



Strengthening Flood Forecasting in ASEAN Member States through Regional Trainings and Coordination

Module 1

Numerical Weather Prediction

Tomoki Ushiyama
Senior Researcher
ICHARM, PWRI

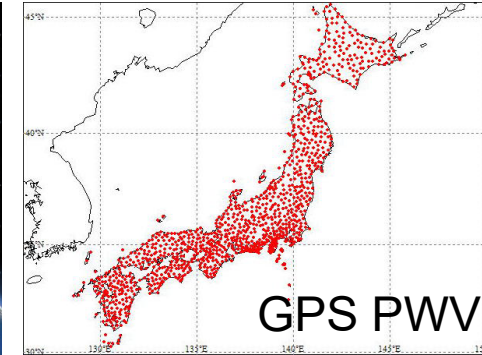
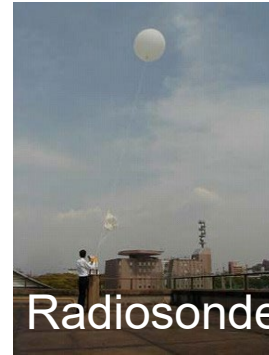


WORLD
METEOROLOGICAL
ORGANIZATION



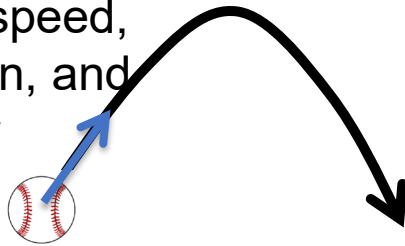
Numerical Weather Prediction (NWP)

Observation data



NWP is an initial value problem.

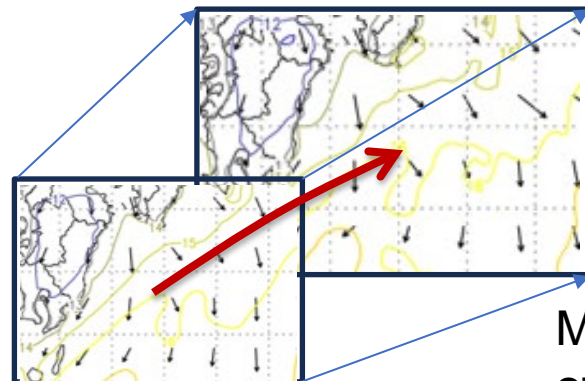
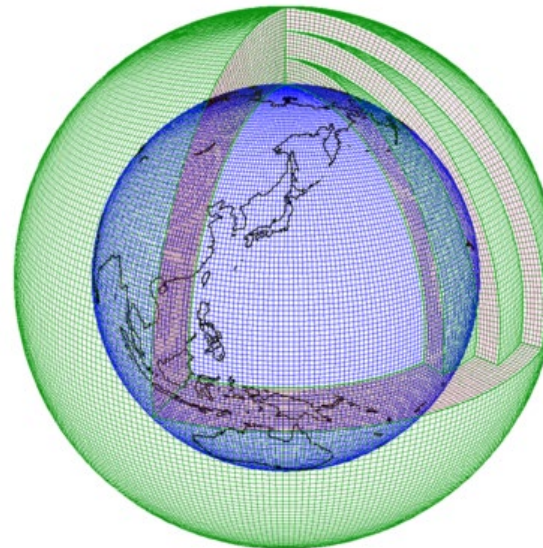
Initial speed,
position, and
gravity



Movement
of a ball

Make initial condition
(Data assimilation)

Numerically integrate the
model to predict the
future situation.



Movement
of a fluid

Momentum
equation

$$\frac{du}{dt} - \left(f + \frac{\tan \phi}{a} u \right) v = -\frac{\partial p}{\rho a \cos \phi \partial \lambda} + F_\lambda$$

$$\frac{dv}{dt} + \left(f + \frac{\tan \phi}{a} u \right) u = -\frac{\partial p}{\rho a \partial \lambda} + F_\phi$$

$$\frac{dw}{dt} = -\frac{\partial p}{\rho \partial z} - g + F_z$$

Mass
conservation

$$\frac{dp}{dt} + \rho \left[\frac{1}{a \cos \phi} \frac{du}{d\lambda} + \frac{1}{a \cos \phi} \frac{\partial(v \cos \phi)}{\partial \phi} + \frac{\partial w}{\partial z} \right] = 0$$

Thermodynamic
equation

$$c_v \frac{dT}{dt} + p \frac{d\alpha}{dt} = Q$$

Equation of
state

$$p = \rho RT$$

Total derivative
on sphere

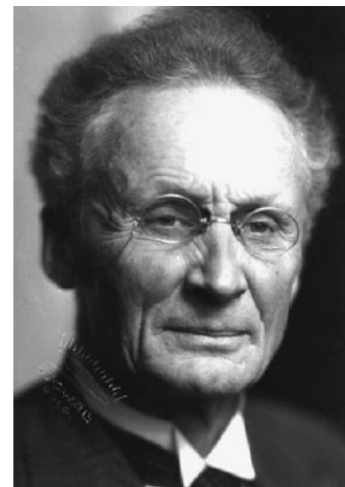
$$\frac{d}{dt} = \frac{\partial}{\partial t} + \frac{u}{a \cos \phi} \frac{\partial}{\partial \lambda} + \frac{v}{a} \frac{\partial}{\partial \phi} + w \frac{\partial}{\partial z}$$

$$(\lambda, \phi, z : \text{longitude, latitude, height}), \alpha = 1/\rho, f = 2\Omega \sin \phi$$

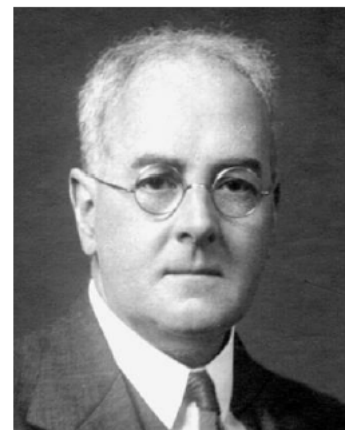


History of the numerical weather predictions

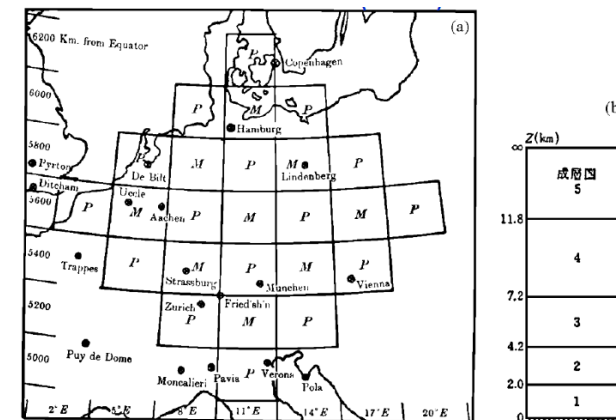
- 1904: Vilhelm Bjerknes developed the primitive equations of the atmospheric motion
- 1922: Lewis Fry Richardson tried to integrate the primitive equations to predict European weather by manual computers. It takes 6 weeks to get weather forecast of 6 hours later, and the results was unrealistic. However, it was the first trial of NWP and called "Richardson's dream".



