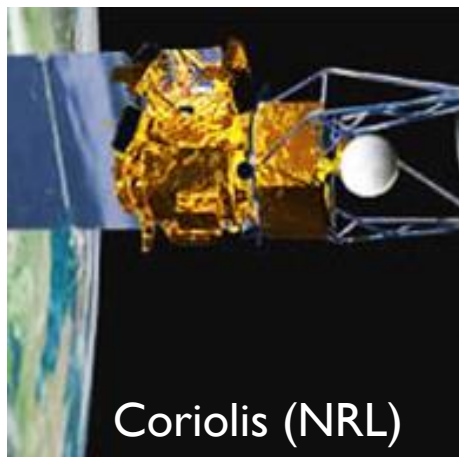


Operational for JMA (Low Orbit Satellite)



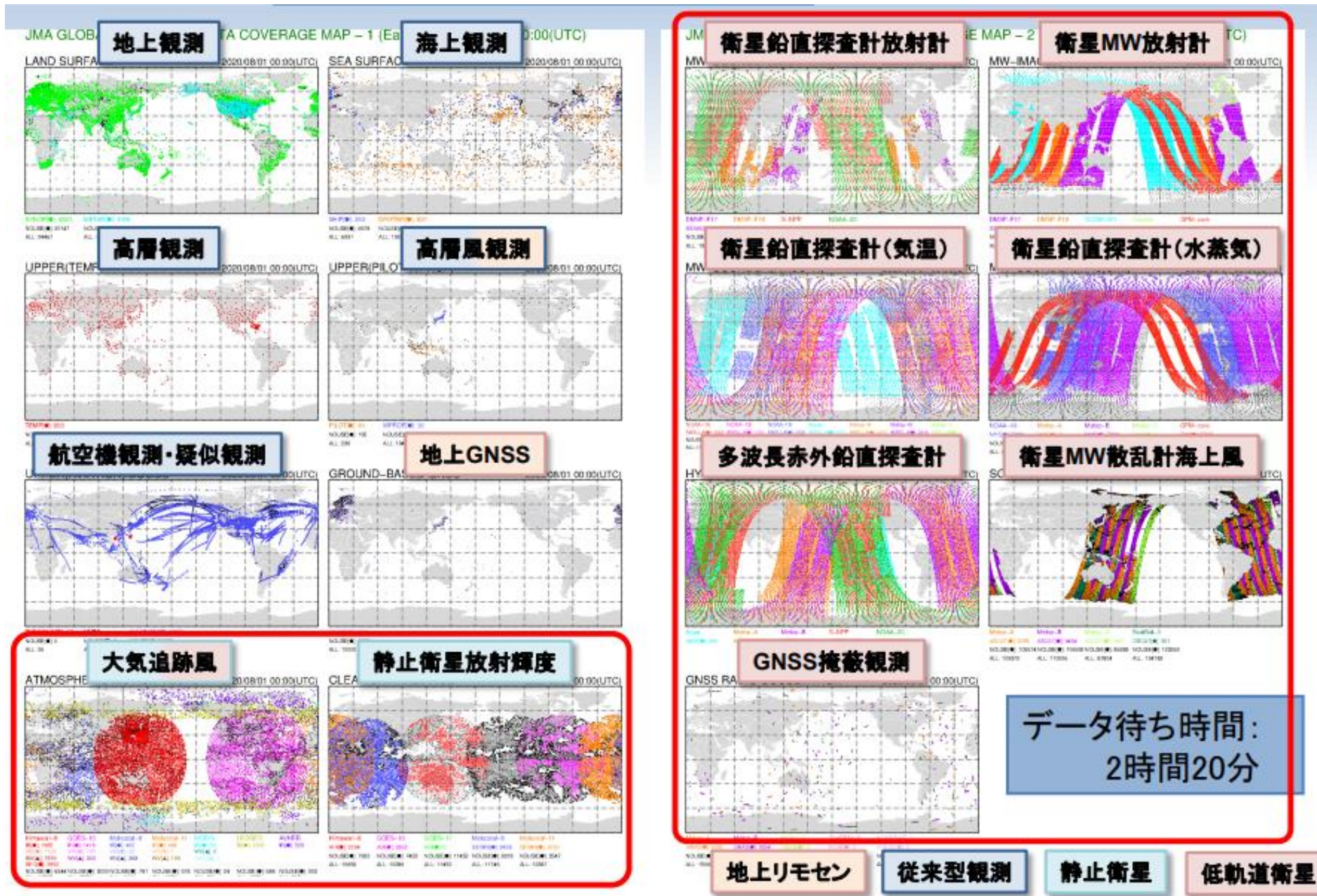
Observations used for numerical forecasting

Earth observation satellite (Low Orbit Satellite)



Distribution of assimilation observation data

Example



JMA
Aug., 1, 2020 UTC

Use of Satellite Data in Numerical Forecasting by JMA

Type	Satellite/Sensor	Global analysis	Mesoscale analysis	Local analysis
Microwave sounder	NOAA15,18,19, Metop-A,-B,-C(※),Aqua/AMSU-A	Brightness temperature	Brightness temperature	Brightness temperature
	NOAA18,19,Metop-A,-B,-C(※)/MHS	Brightness temperature	Brightness temperature	Brightness temperature
	DMSP-F17,18/SSMIS	Brightness temperature	—	—
	Suomi-NPP,NOAA20/ATMS	Brightness temperature	—	—
	Megha-Tropiques/SAPHIR	Brightness temperature	—	—
Infrared sounder	Aqua/AIRS	Brightness temperature	—	—
	Metop-A,B/IASI	Brightness temperature	—	—
	Suomi-NPP,NOAA20/CrIS	Brightness temperature	—	—
Microwave imager	DMSP-F17,18/SSMIS	Brightness temperature	Brightness temperature Precipitation intensity	Brightness temperature
	GCOM-W/AMSR2	Brightness temperature	Brightness temperature Precipitation intensity	Brightness temperature Soil moisture content
	GPM-core/GMI	Brightness temperature	Brightness temperature Precipitation intensity	Brightness temperature
Visible/Infrared imager	Himawari-8	Brightness temperature of clear sky, Wind	Brightness temperature of clear sky, Wind	Brightness temperature of clear sky, Wind
	GOES-16	Brightness temperature of clear sky, Wind	—	—
	Meteosat-8,11	Brightness temperature of clear sky, Wind	—	—
	NOAA15,18,19,Metop-A,-B/AVHRR	Atmospheric wind	—	—
	Aqua,Terra/MODIS	Atmospheric wind	—	—
	LEO GEO composite image	Atmospheric wind	—	—
Scatterometer	Metop-A,-B,-C(※)/ASCAT	Wind above sea	Wind above sea	Soil moisture content
	ScatSat-1/OSCAT	Wind above sea	—	—
GNSS occultation	Metop-A,-B/GRAS	Refractive angle	Refraction factor	—
	TerraSAR-X/IGOR	Refractive angle	Refraction factor	—
	TanDEM-X/IGOR	—	Refraction factor	—
	COSMIC/IGOR	Refractive angle	Refraction factor	—
Precipitation radar	GPM/DPR	—	Relative humidity	—

(※) Metop-C/AMSU-A, MHS,
ASCAT are used for global analysis.

Challenges in assimilating and using satellite data

- ◆ Support for new satellite data and upgrading of existing data processing
 - ✓ Gathering the latest information on new satellites and sensors
 - ✓ Detailed understanding of data characteristics (Development of quality control and bias correction process, setting of observation error)
 - ✓ Assimilation impact experiments and evaluations (Observing System Experiment (OSE) is the basis (global → meso → local analysis))
- ◆ Early and stable data acquisition
 - ✓ Request and build a fast and stable observation, communication, and processing system
 - Multiple pathways: GTS, Internet, telecommunications satellites
 - Utilization of DBNet (direct reception network)
 - ✓ Early acquisition of new data
- ◆ Cooperation with international satellite processing and data assimilation centers

Brightness temperature data types and main issues

Type	Satellite/Sensor	Assimilation	Short-term issues	Medium- long-term issues
Microwave Temperature sounder	AMSU-A, ATMS, SSMIS, MWTS2, MTVZA-GY	Assimilating the clear sky	New Sensor Use of unused channels	Global assimilation Lower channel land assimilation Small satellite
Microwave Water vapour sounder	MHS, ATMS, GMI, SSMIS, SAPHIR, MWHS2, MTVZA- GY	Global assimilation (patially)	All-day assimilation (remaining)	Application of global assimilation to meso and local analysis Small Satellite
Microwave imager	AMSR2, GMI, SSMIS, WindSat, MWRI, MTVZA-GY	Global assimilation (patially)	New Sensor	Application to meso and local analysis
Hyperspectral Infrared sounder	IASI, AIRS, CrIS, HIRAS, IKFS2, GIIRS	Assimilating the clear sky Temperature channel	More Channels Addition of water vapor channel	Application to meso and local analysis New sensor Interchannel error correlation Global assimilation
Geostationary Satellite Infrared brightness temperature (CSR,ASR)	Himawari, Meteosat, GOES, GK2A	Assimilating the clear sky, Assimilation of terrestrial data for ch with sensitivity to lower layers	New Sensor Satellite switchover	Use of CO2 Channels Global assimilation
Common type		Outer Loop Hybrid assimilation (global) Variational Bias Correction (meso)	Observation error Observation density Optimization RTTOV update Model layer change support	Observation error Observation density Optimization Observation error phase function

Satellite data use issues that should promote collaboration

◆ Assimilative use of new satellite data

✓ Hyperspectral infrared sounder

- Global trend toward geostationary satellites (GIIRS/FY-4A (China), IRS/MTG-S (Europe))
- Increase in the number and performance of sensors onboard polar-orbiting satellites (HIRAS/FY-3D (China), IKFS-2/Meteor-M N2 series (Russia), IASI-NG (France))

✓ Doppler Wind Rider : High assimilation impact in ECMWF, operational used

- ALADIN/Aeolus (Europe)

✓ GNSS occultation observation

- Commercialization using small satellites by private companies

✓ Microwave observation by small satellite

- TROPICS (USA)
- U.S. agencies also participate in data evaluation

✓ Long elliptical orbit (Tundra) satellite

◆ Knowledge of international trends, data quality and usage is important

✓ Selection of satellite data to be assimilated and used with priority

Satellite data use issues that should promote collaboration

◆ Advanced data assimilation (pre)processing

✓ Global assimilation of brightness temperature

□ Microwave

- Under operation by JMA (global analysis only, mainly water vapor CH): AMSR2/GCOM-W, GMI/GPM, SSMIS/DMSP, MHS/NOAA, MHS/Metop, WindSat/Coriolis, MVRI/FY-3C, SSMIS/DMSP, MHS/NOAA, MHS/Metop, WindSat/Coriolis, MVRI/FY-3C
- Meso- and local analysis and global assimilation of temperature sounders are not yet available.

□ Infrared

- Assimilation of Himawari 8 data (under developing)

✓ Use of microwave radiometers and hyperspectral infrared sounders on land

- Utilization of Dynamic Emissivity (Microwave)

✓ Observation error optimization (observation error correlation)

✓ Assimilation and utilization of high-resolution and high-frequency observation data

✓ Polar-orbiting satellite hyperspectral infrared sounder (IASI, CrIS)

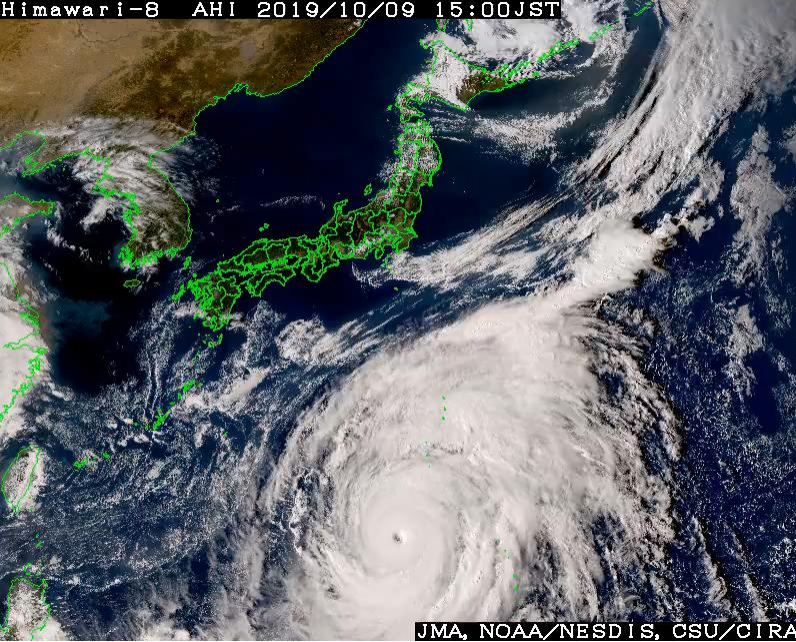
- Not yet fully utilizing the data.

◆ Knowledge of quality control, bias correction, and observation error settings are important

Key Issues



- ◆ International collaboration for satellite data assimilation is important
- ◆ Assimilative use of new satellite data
 - ✓ Sharing of the world's most advanced new satellite and sensor data
 - ✓ Knowledge of data quality and usage
 - ✓ Selection of satellite data with high assimilation impact and to be prioritized for use
- ◆ Advanced data assimilation (pre)processing
 - ✓ Detailed understanding of data characteristics
 - Characterization of data that are difficult to assimilate and use (land, sea ice, cloud area data, etc.)
 - Quality control, bias correction, evaluation of observation errors
 - ✓ Joint development of new quality control, bias correction, and observation error setting methods
 - Observation data affected by cloud coverage and ground surface
 - Assimilation and utilization of high-resolution and high-frequency observation data, etc.
 - ✓ Development and accuracy verification of observation operators (radiative transfer model (RTTOV), etc.)



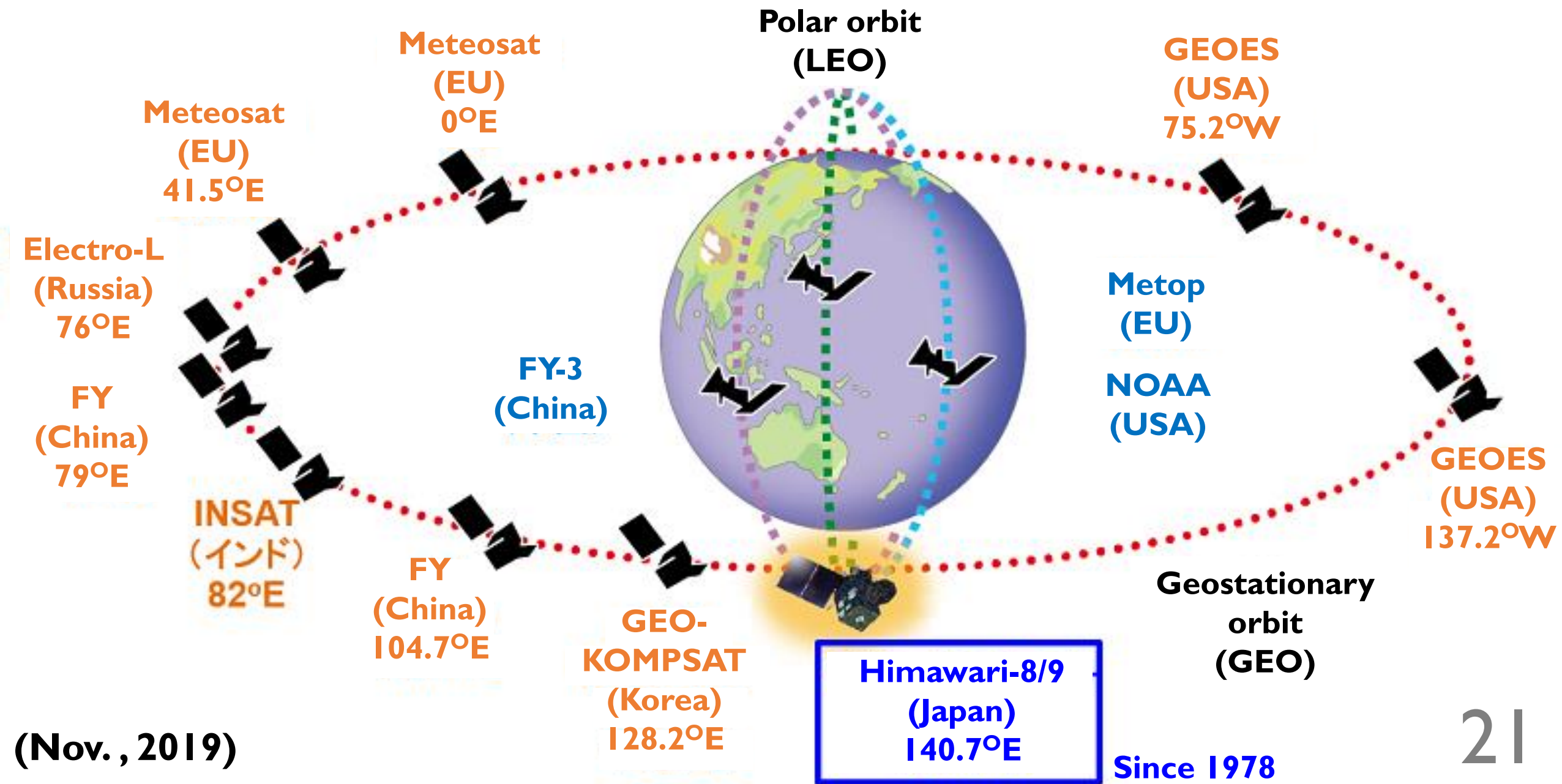
JMA, NOAA/NESDIS, CSU/CIRA

Hagibis, 2019

(Saffir-Simpson hurricane wind scale; SSHWS)

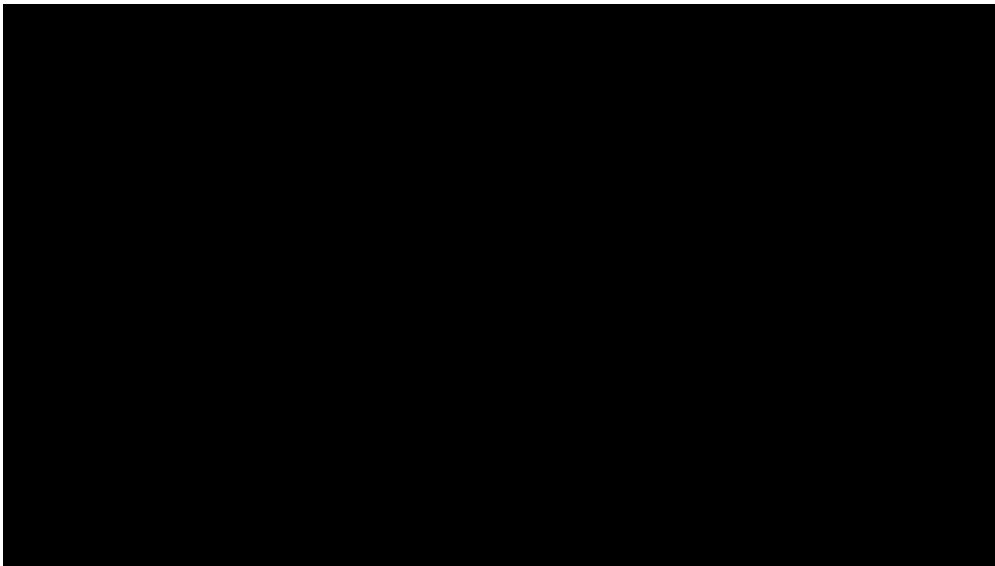
Geostationary Meteorological Satellite Himawari-8/9

Global Weather Satellite Network



Himawari-8/9

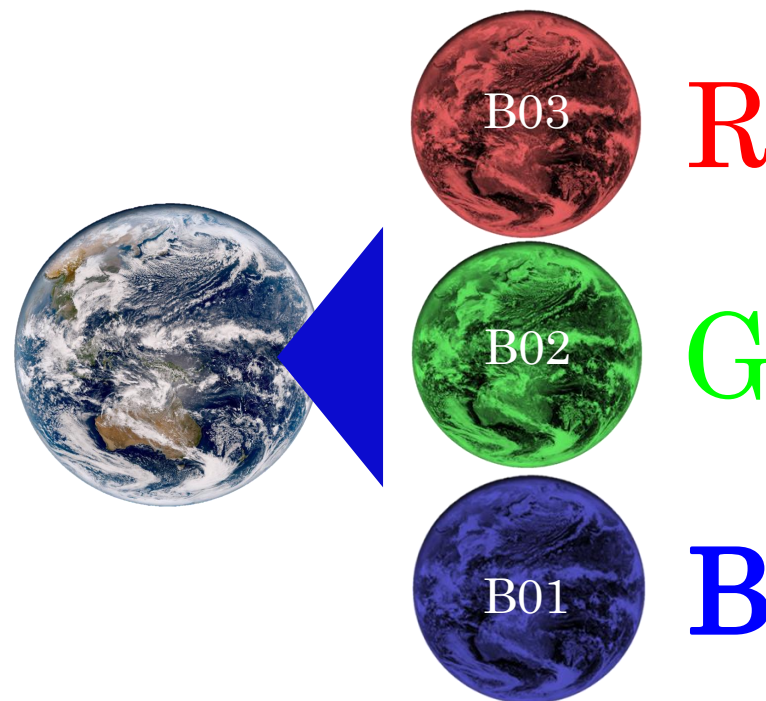
	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	
Himawari 8	Satellite Manufacturing and launch						Observation								Standby							
Himawari 9	Satellite Manufacturing and launch								Standby						Observation						Standby	



Overview of Observation Functions

Himawari Standard Data

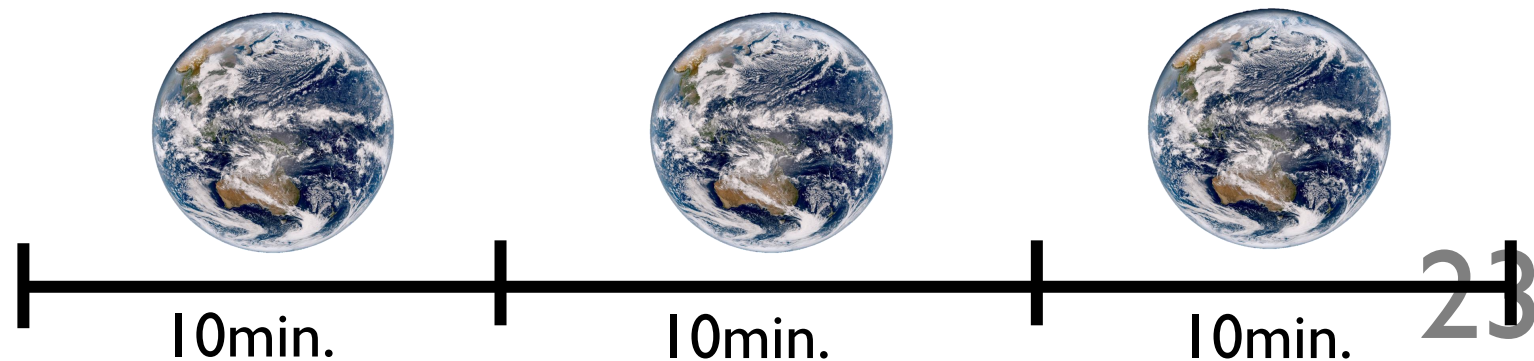
Wave length (μm)	Band number	An example of a possible application Example
0.47	1	Vegetation, aerosol
0.51	2	Vegetation
0.64	3	Vegetation
0.86	4	Vegetation, aerosol
1.6	5	classification of the sutras and their teachings
2.3	6	cloud radius
3.9	7	Lower clouds and fog
6.2	8	upper water vapor
6.9	9	upper-middle level water vapor
7.3	10	mid-level water vapor
8.6	11	SO ₂
9.6	12	Total ozone
10.4	13	Cloud Top Information
11.2	14	sea surface water temperature
12.4	15	sea surface water temperature
13.3	16	Cloud top altitude



Spatial resolution

VIS : 0.5 ~ 1 km
NIR/IR : 1 ~ 2 km

Observational intervals and areas



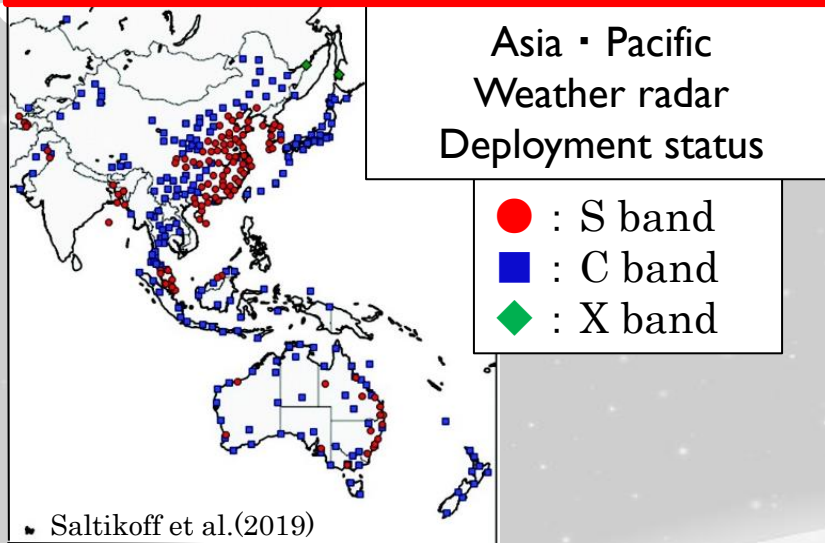


Development of Satellite Rainfall Products using Himawari Meteorological Satellite Data

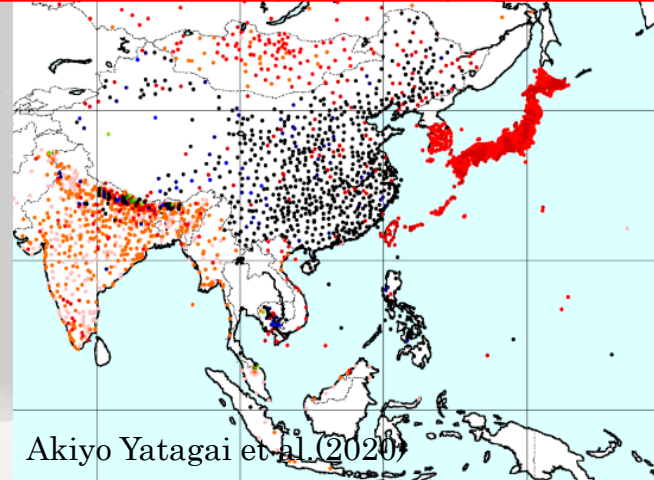
2 Background



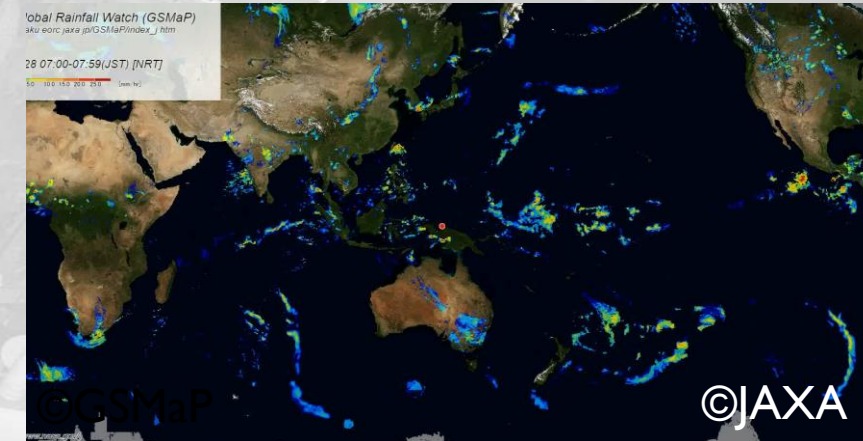
Lack of weather radar



Lack of ground rain gauge



Satellite precipitation lacking accuracy



Meteorological observation networks are still inadequate

Unable to be used as a quantitative value in rainfall-runoff calculations because of low accuracy

The development of new high-precision satellite rainfall is expected to significantly expand the range of applications for technology.

Ex.) rainfall-runoff calculations, water resources management, weather control

2 Purpose

6 The goal

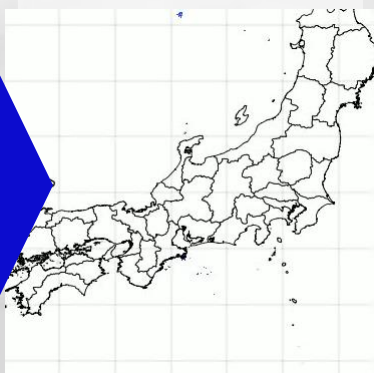
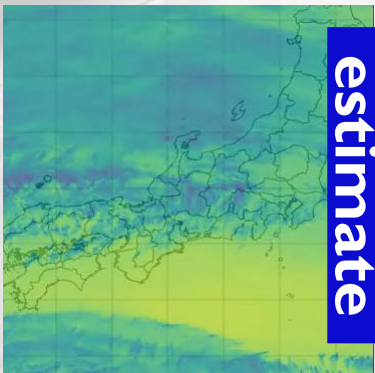
Development of satellite rainfall products that can be used as quantitative values contributing to hydrological analysis in the Asia-Pacific region

1. Creating a deep learning model in Japan, which has high-quality weather data

2. Apply the created deep learning model to the Himawari observation area

Cloud image

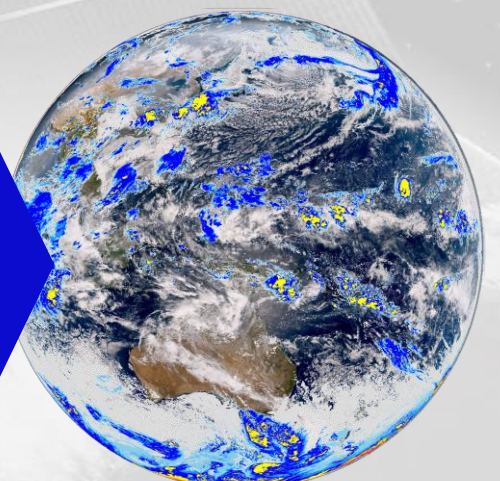
Rainfall



rainfall
estimate



rainfall
estimate



7 Input data

Brightness temperature data (Observation data of Himawari)

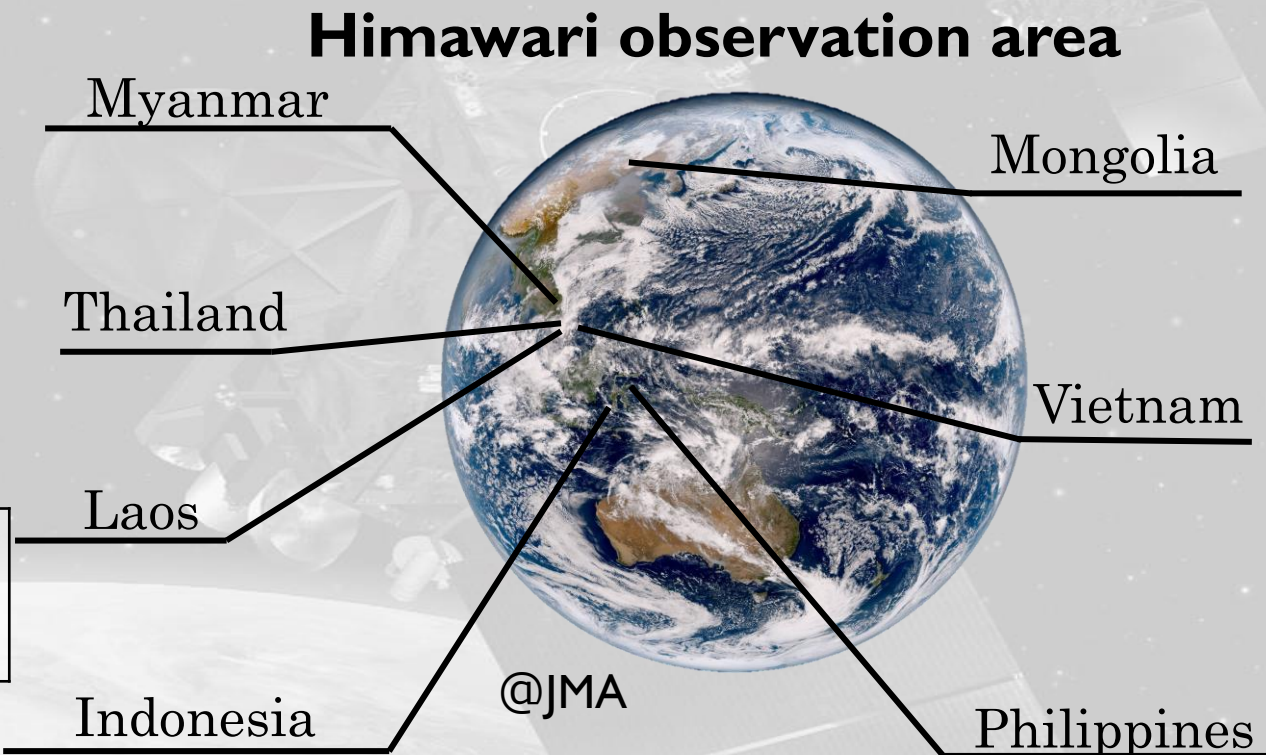
Spatial resolution : 2km
Observation frequency : 10min

Himawari 8/9 gridded data
(CEReS@Chiba univ. Japan)

Input data

Geographic information data

Elevation	MERIT DEM (Tokyo univ. Japan)
latitude and longitude	



Rainfall data(supervised data)

**Supervised
data**

Spatial resolution : 1km
Observation frequency : 10min

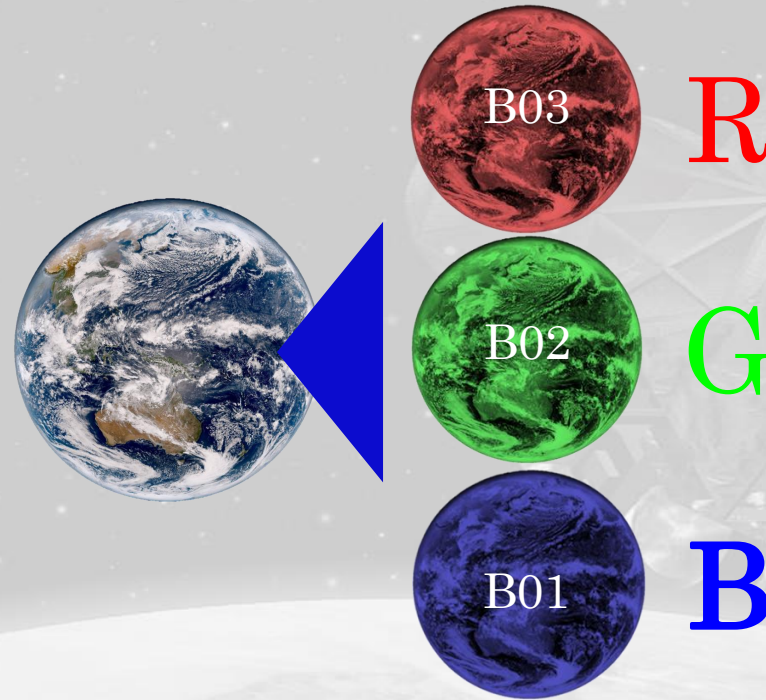
National Synthetic Radar GPV 1km
Precipitation Intensity Data (JMA)