Bjerknes



Richardson



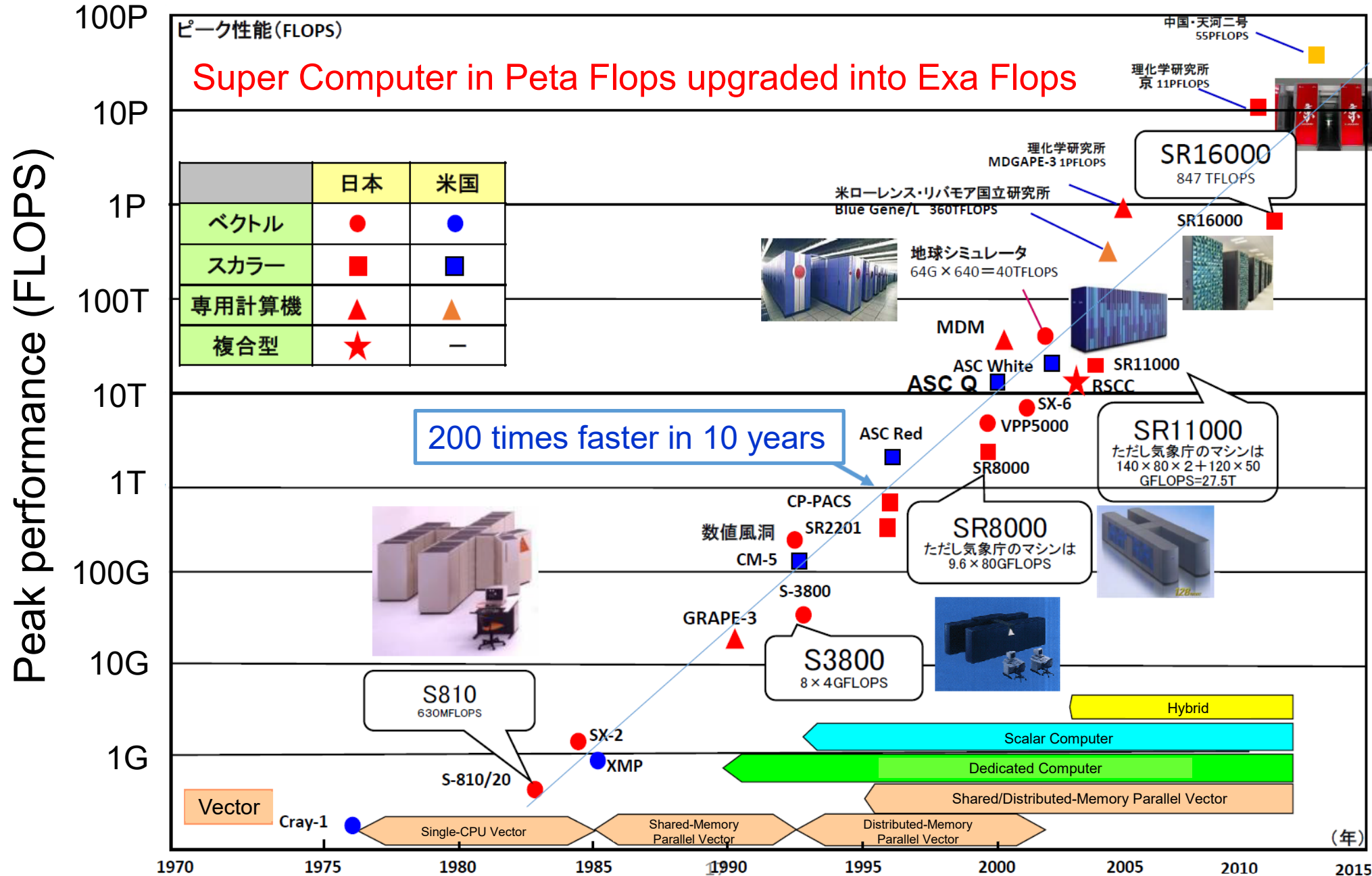
A model which Richardson used, with the horizontal grid interval of 200km and 5 vertical layers.



Richardson proposed a conductor control 64,000 calculator to make real time forecasting possible in a big venue.

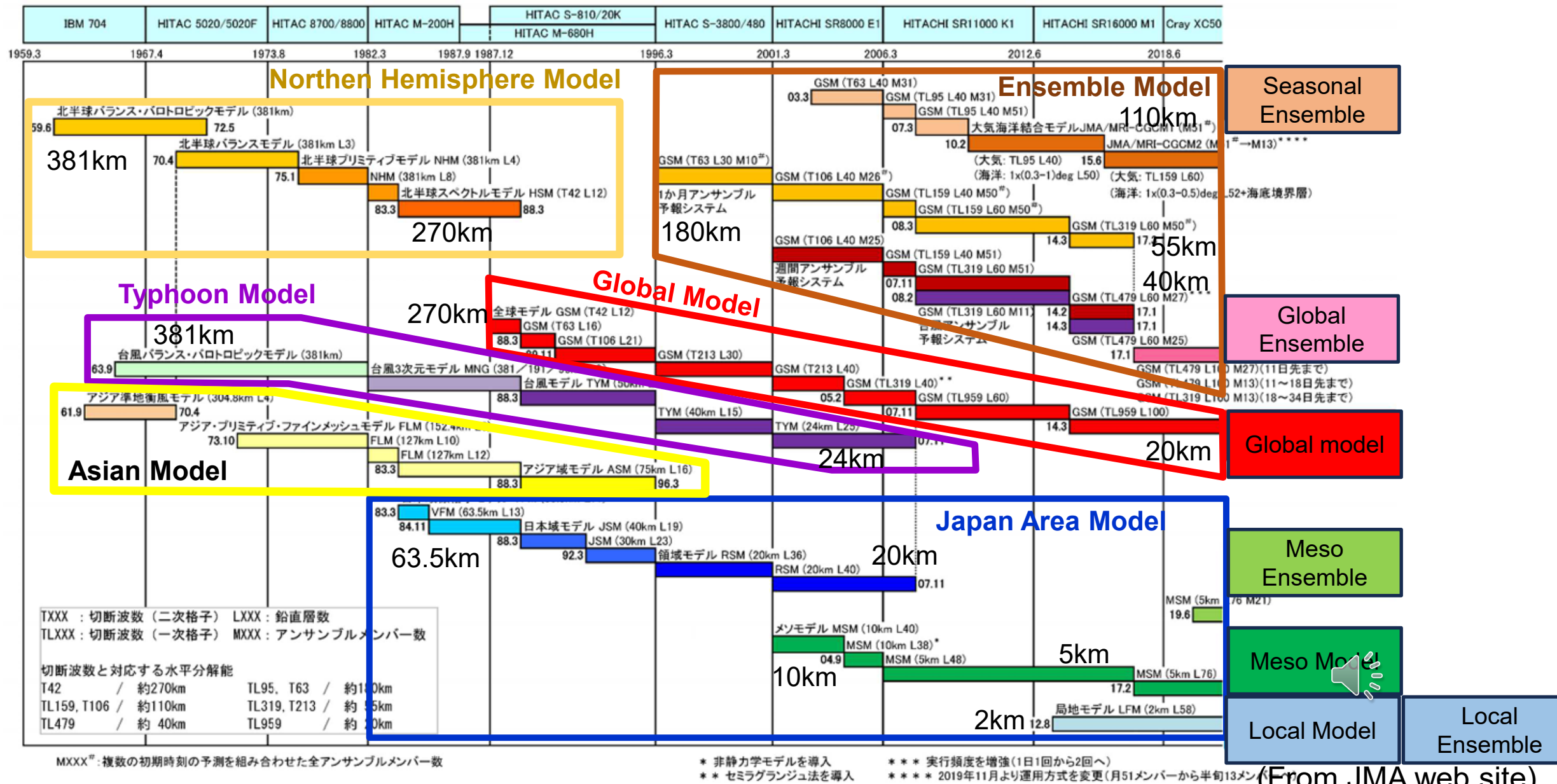
(From JMA web site)