2 Data



Himawari Standard Data

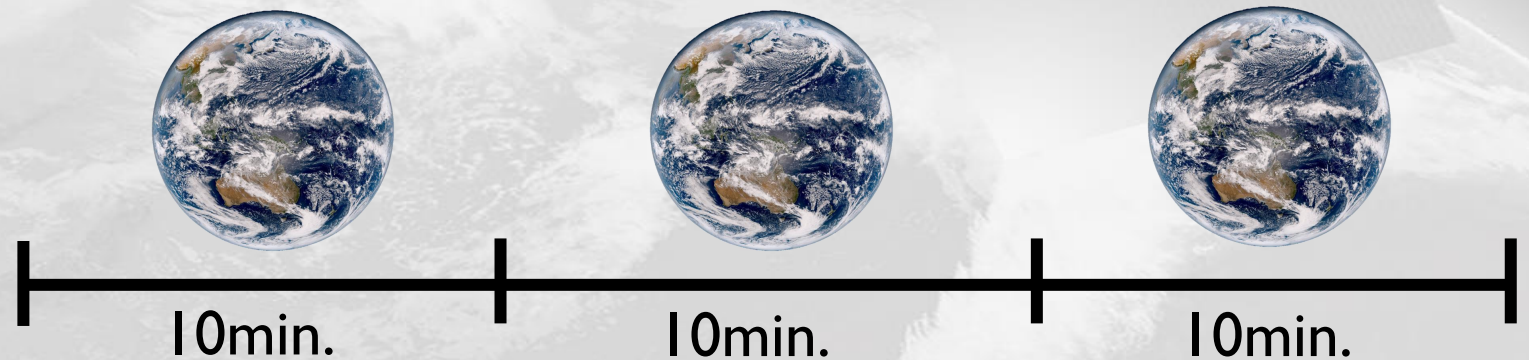
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Spatial resolution

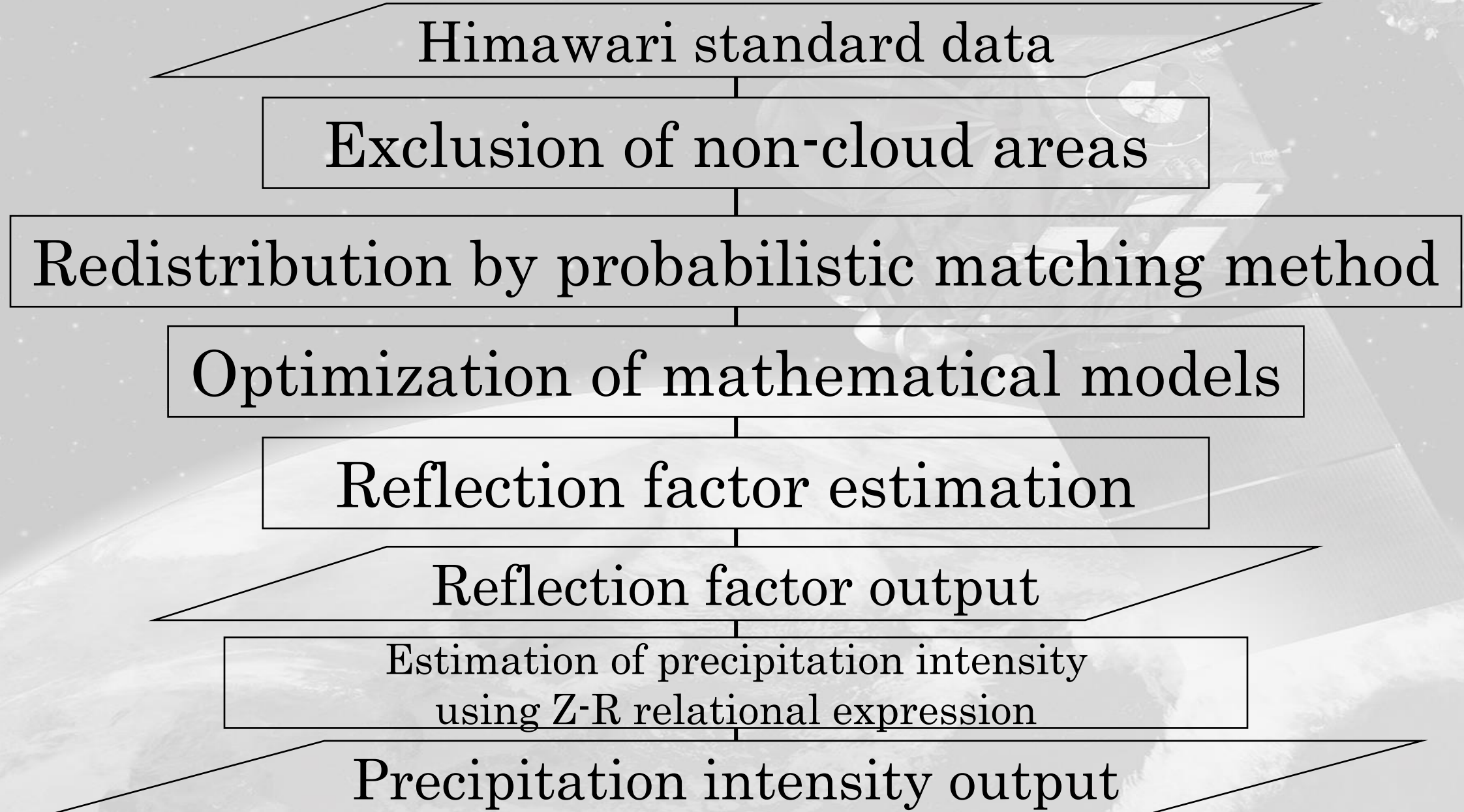
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Observational intervals and areas



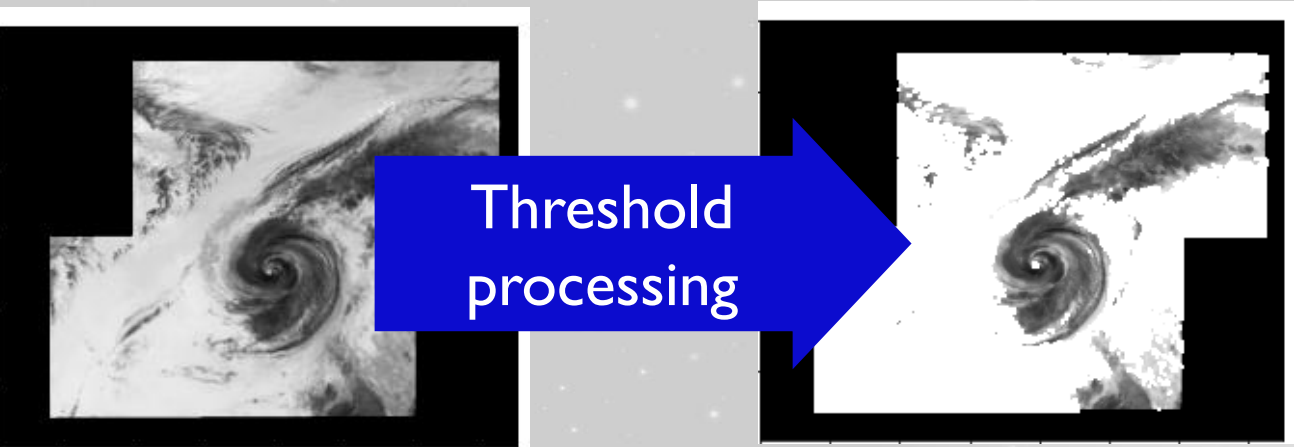
Radar reflex factor

5 Estimation of reflection factor

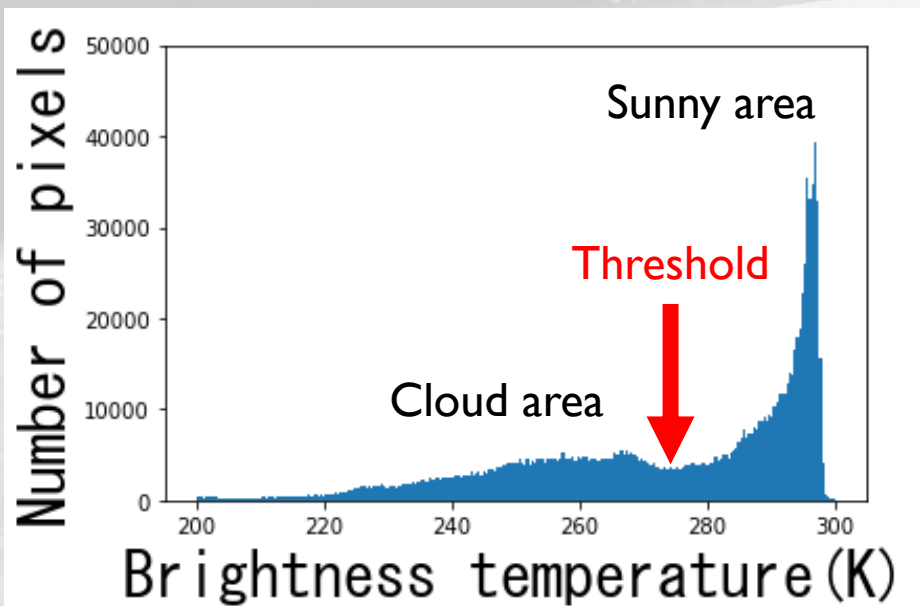


Exclusion of non-cloud areas

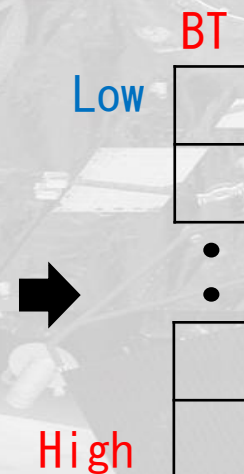
probabilistic matching method

A diagram showing the process of thresholding. On the left is a grayscale satellite image of a cyclone. A large blue arrow points from this image to the right, where the same image is shown with a white threshold applied, making the cloud areas white and the background black.

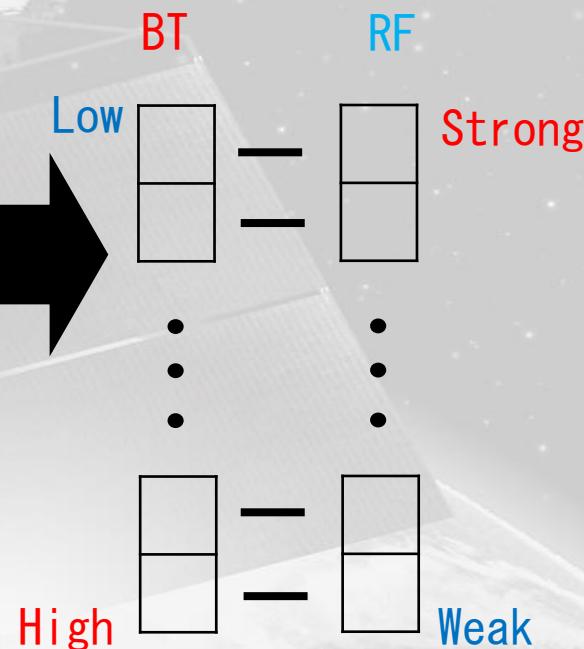
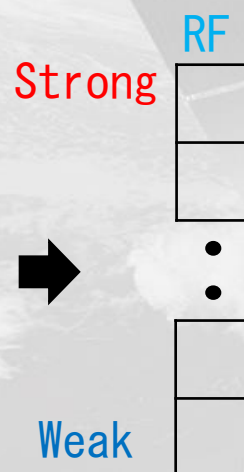
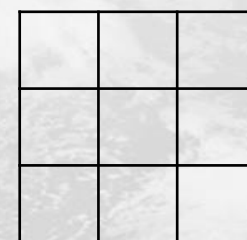
Threshold
processing



Brightness
temperature



Reflection
factor



5 Reflection factor estimation



Mathematical model

Previous studies

$$R = w_1 + w_2 \exp[w_3 (T_b + w_4)^{w_5}] \quad \text{Yang Hong et al. (2004)}$$

R : precipitation intensity(mm/h)

T_b : brightness temperature(K)

This study

w_i : parameters

$$Z = w_1 + w_2 \exp[w_3 (T_b + w_4)^{w_5}]$$

Z : radar reflection factor(mm^6/m^3)

T_b : brightness temperature(K)