Development of Super Computers



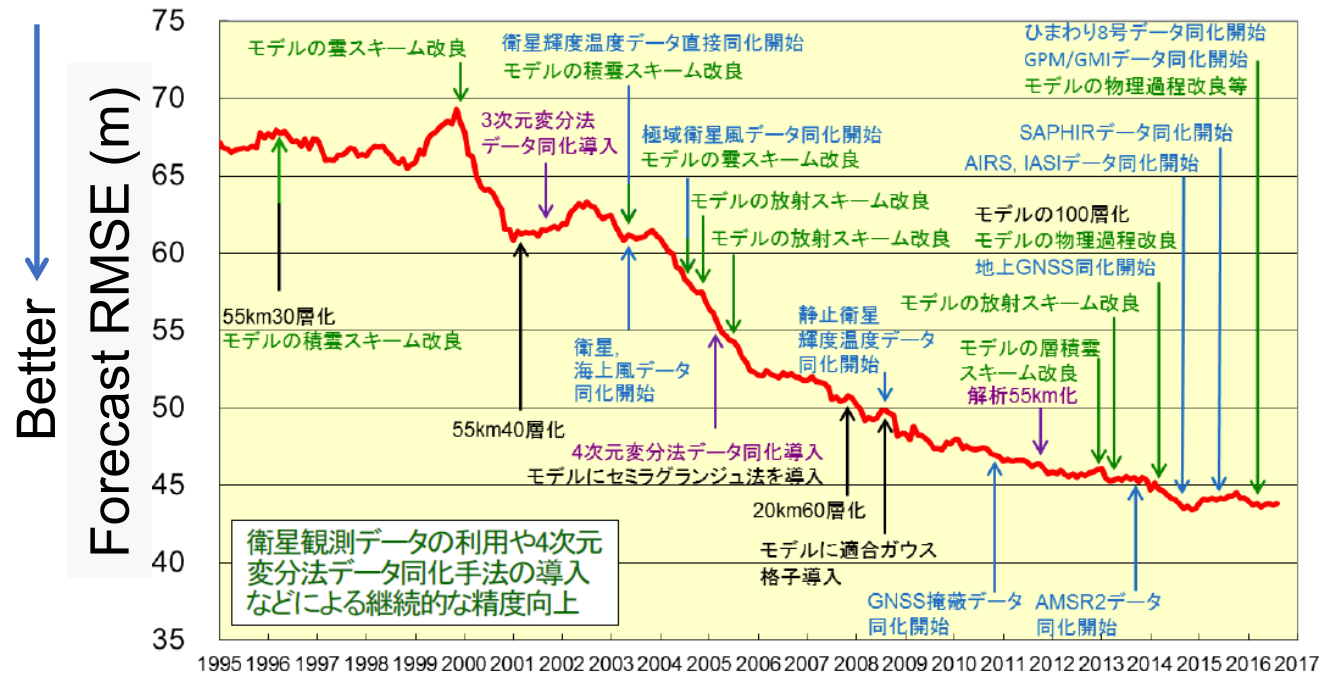
(From JMA)

History of super-computer and NWP system in JMA



Update of the accuracy of NWP in JMA

JMA Forecast error (5day) of pressure at about 5km height
(H at 500hPa, Northern hemisphere)



Major improvement of JMA Global forecast system

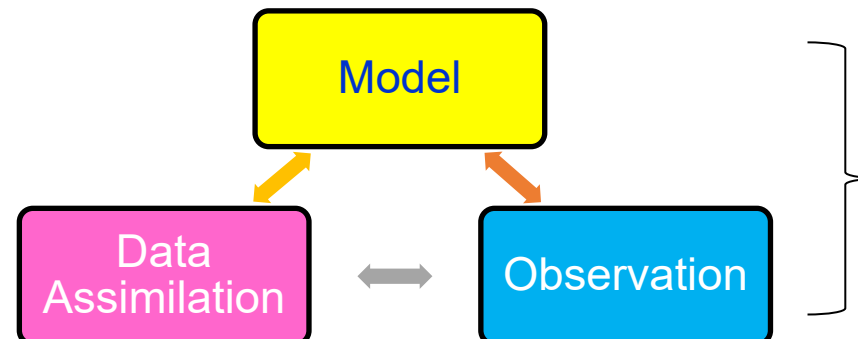
Green: Model physical process,

Black: Model dynamical frame, resolution,

Purple: Data assimilation system,

Blue: New observation data were assimilated

Major improvement of JMA Global forecast system



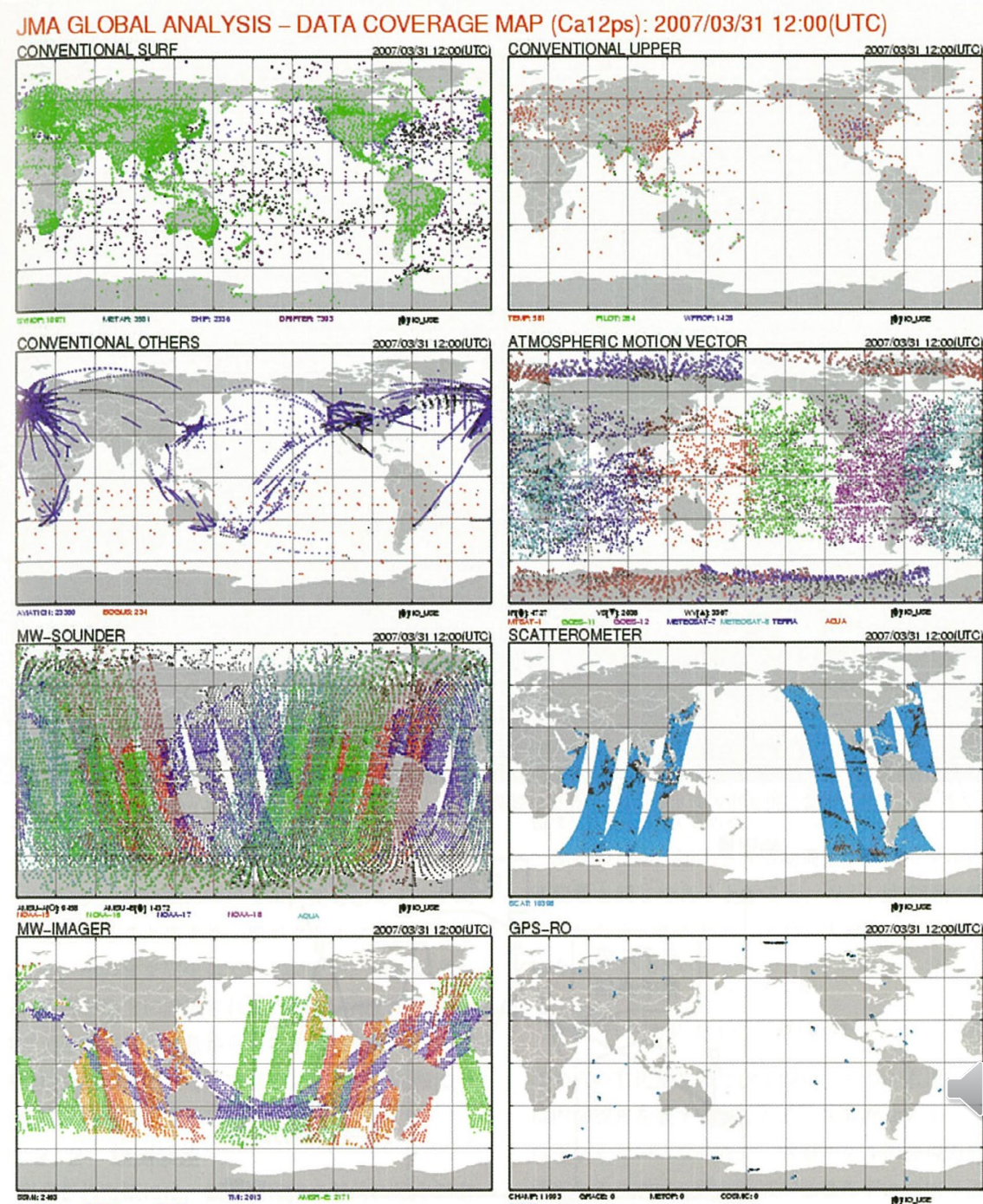
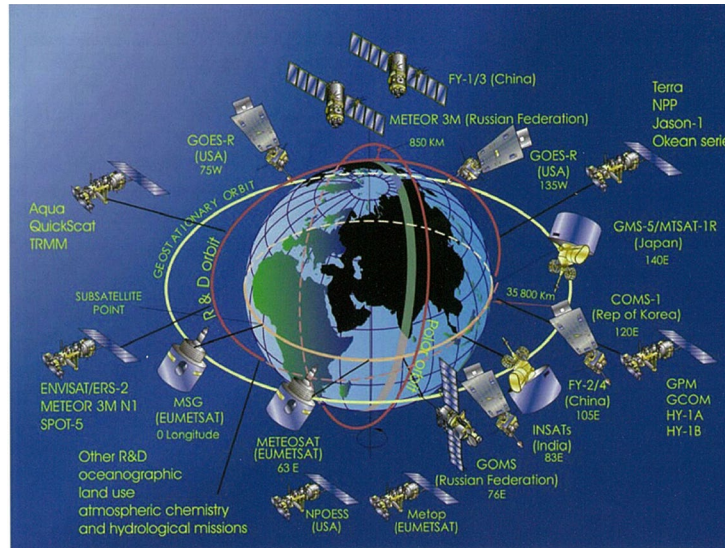
All important to improve NWP



(From JMA web site)

Assimilated data for operational NWP 2007

Observation data used in JMA operational global analysis. Surface, Aircraft, Microwave sounder, Microwave imager, Upper air sounding (radiosonde), AMV (atmospheric motion vector by geosynchronous satellites), scatterometer, GPS Radio Occultation.