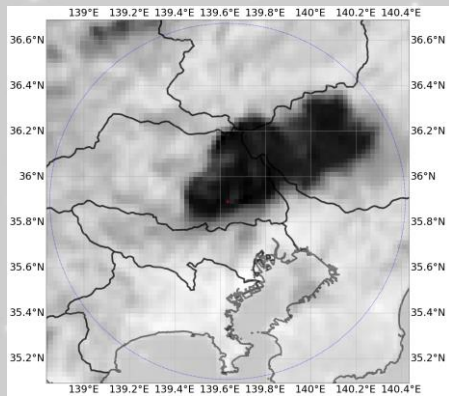
w_i : parameters

5 Reflection factor estimation

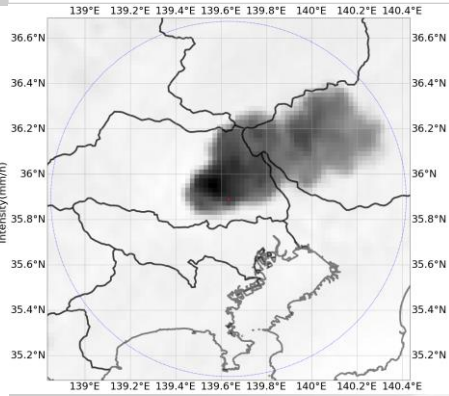


Himawari Standard Data

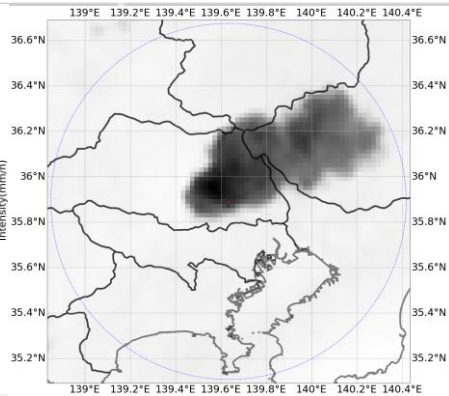
Band07



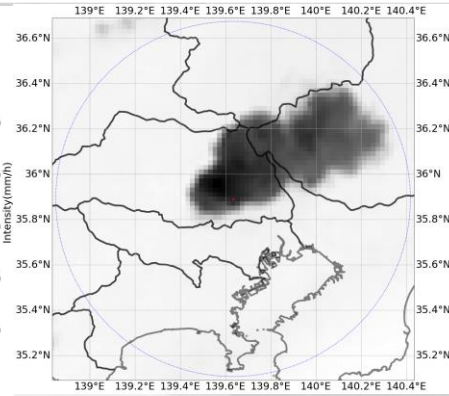
Band08



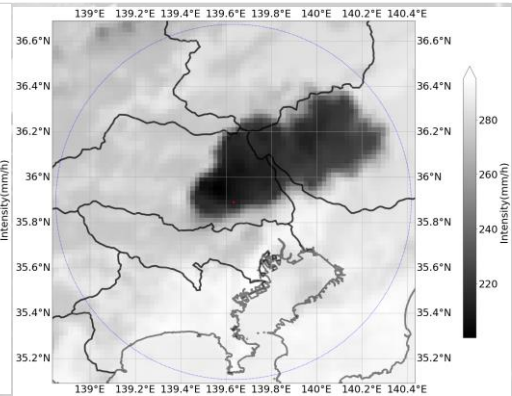
Band09



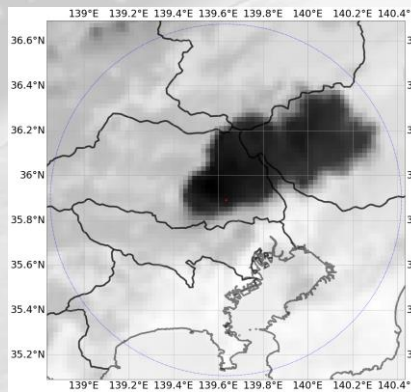
Band10



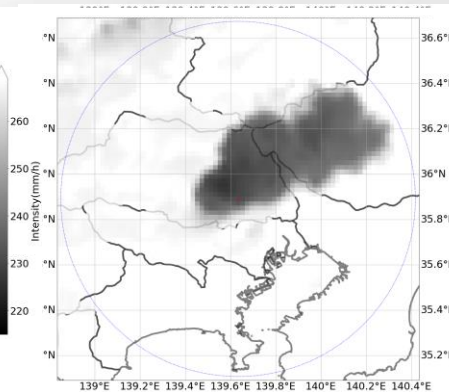
Band11



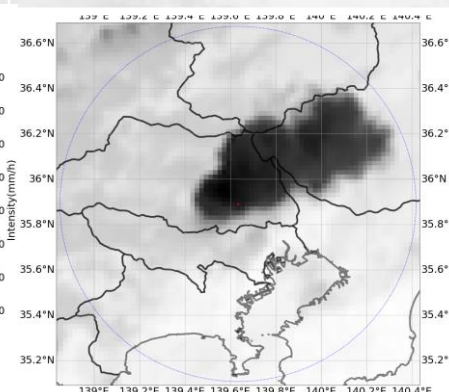
Band12



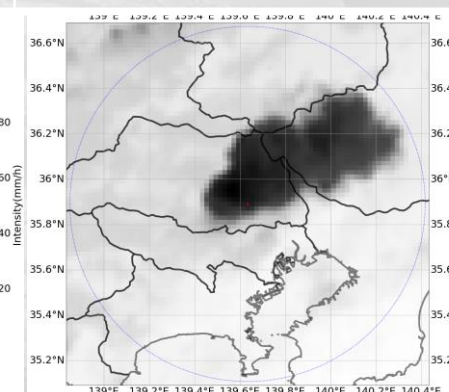
Band13



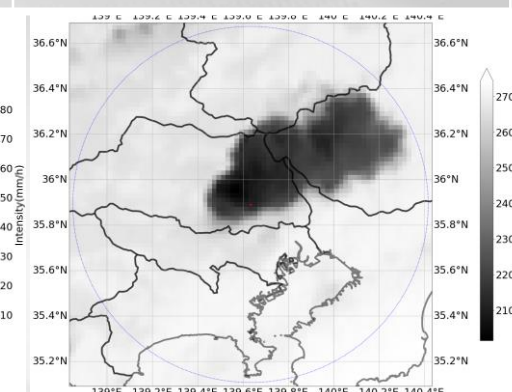
Band14

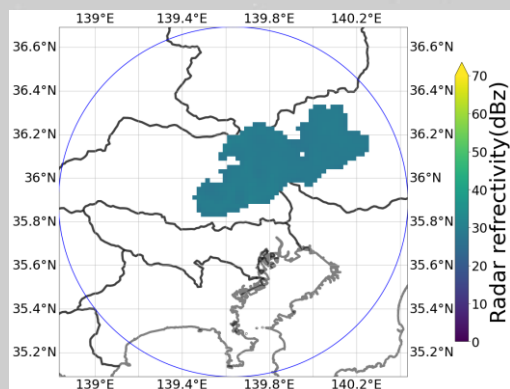
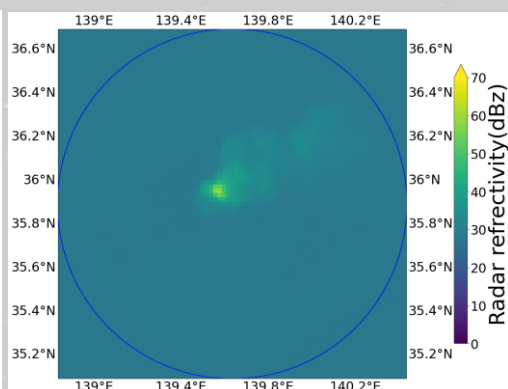
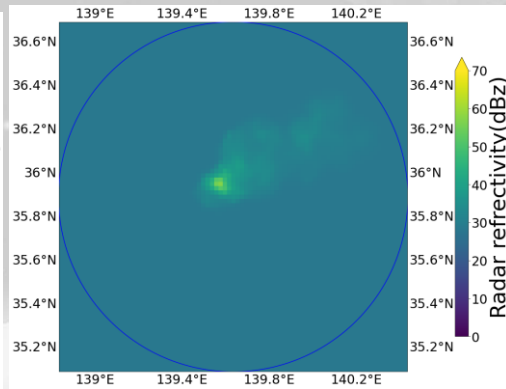
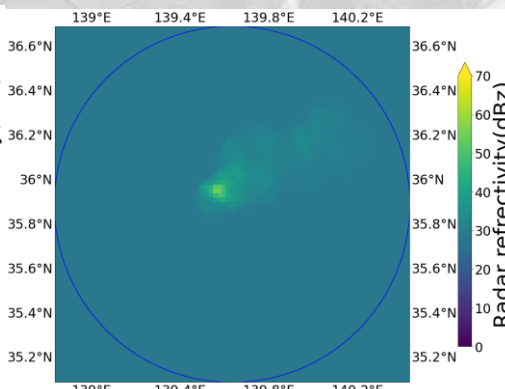
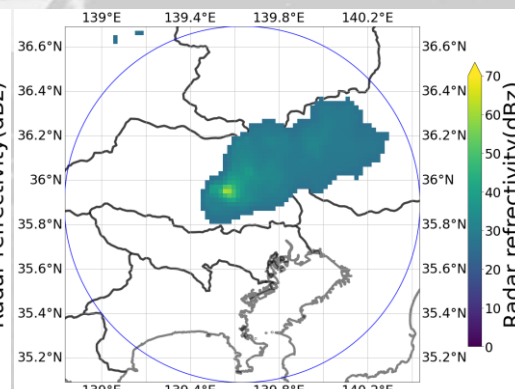
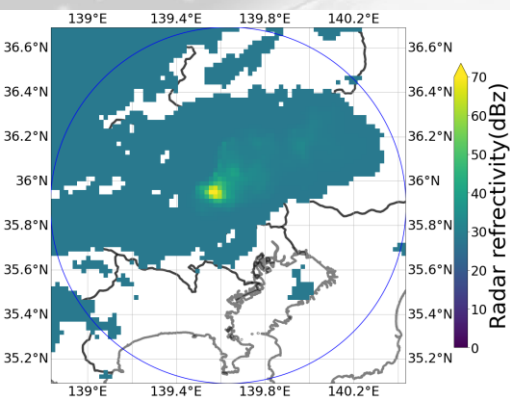
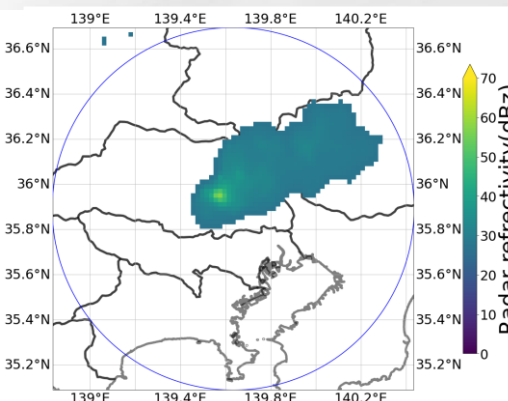
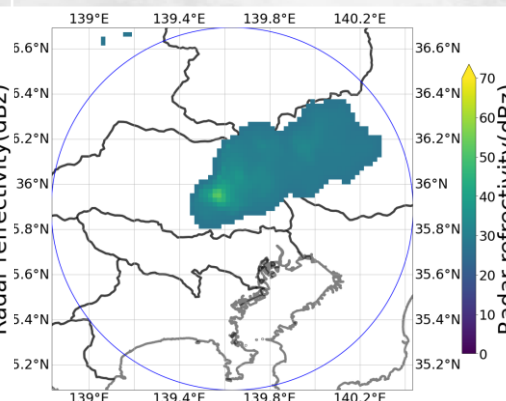
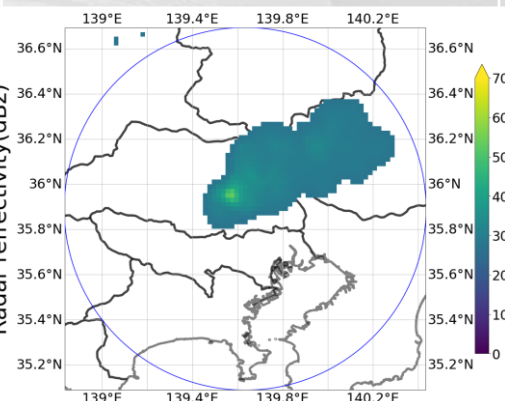
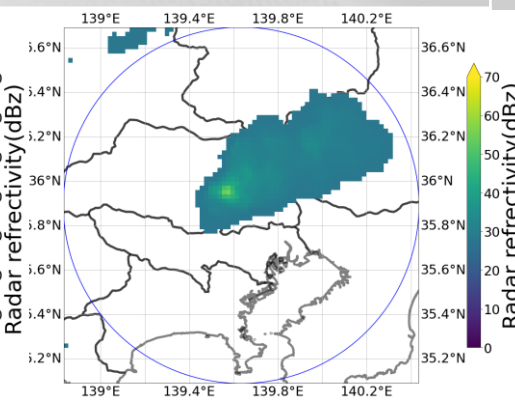


Band15



Band16



Reflection factor estimation **results****Band07****Band08****Band09****Band10****Band11****Band12****Band13****Band14****Band15****Band16**

5 Precipitation intensity estimation



Z-R relational expression

$$Z = 200R^{1.6}$$

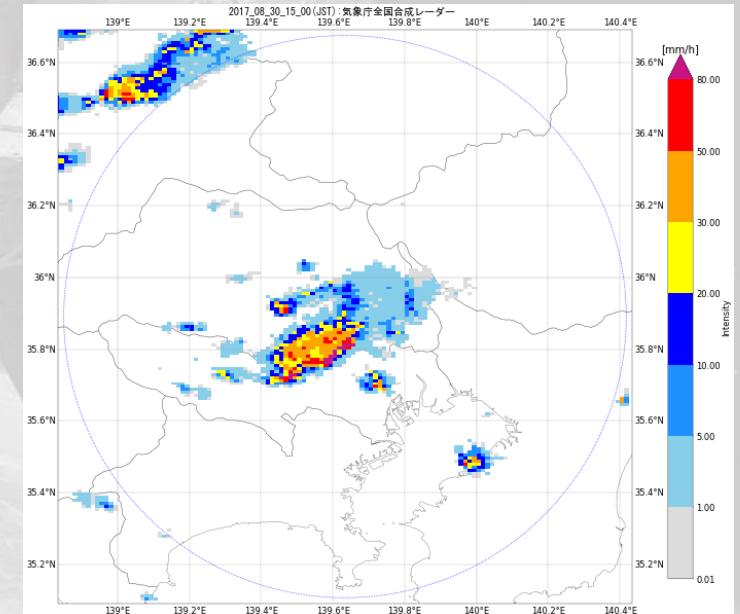
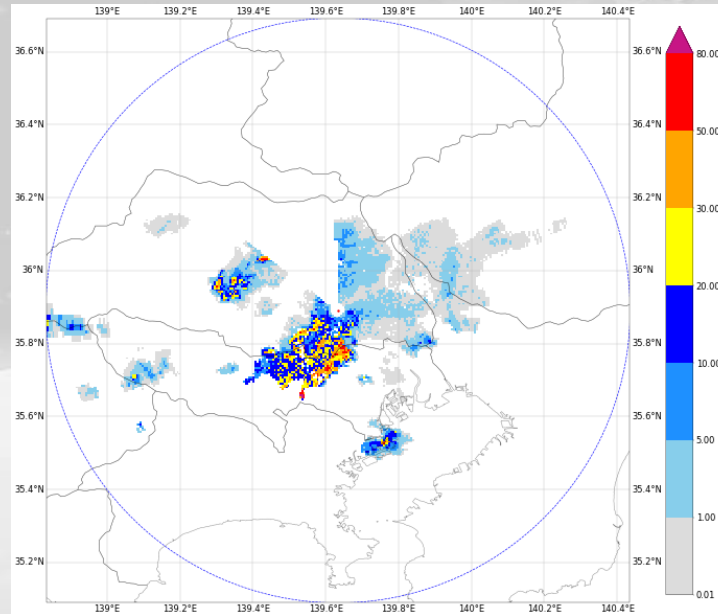
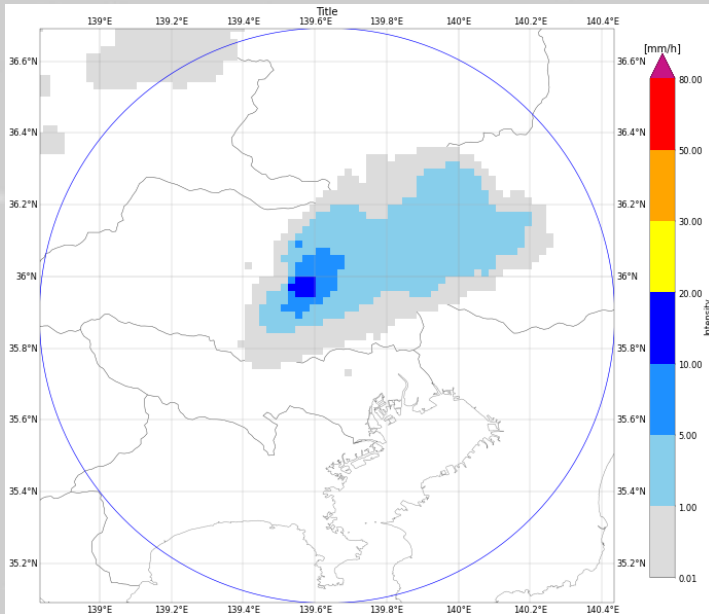
Z: radar reflection factor(mm^6/m^3)

R: precipitation intensity(mm/h) J.S.Marshall et al.(1955)

Estimation result

X-band MP radar

C-band radar GPV



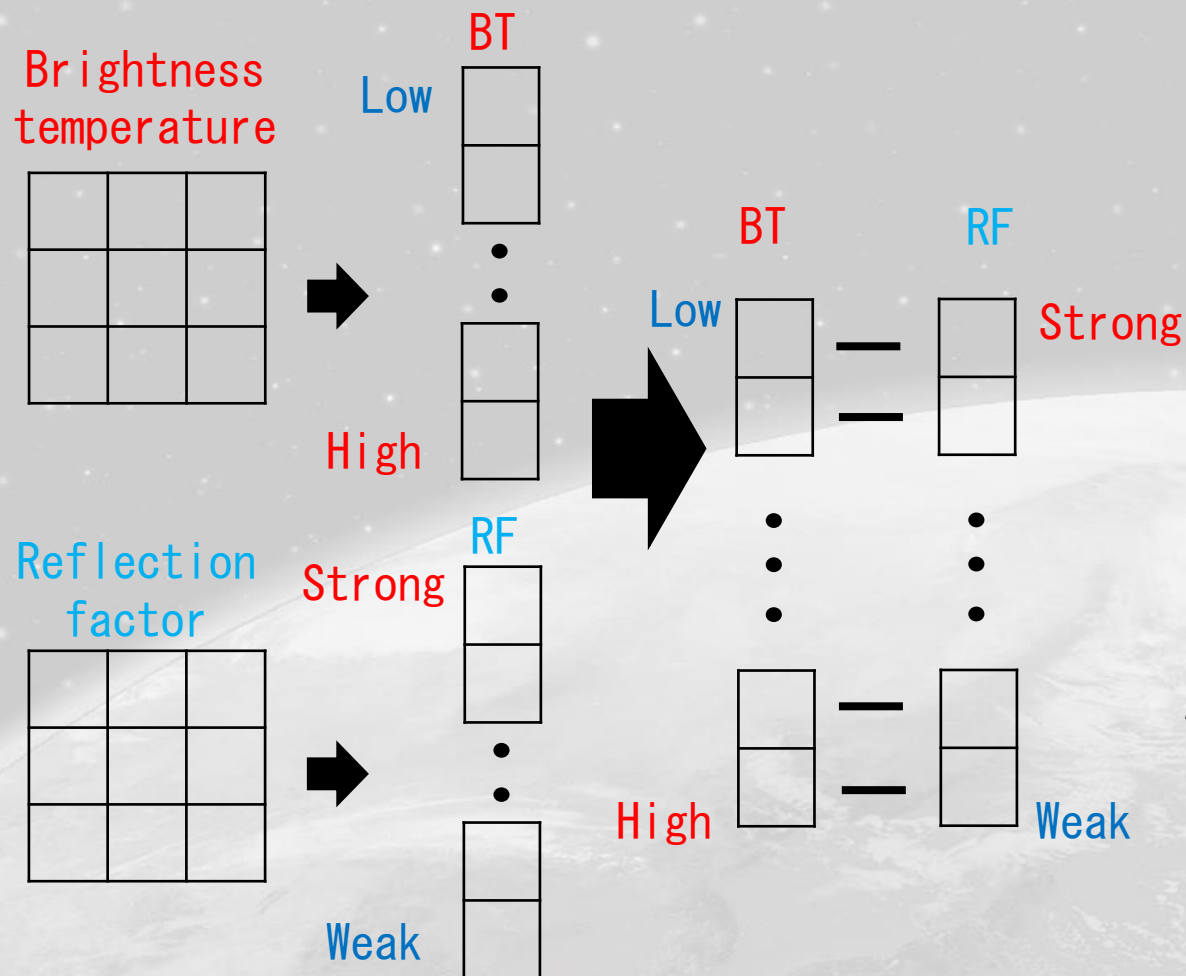
	Band07	Bnad08	Band09	Band10	Band11	Band12	Band13	Band14	Band15	Band16
RMSE (mm/h)	5.44	47.05	93.12	67.14	45.72	17.89	34.35	40.27	22.31	150.55
MAE (mm/h)	2.82	2.68	3.51	3.15	8.08	2.19	6.96	7.54	6.08	15.00

Nadaraya Watson

10 Precipitation intensity estimation



Probabilistic matching method



Nadaraya-Watson estimator

$$E(Y|X = x) = \frac{\sum_{i=1}^n K_{\sigma}(x^*, x_i) y_i}{\sum_{j=1}^n K_{\sigma}(x^*, x_j)}$$

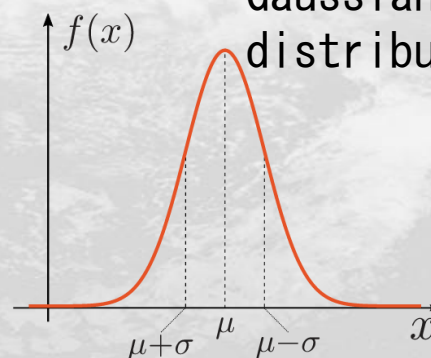
kernel function

$$K_{\sigma}(x^*, x_j) = \exp\left(\frac{-1}{2\sigma^2} \|x^* - x_j\|^2\right)$$

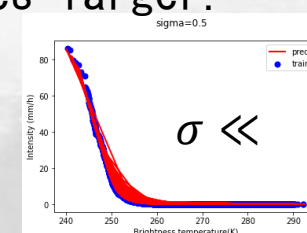
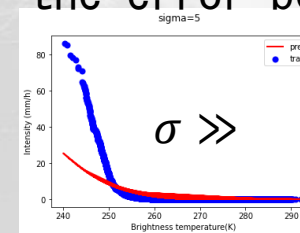
X : brightness temperature

Y : precipitation intensity

Gaussian distribution



When the bandwidth σ is large, the variance becomes smaller but the error becomes larger.