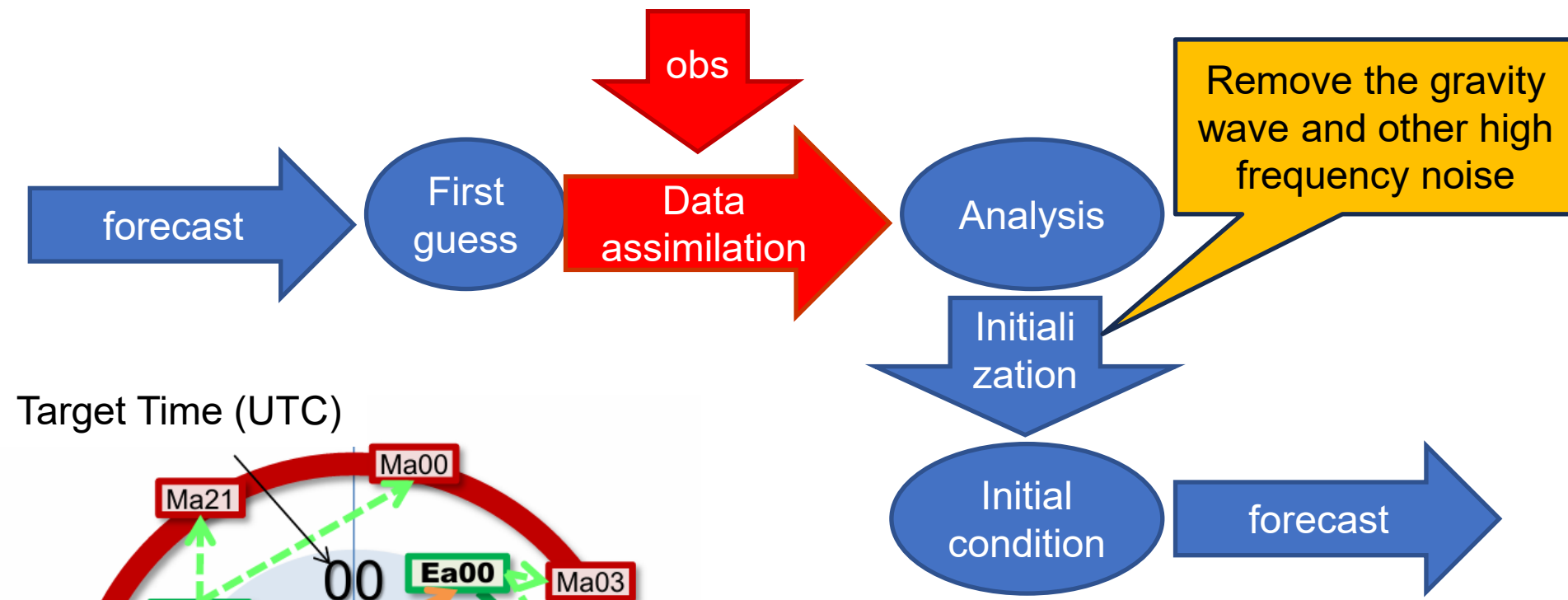


(From JMA web site)

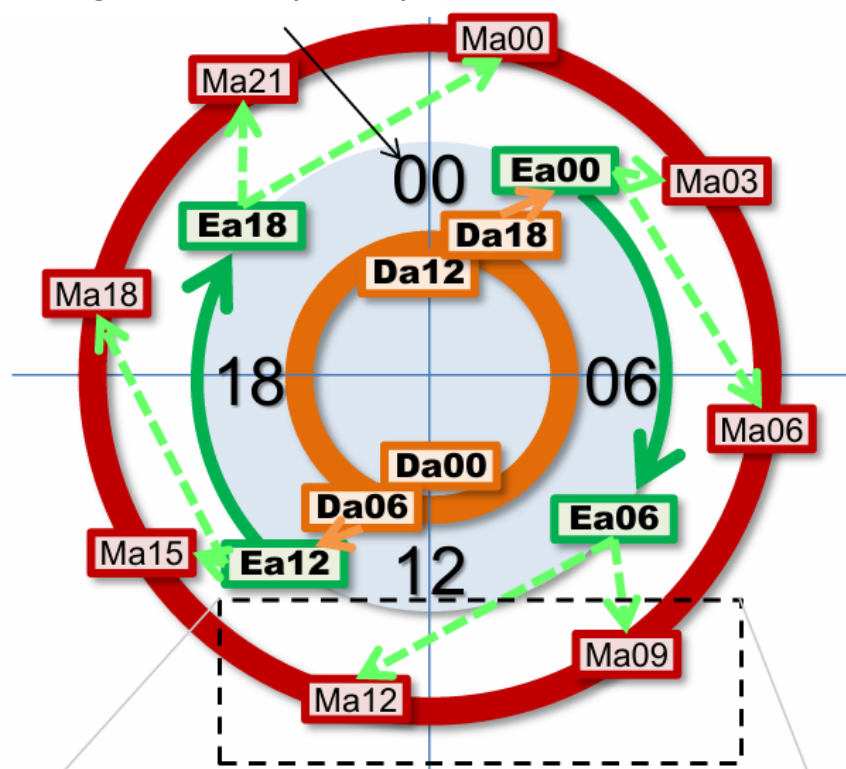


(From JMA web site)

Analysis forecast cycle



Target Time (UTC)



Global Cycle Analysis (Da):