11 Result

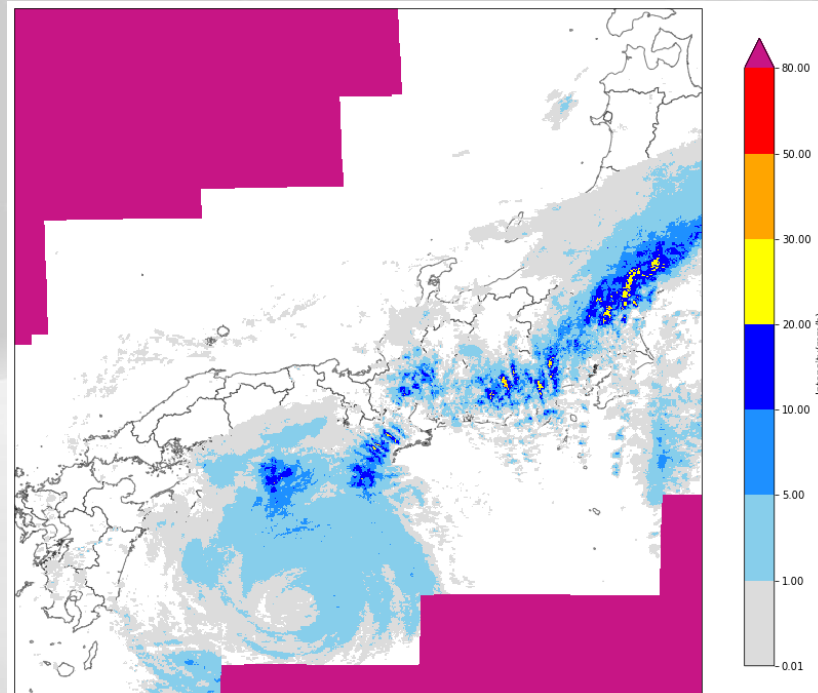
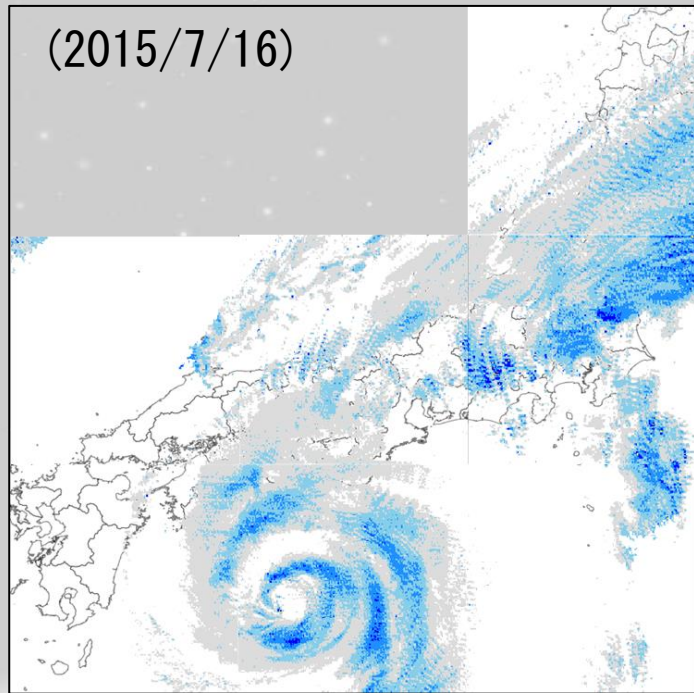


1 hour accumulated precipitation
(resolution 2km x 2km)

Estimated

Observed

(2015/7/16)



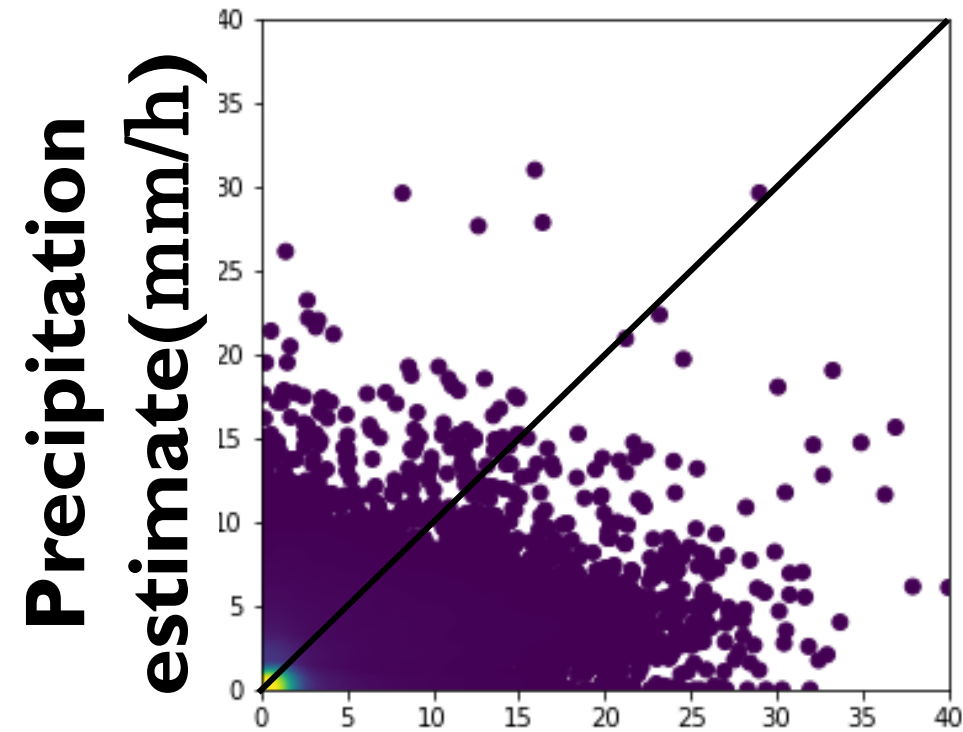
RMSE

MAE

2.060(mm/h)

1.029(mm/h)

Tendency of estimates
to be underestimates

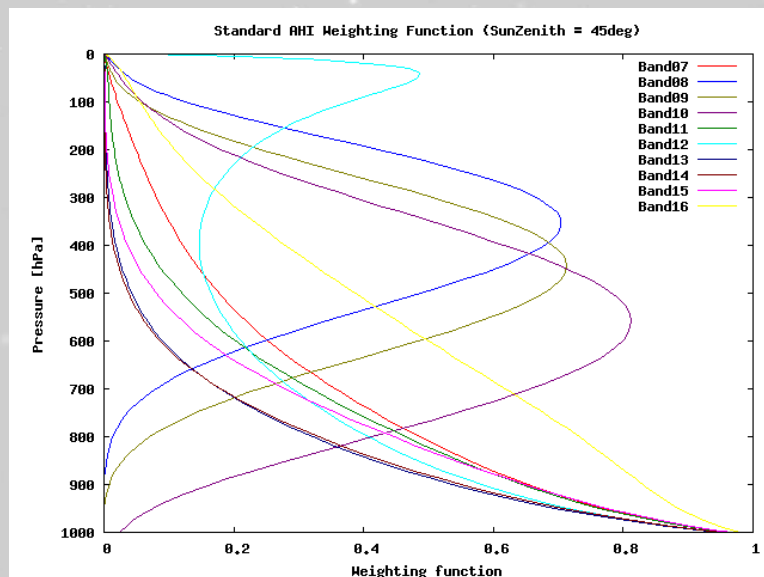


Precipitation estimate(mm/h)
Precipitation observed value(mm/h)

HiDREDv2

(HIMAWARI Data Rainfall Estimation using Deep learning ver.2)

Sensitive altitudes for each infrared wavelength band



1. Use cosine similarity to avoid high collinearity between bands

$$\cos(BT_1, BT_2) = \frac{BT_1 \cdot BT_2}{\|BT_1\| \|BT_2\|}$$

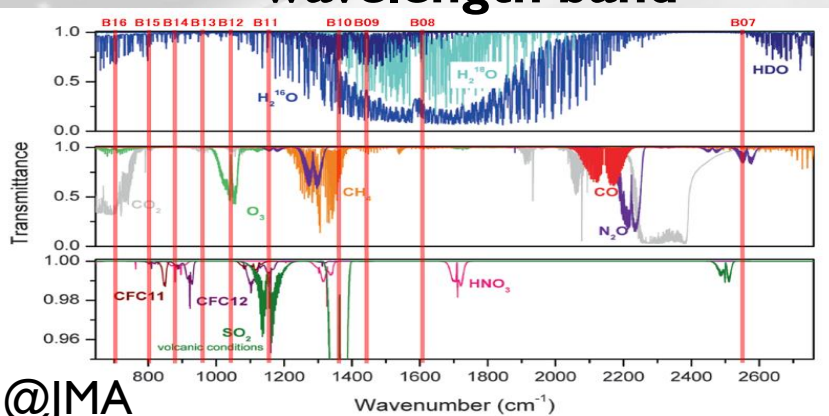
BT_1, BT_2 : single-band image

2. Calculate correlation between single-band, difference images and precipitation

absolute correlation coefficients of ≥ 0.25

IR data creates 5 channels

Sensitive gases in each infrared wavelength band



Upper water vapor

Upper and middle level water vapor Vertical distribution

Lower water vapor

Cloud top altitude

Cloud Optical Thickness

4 Loss function design



1

Weather satellite
(Himawari8,9)

cloud
grain

Brightness temperature

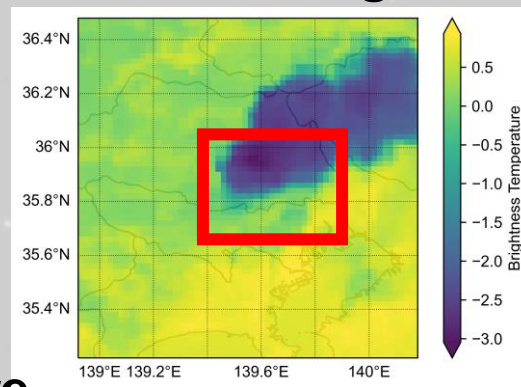
drizzle
grain

reflex
factor

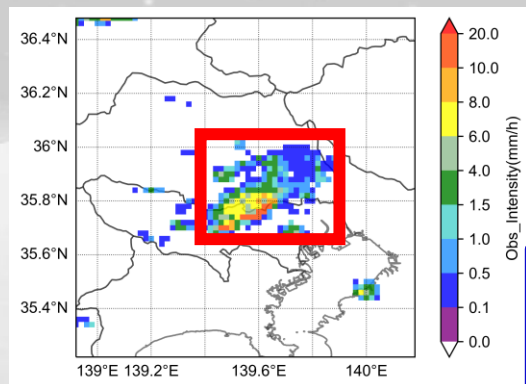
Rain
drops

Precipitation rate

Cloud image



Radar rainfall



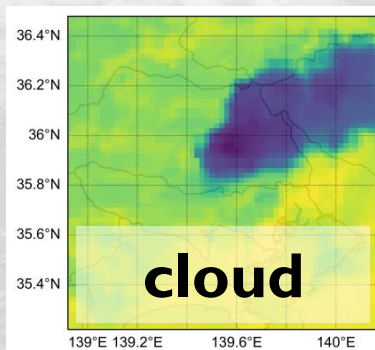
Proposed loss function

$$FSS_Loss_{(n)} = \frac{MSE_{(n)}}{MSE_{(n)ref}}$$

$$MSE_{(n)ref} = \frac{1}{N_x N_y} \sum_{i=1}^{N_x} \sum_{j=1}^{N_y} [O^2(n)_{i,j} + F^2(n)_{i,j}]$$

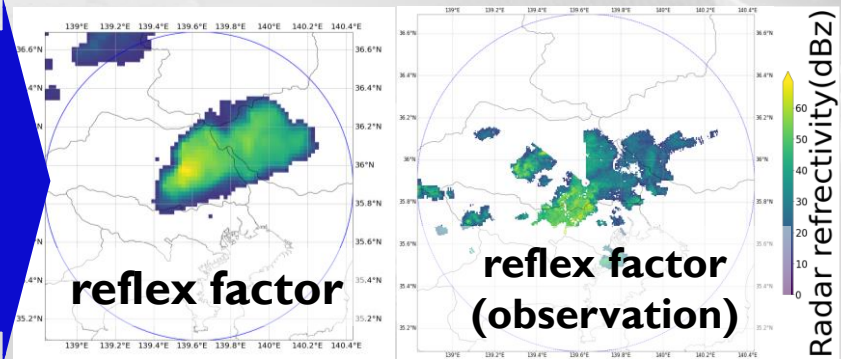
Estimation of reflection factors
more closely related to clouds

estimate

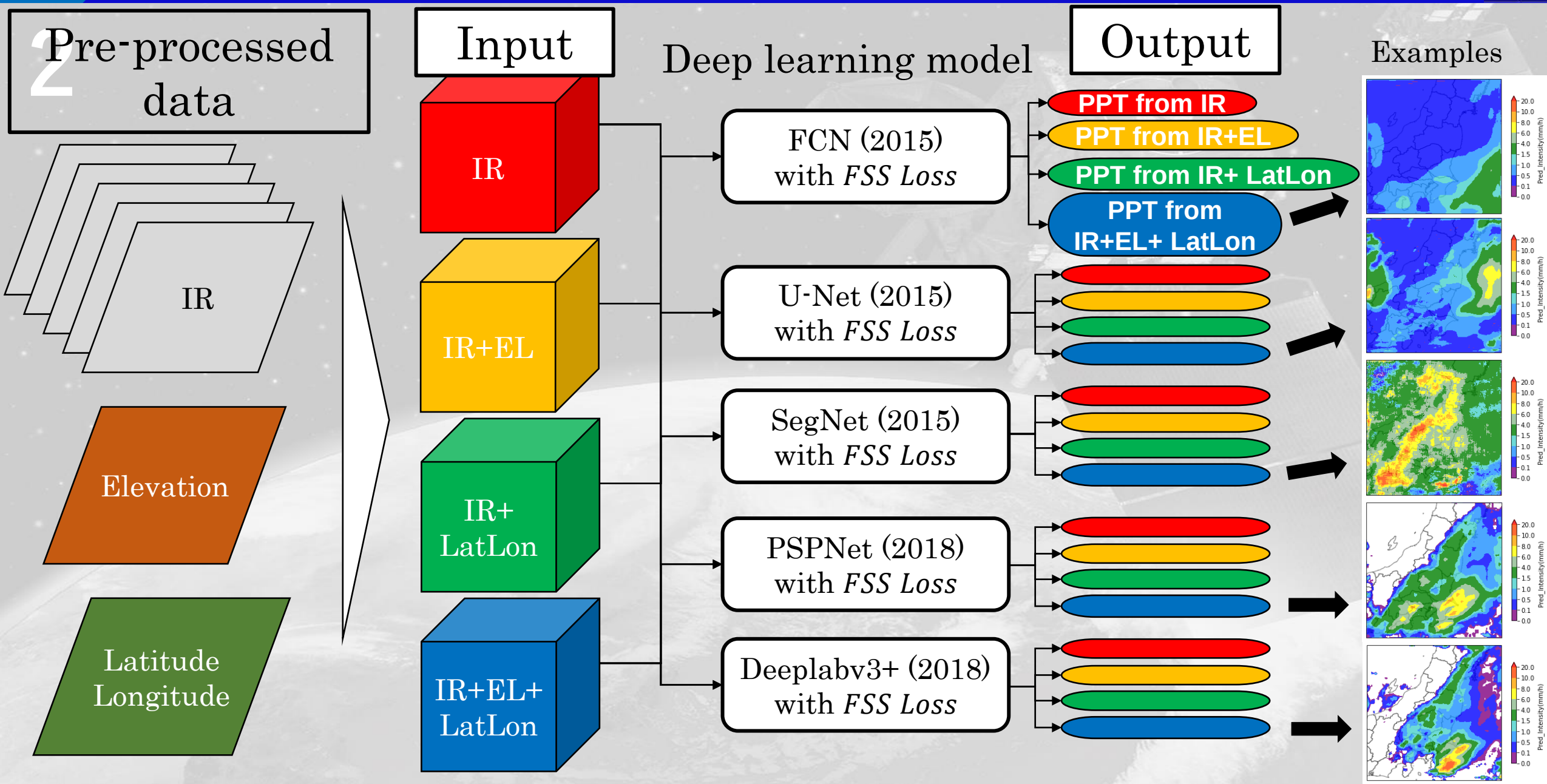


reflex factor

reflex factor
(observation)