- Analysis to keep the accuracy.
- Waiting observation for 11h50m, 7h50m

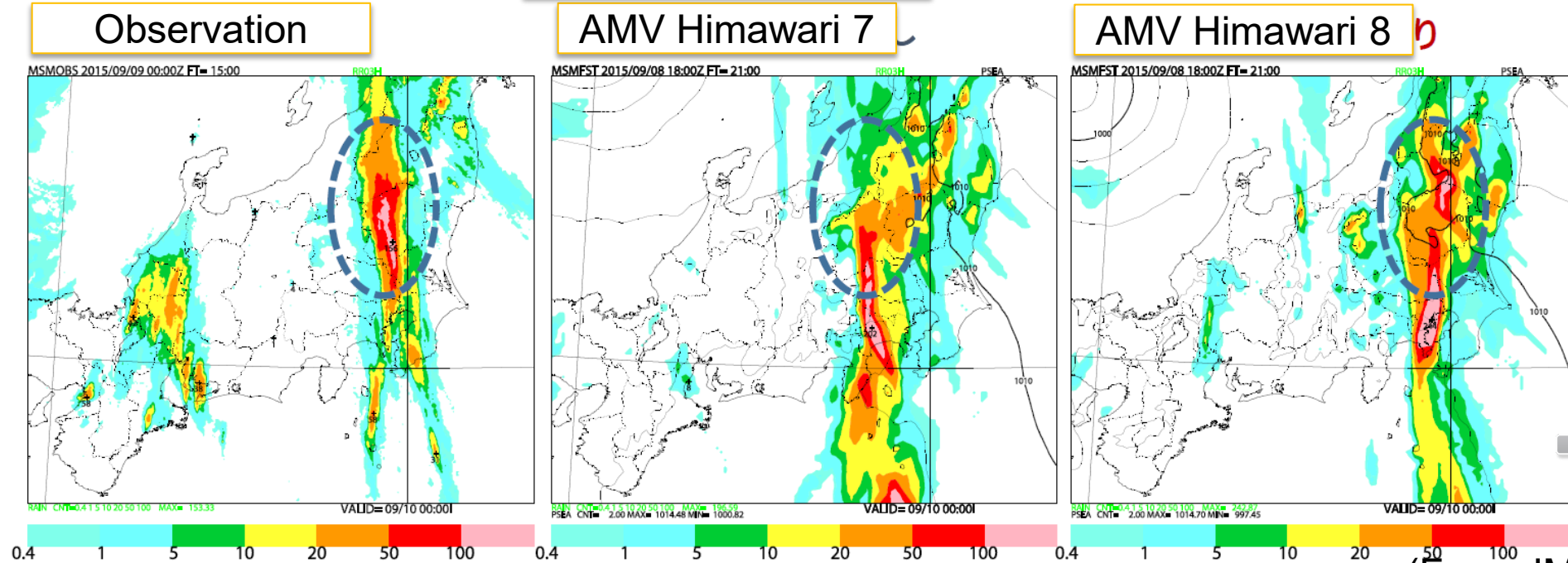
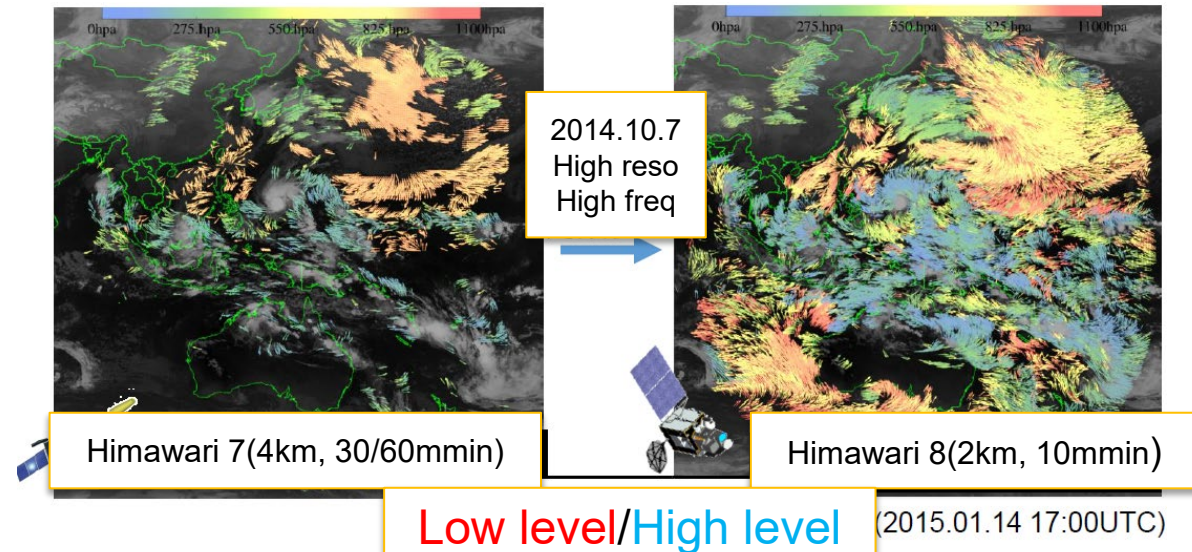
Global Early Analysis (Ea):

- Give initial condition for global forecast
- First guess is given from the Da.
- Waiting observation for 2h20m.

Mesoscale Analysis

(From JMA web site)

Effect of assimilating new satellite data



Effect of assimilating GNSS data

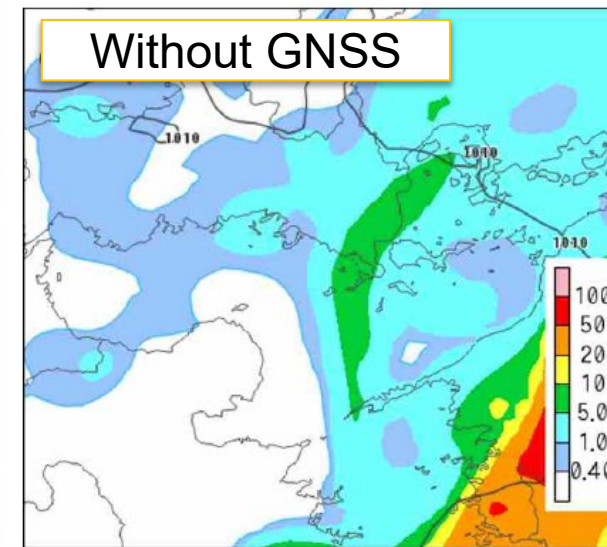
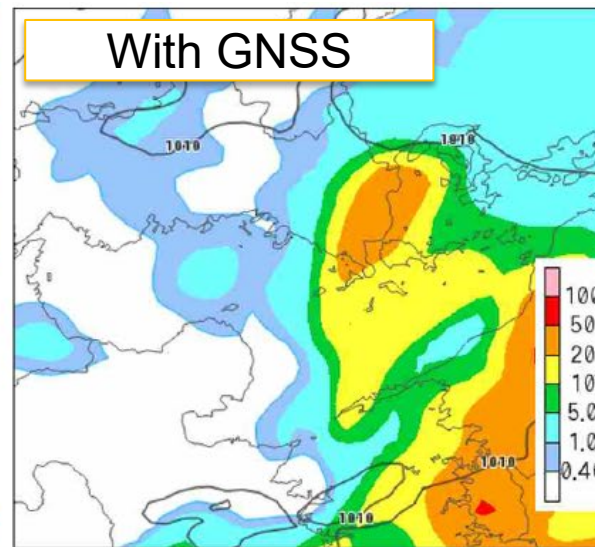
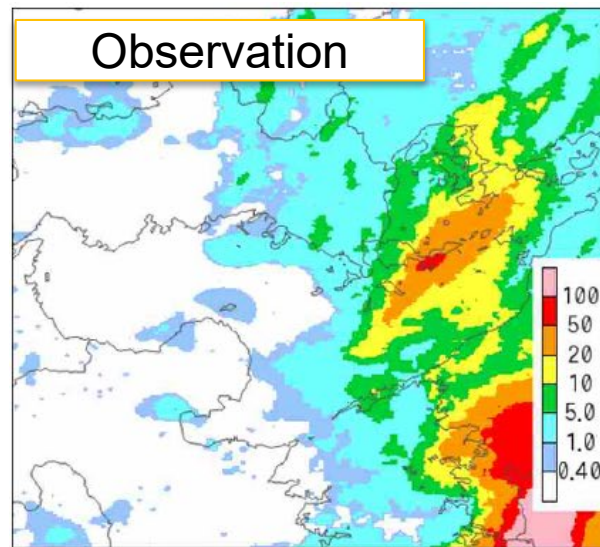
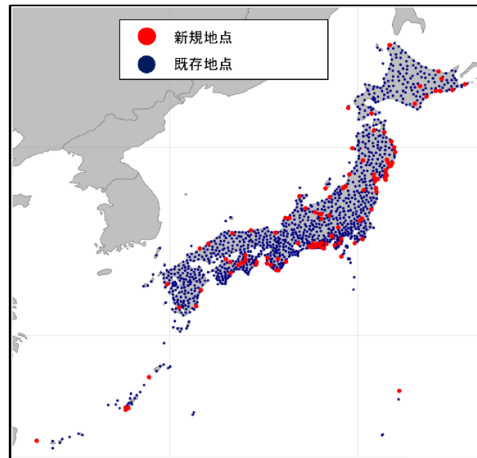
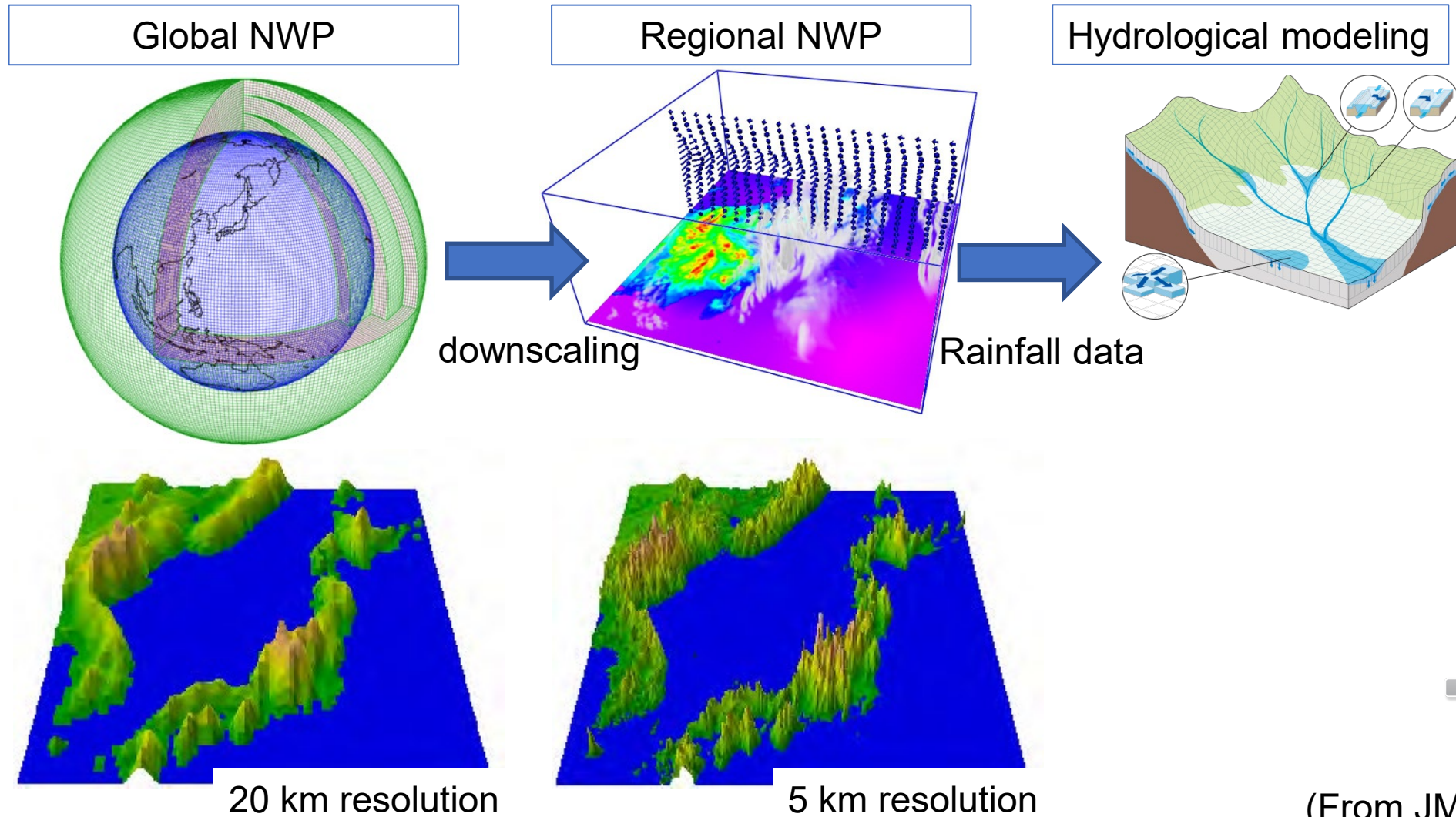