4 Method 1 (Comparison of training data and model)

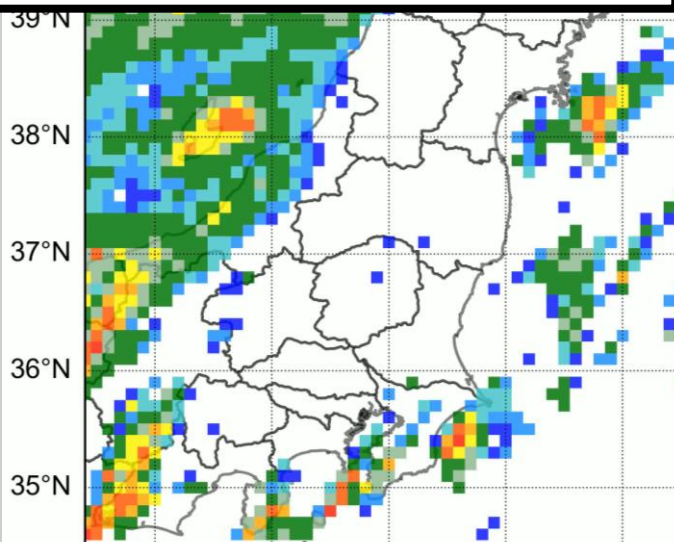


4 Result

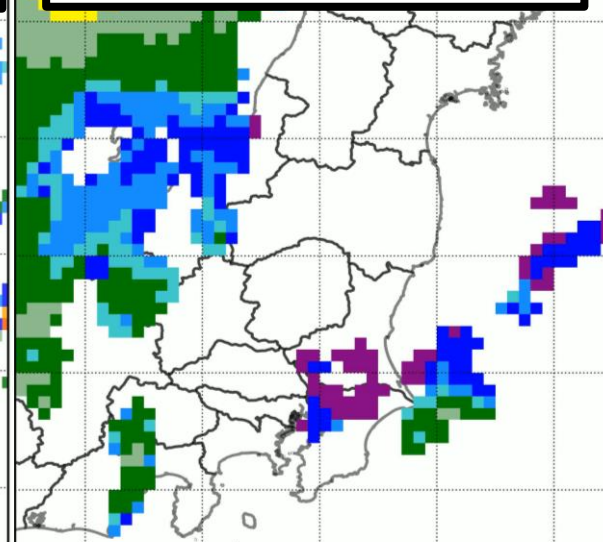
3



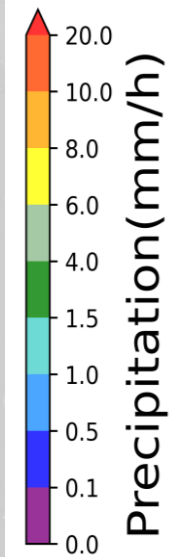
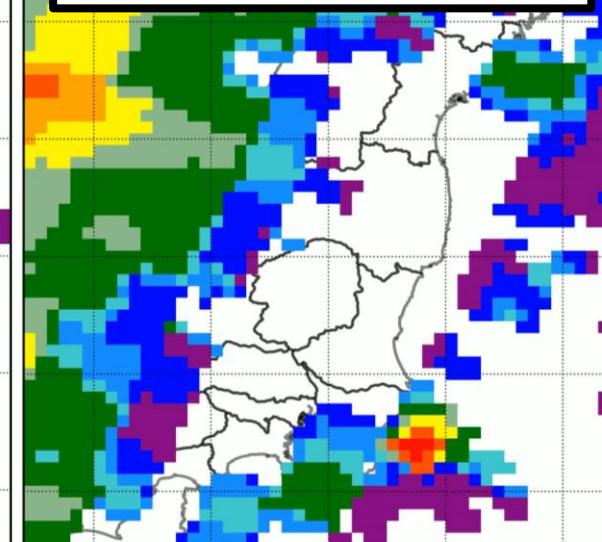
Ground truth (Radar)



GSMaP_NOWv6

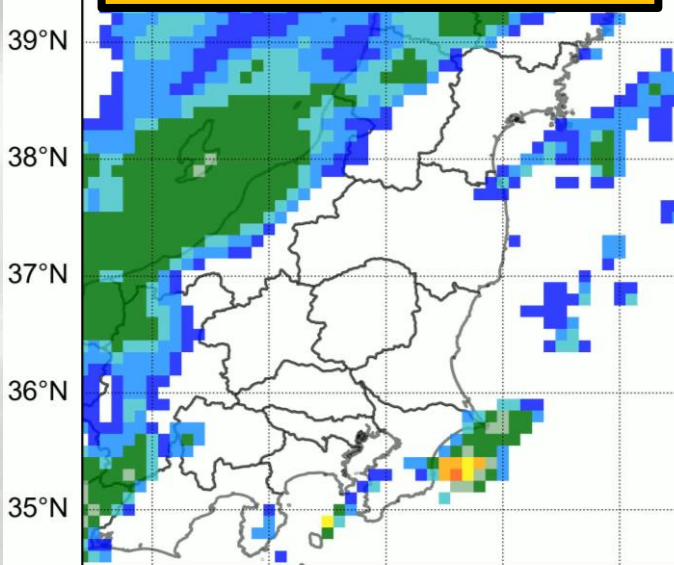


GSMaP_MVKv7

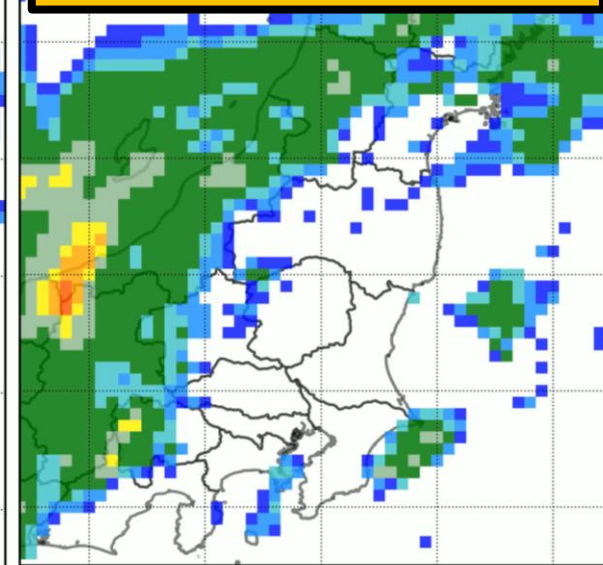


Proposed models

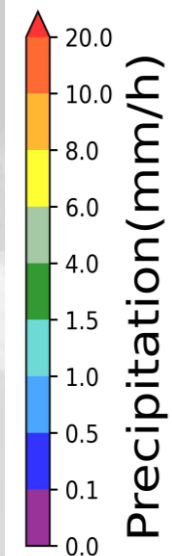
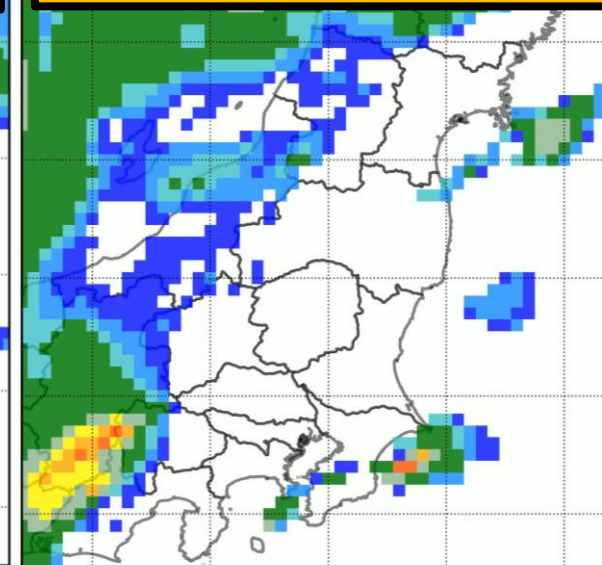
PSPNet(IR+EL)



PSPNet(IR+EL+LatLon)



DeepLabv3+(IR+LatLon)

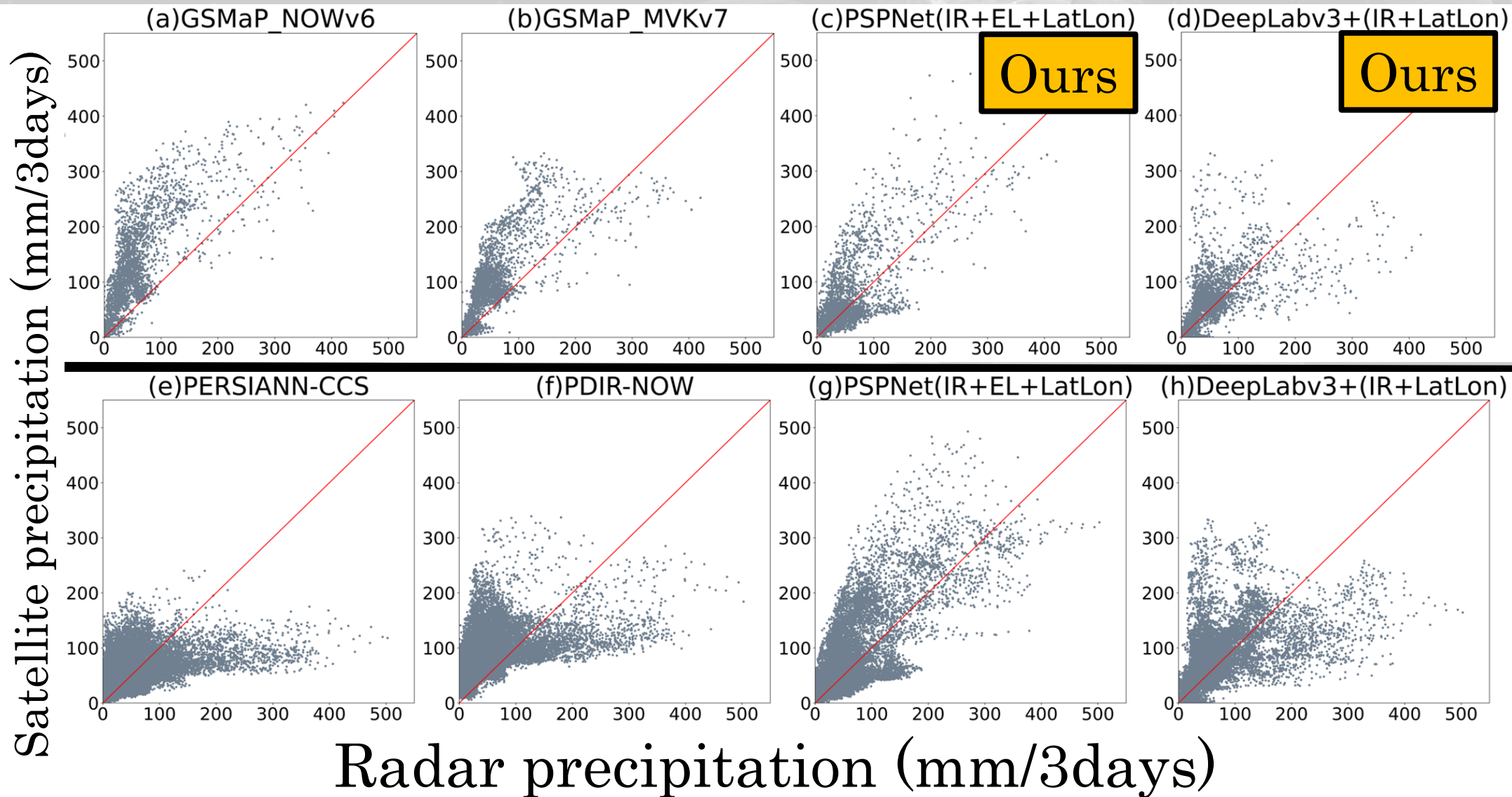


44 Result



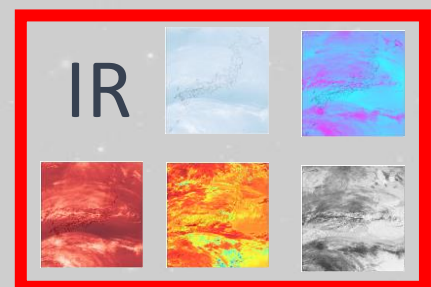
Comparison of each satellite precipitation and radar precipitation

10km
resolution



4km
resolution

45 Method 2 (Creating an original model)



Elevation

Longitude
Latitude

Reference model

Input

Skip concatenate

Option

Output

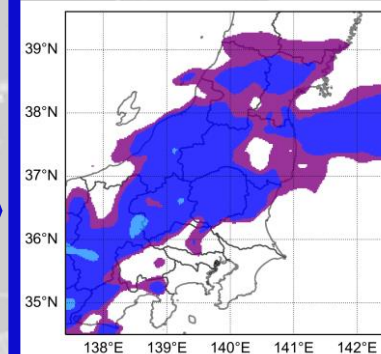
ResNet
(Backbone)

Pyramid pooling
module(PPM)

add

alternative

Rain



活性化関数

Reference model

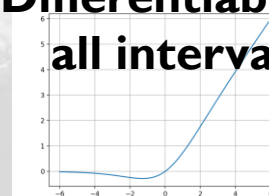
ReLU



alternative

Swish

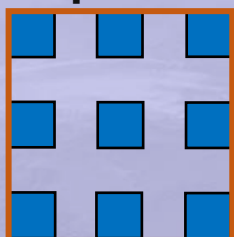
Differentiable in
all intervals



Atrous

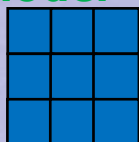
Convolution

Efficiently
secure a wide
receptive field



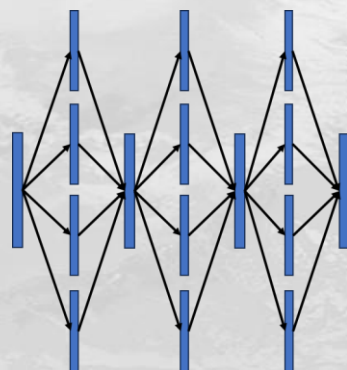
Convolution

Reference
model



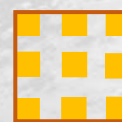
代替

Inception block
Improving
expressiveness as a
function

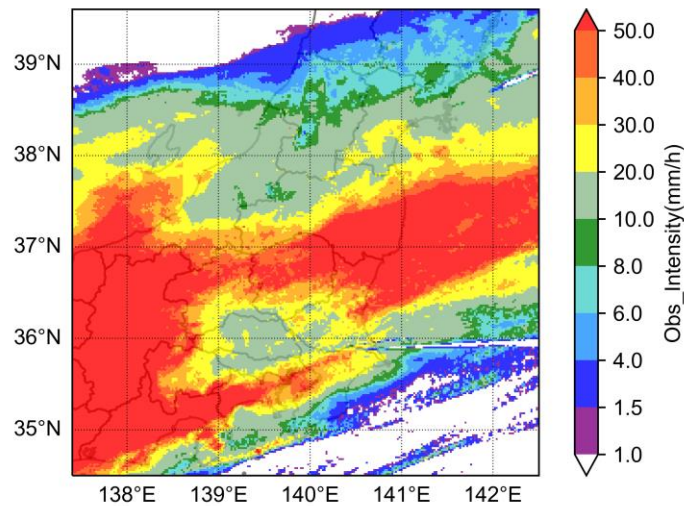


Atrous spatial
pyramid pooling(ASPP)

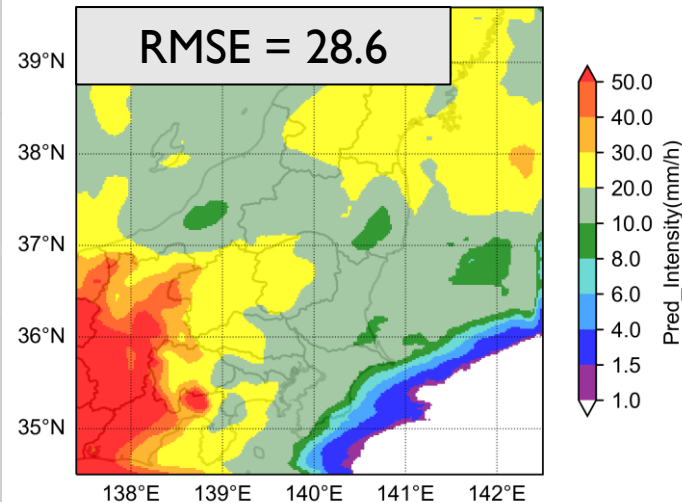
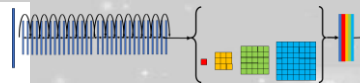
Efficient pooling with
expansion operations



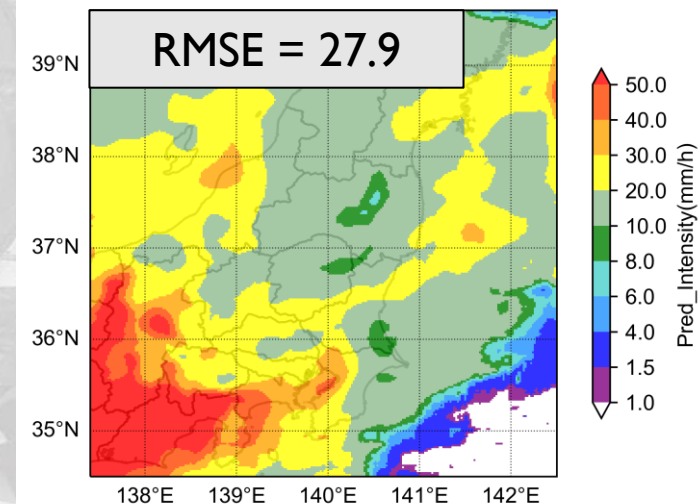
Ground truth (JMA radar)



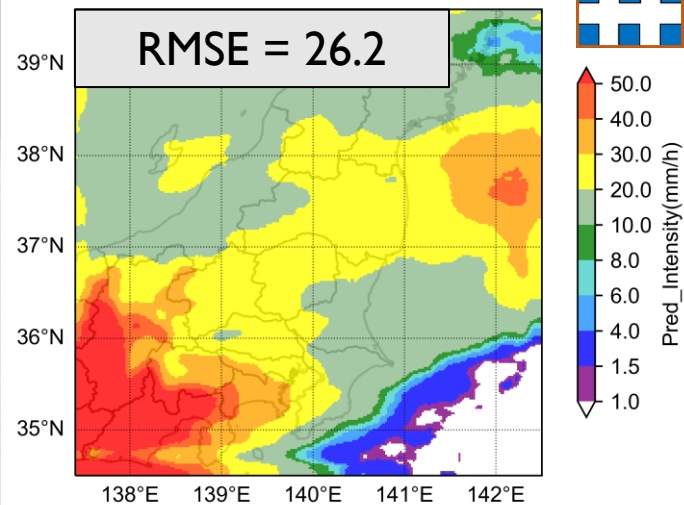
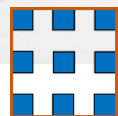
Reference model



PPM → ASPP

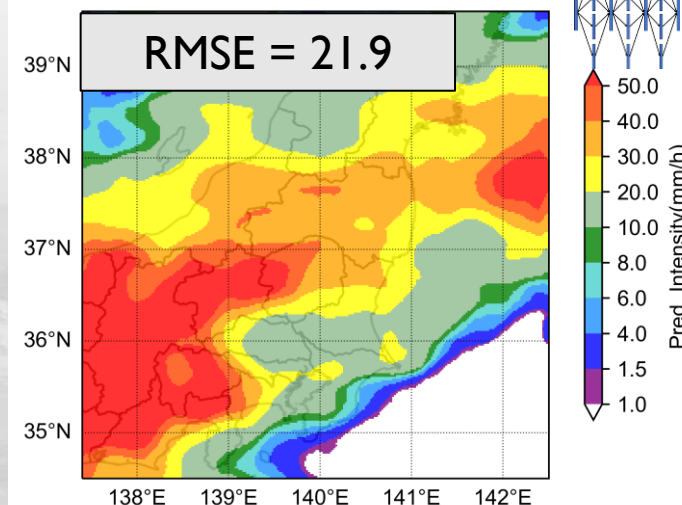
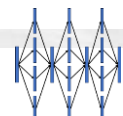


Conv. → Atrous

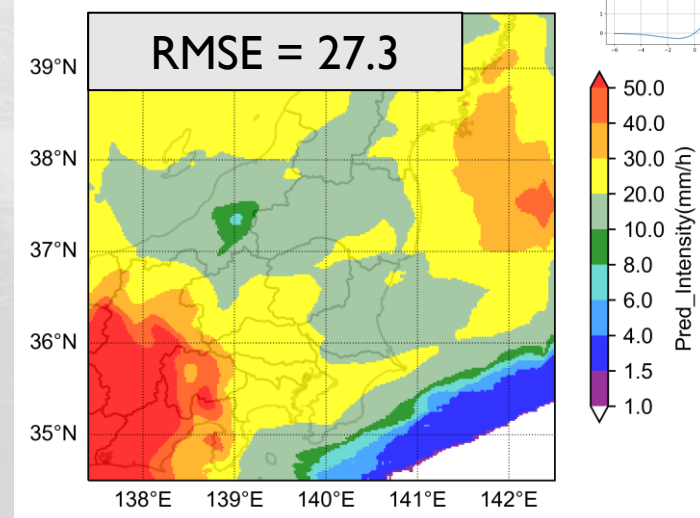
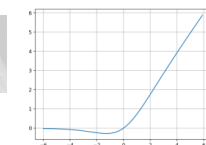


Inception block

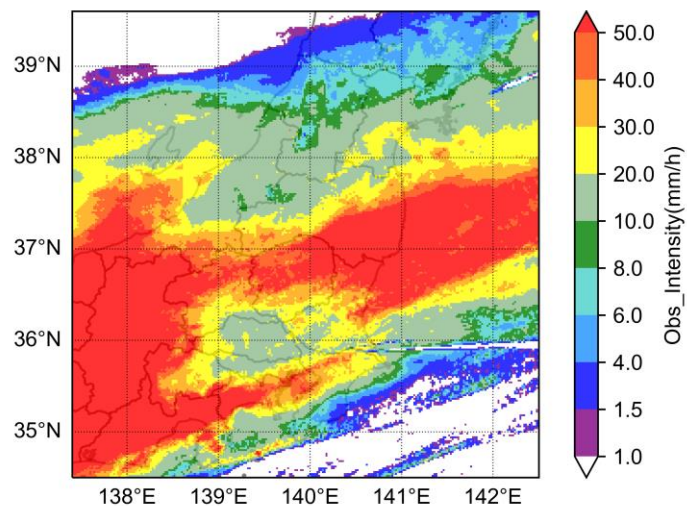
HiDREDv2



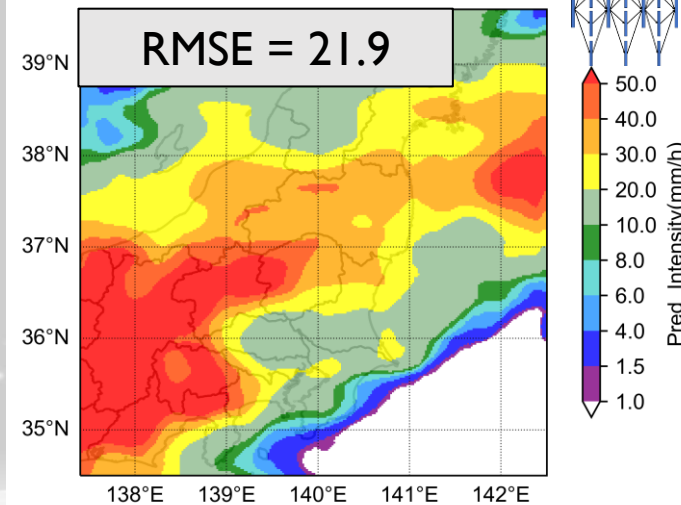
ReLU → Swish



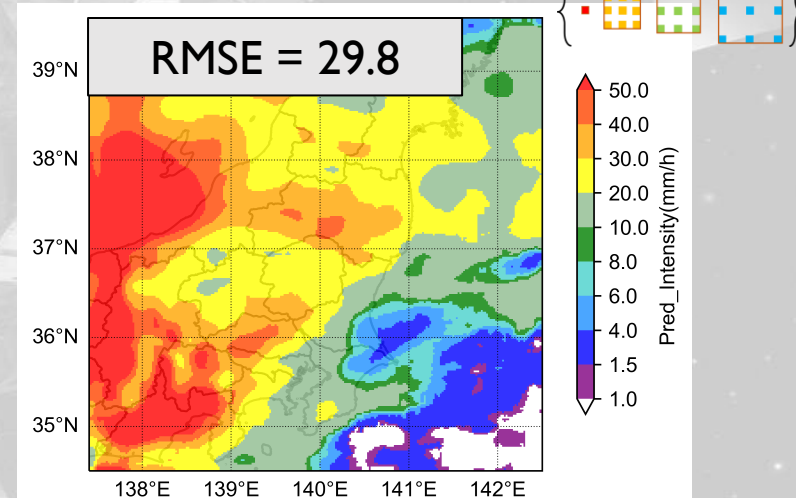
Ground truth (JMA radar)



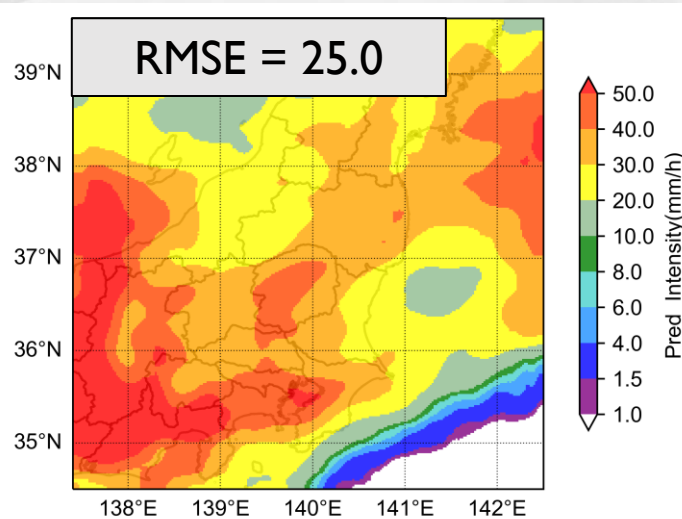
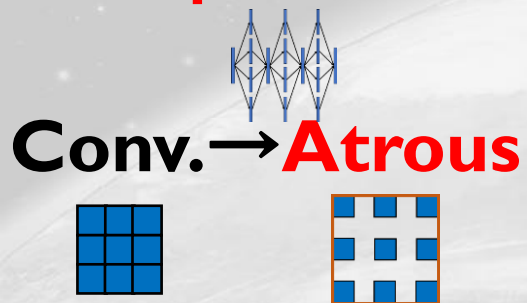
Inception block HiDREDv2



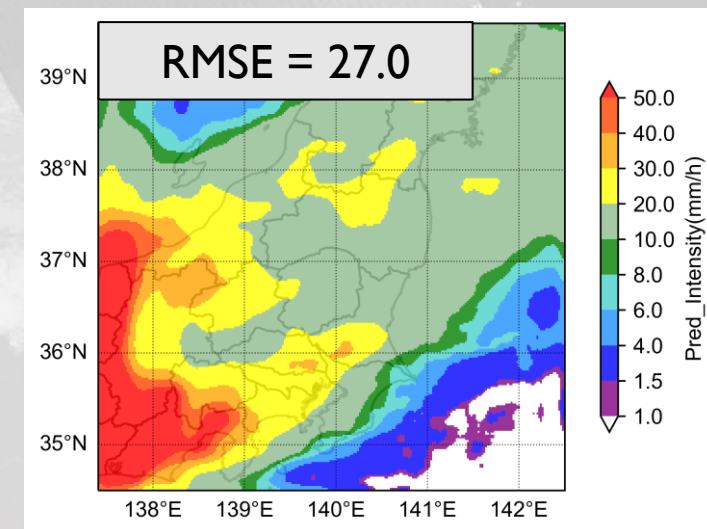
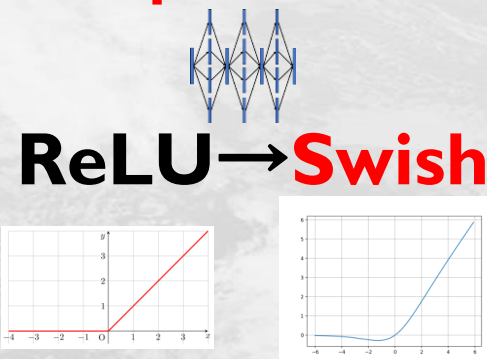
Inception block PPM → ASPP



Inception block



Inception block

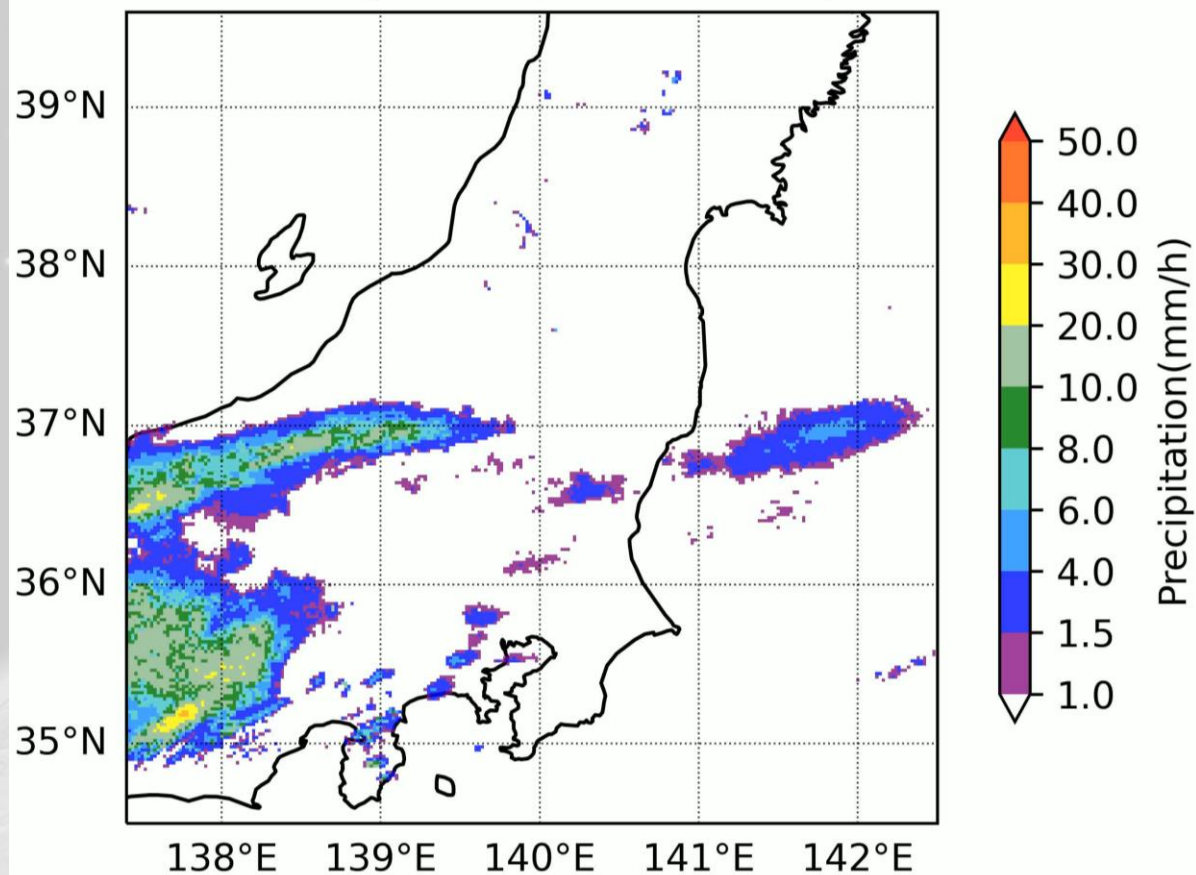


48 Results of rainfall estimation 1



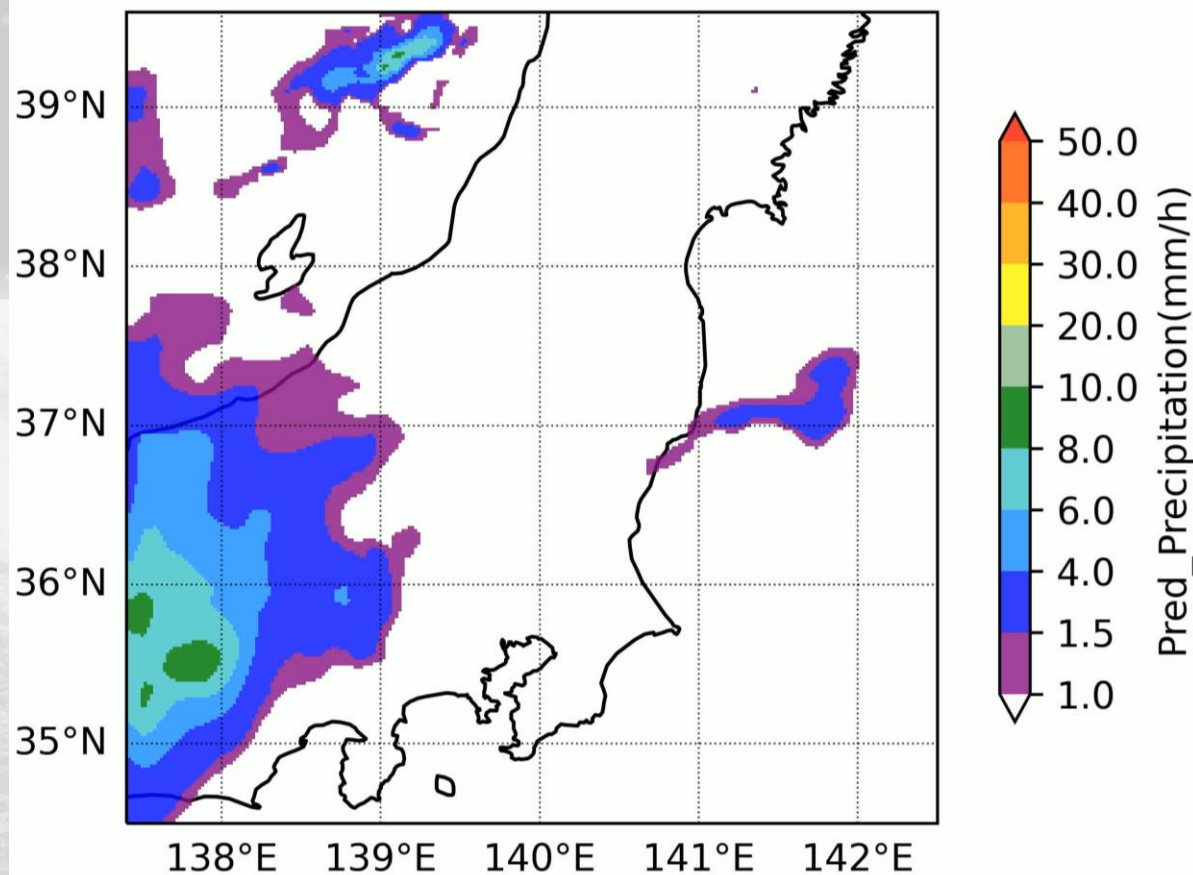
Radar rainfall (**ground truth**)

RADAR_ 2018/07/05 00:00 (UTC)



Estimated result by HiDREDv2

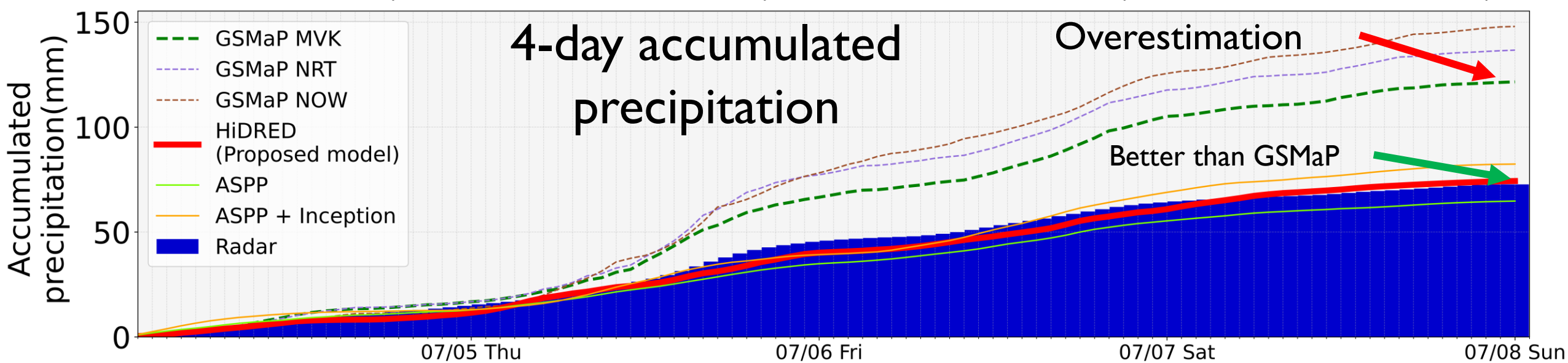
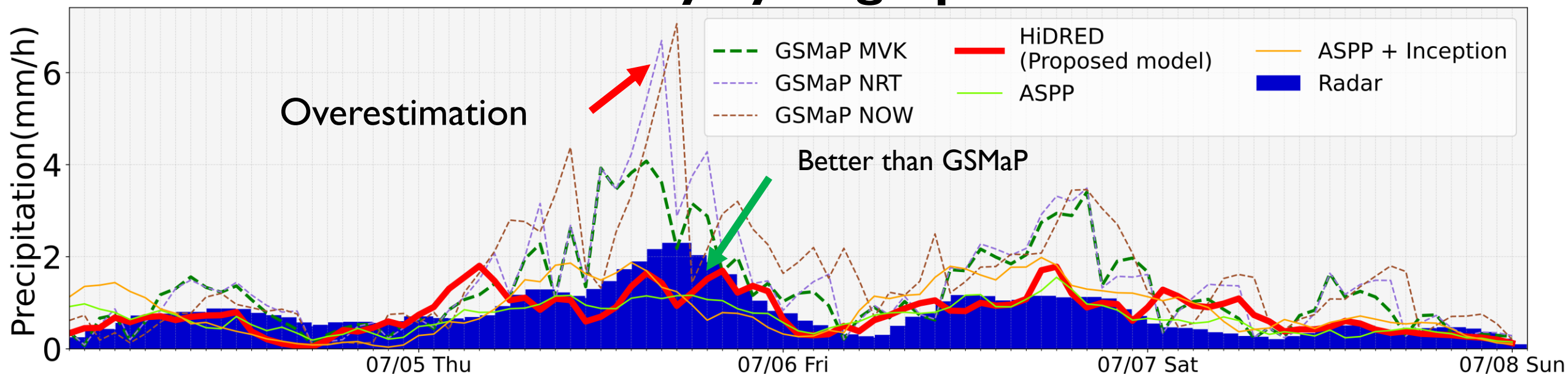
HiDREDv2_ 2018/07/05 00:00 (UTC)



49 Rainfall estimation results 2



4-day hyetograph



50 Applying deep learning models to other countries



Vietnam

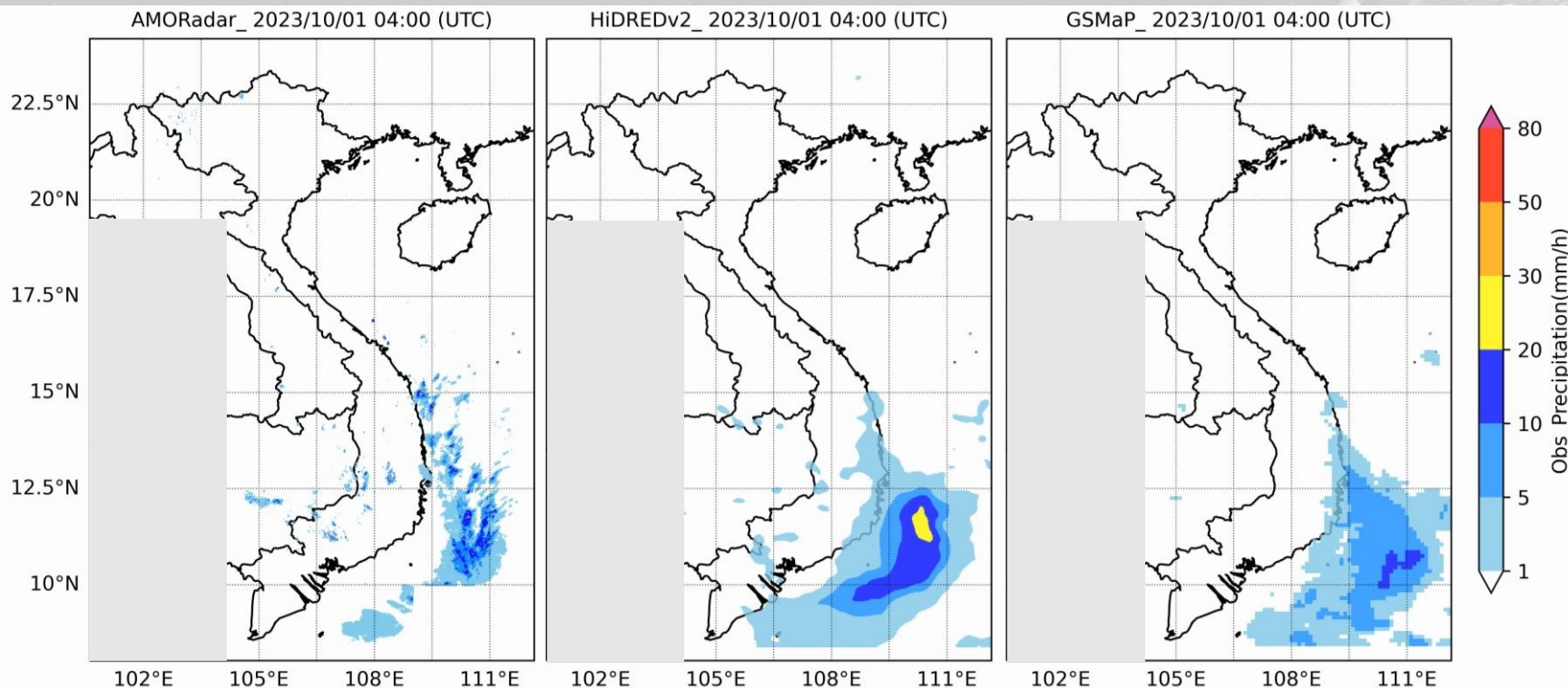


QPE : Quantitative Precipitation Estimation

VNMHA
radar(QPE)

HiDREDv2
(Proposed model)

GSMaP
MVK ver.7

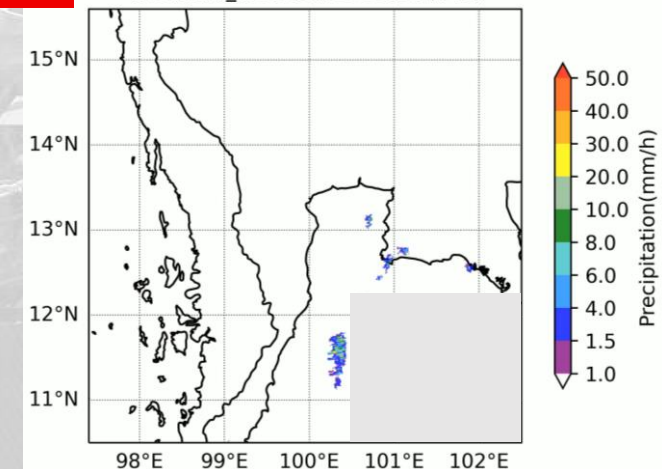


Thailand

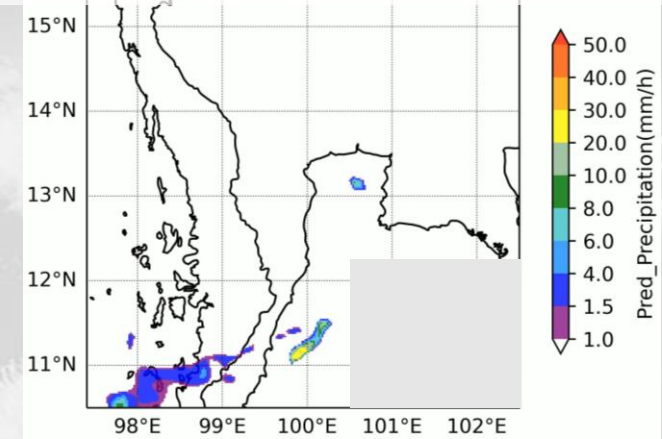


TMD Radar

TMDradar_ 2019/06/06 00:00 (UTC)



HiDREDv2
(Proposed model)



Significant lack of weather forecasts

Heavy rain situation

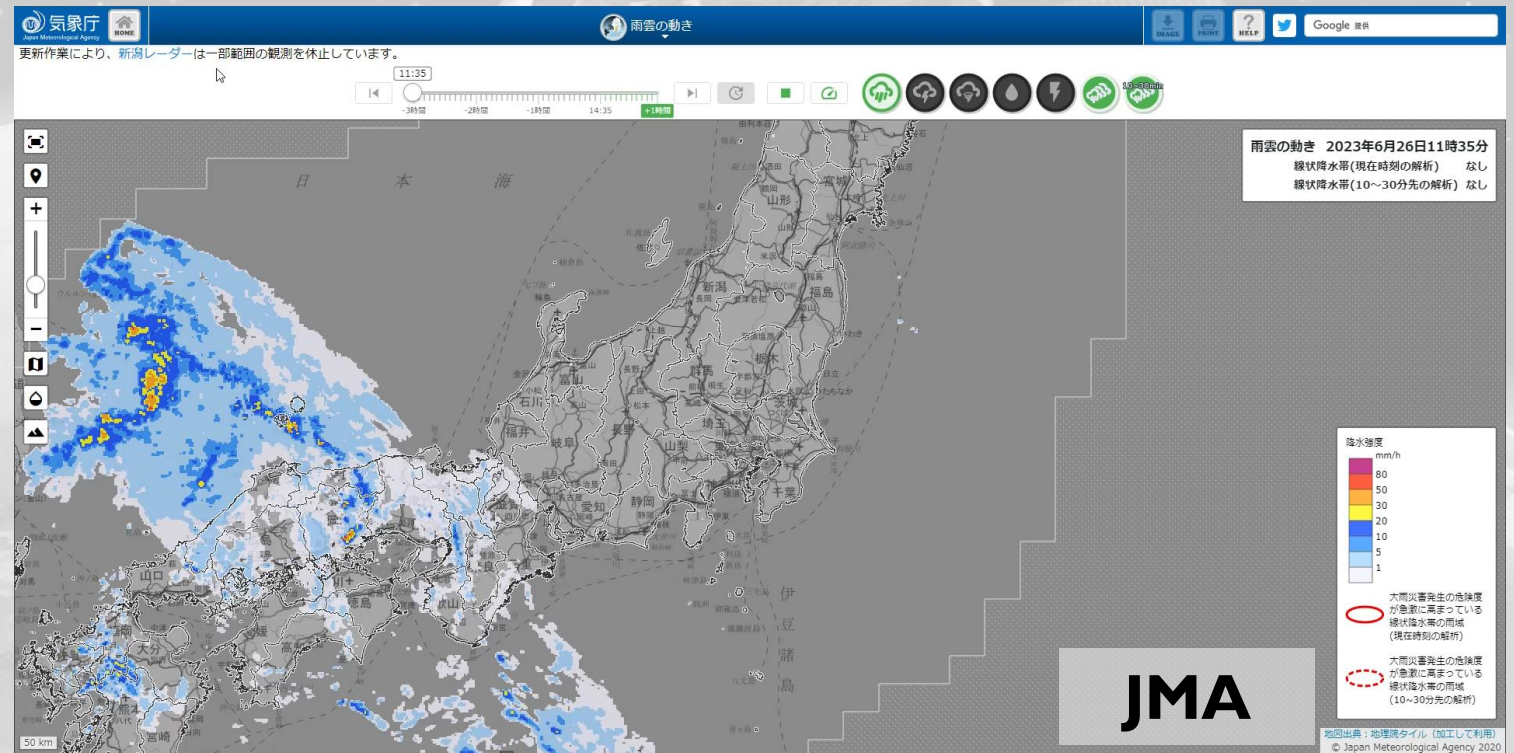
Photographer
Fujimoto



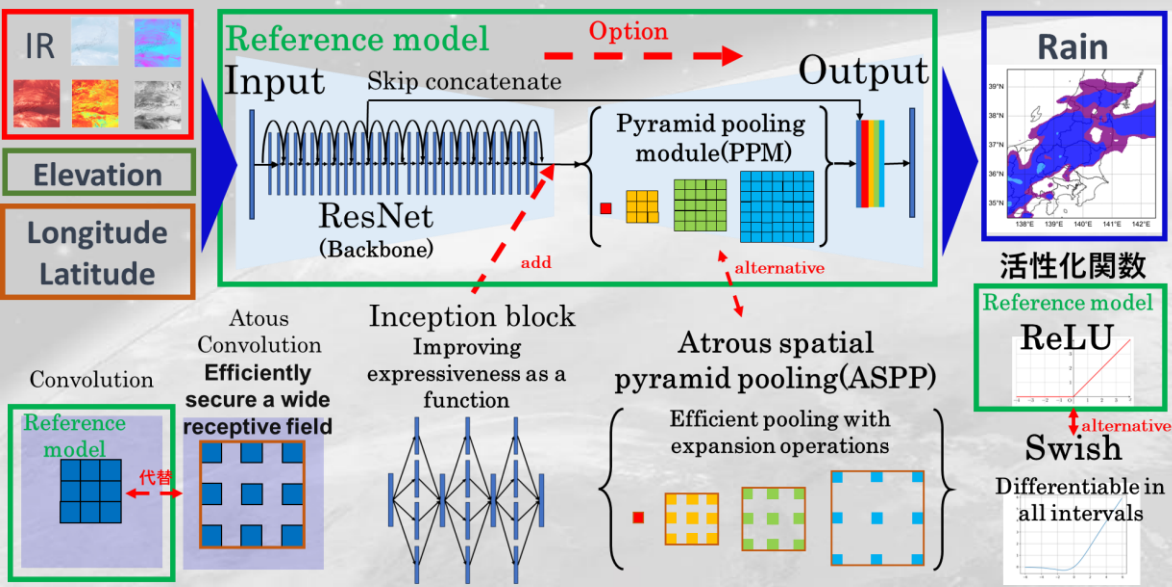
Roads on Koh Samui in southern Thailand flooded due to heavy rain(kyodo)



Satellite rainfall using HiDREDv2
Existing precipitation nowcasting method or
deep learning apply

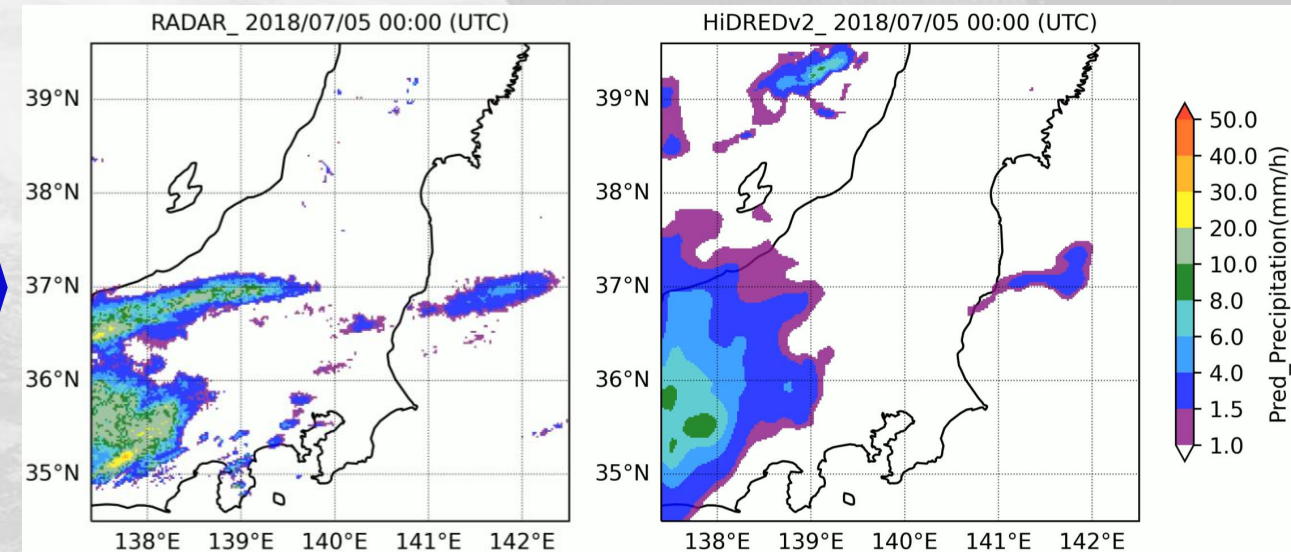


The goal Development of satellite rainfall products that can be used as quantitative values for water disaster prediction in the Asia-Pacific region



Radar
(Ground truth)

Estimation results
using HiDREDv2



Message

- ◆ Current issues in typhoon forecasting
- ◆ Goodness of machine learning approaches such as deep learning as well as physical approaches
- ◆ Please see the Hydrological Research Letters (Fujimoto and Tebakari, 2023)
- ◆ Even if the forecast is not a 100% probability forecast, it can estimate a 70-80% probability forecast or the actual amount of rainfall.