図 4.1.6 2018 年 7 月 7 日 21UTC における前 3 時間降水量 [mm/h] の分布。左が解析雨量、中が TEST の予測値、右が CNTL 予測値。予測値は 2018 年 7 月 7 日 18UTC 初期値の 3 時間予測。

Numerical Weather Prediction (NWP) by regional model

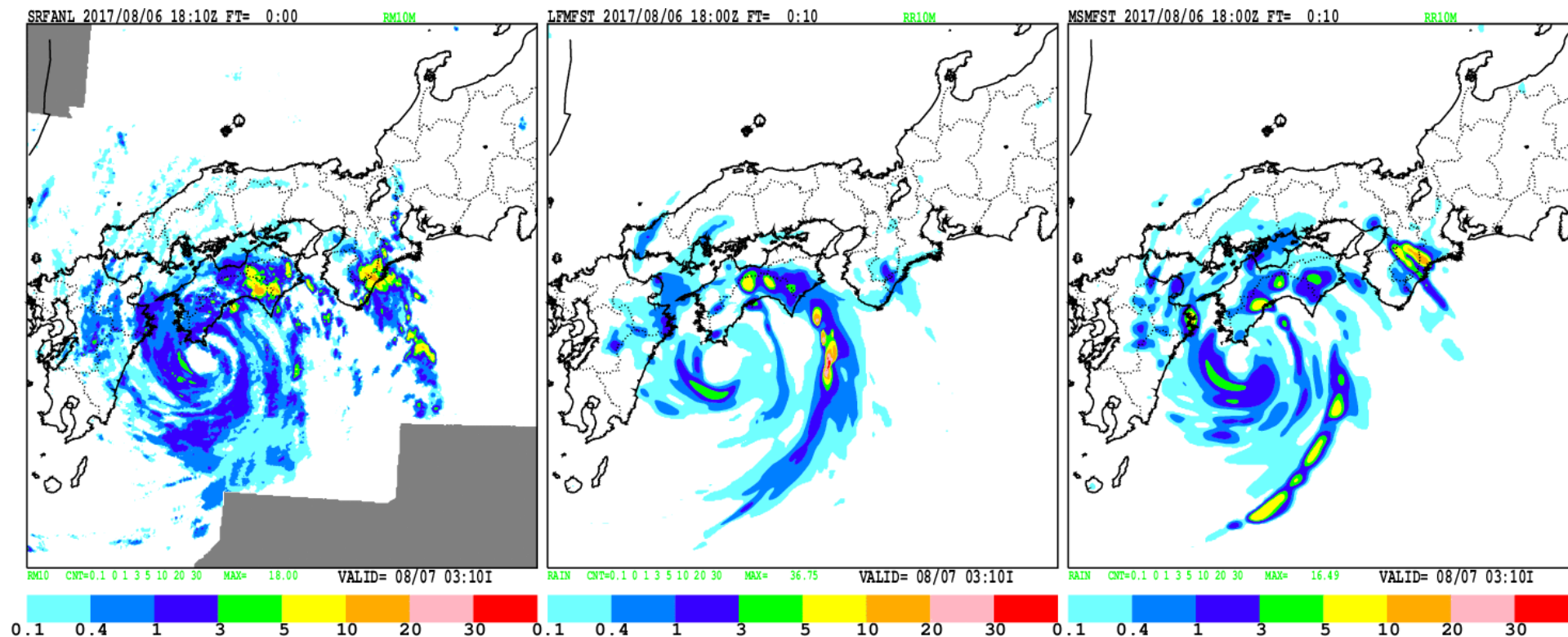


Predicted rainfall

Observation

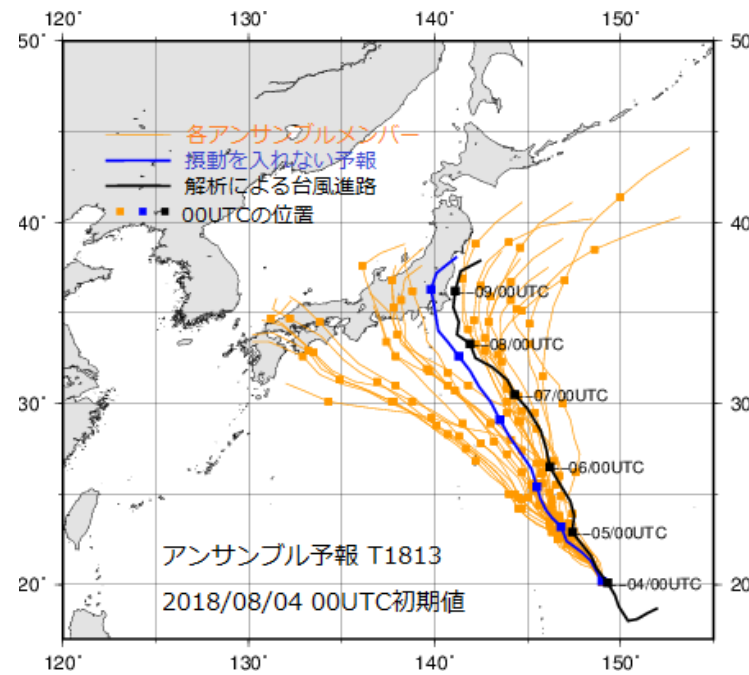
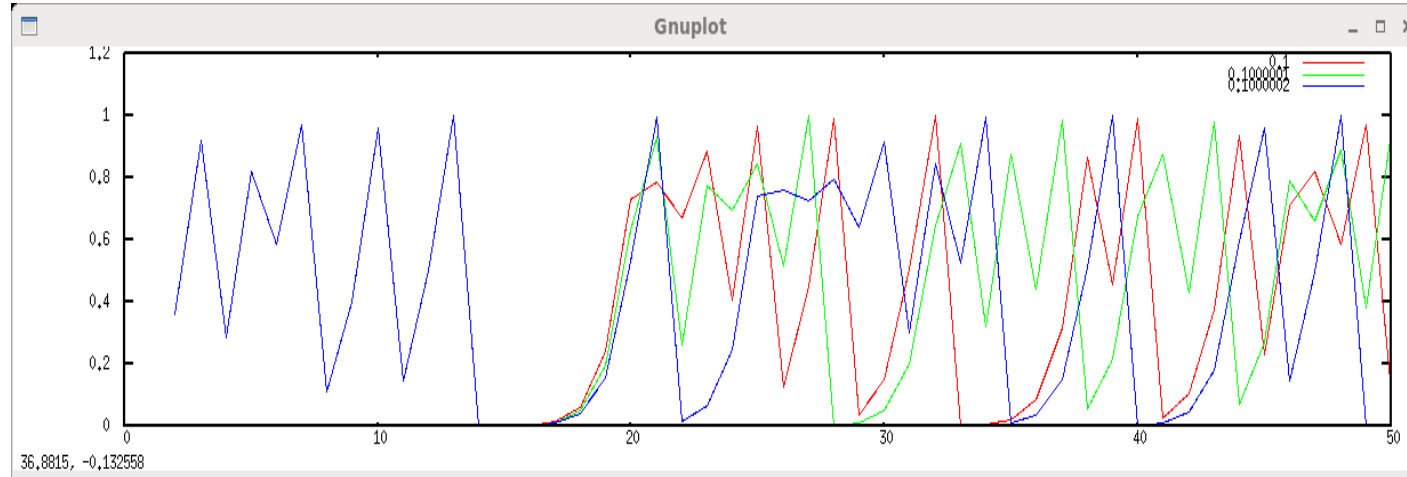
JMA 2km resolution model

JMA 5km resolution model



(From JMA web site)

Ensemble forecasts



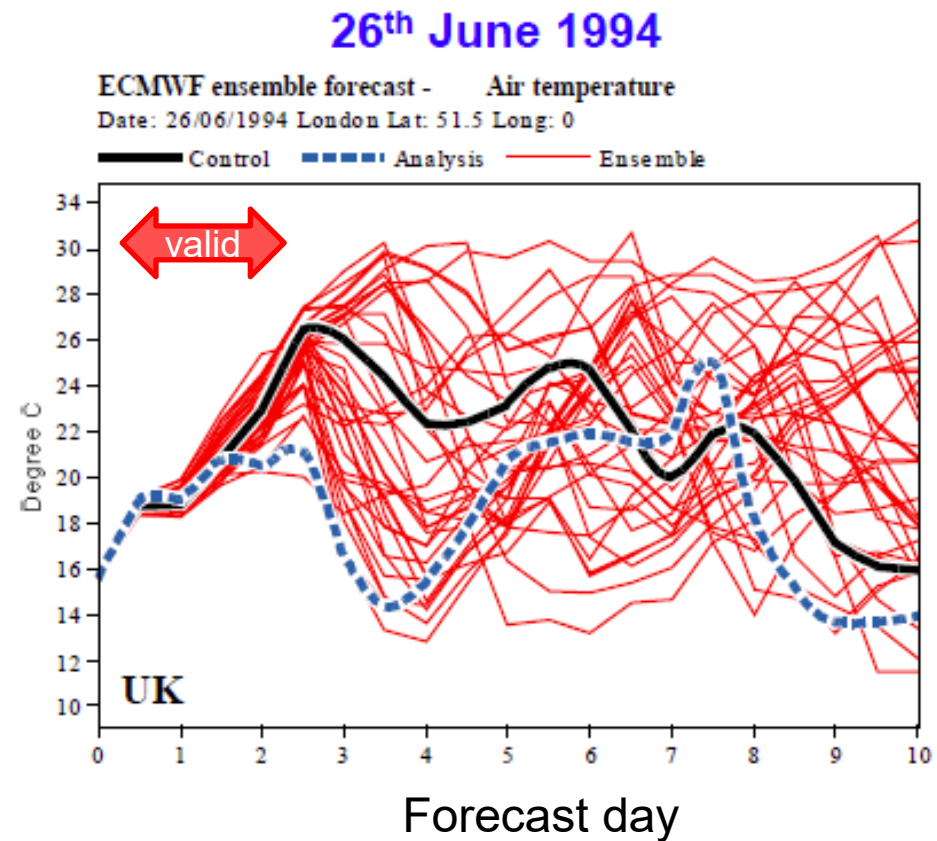
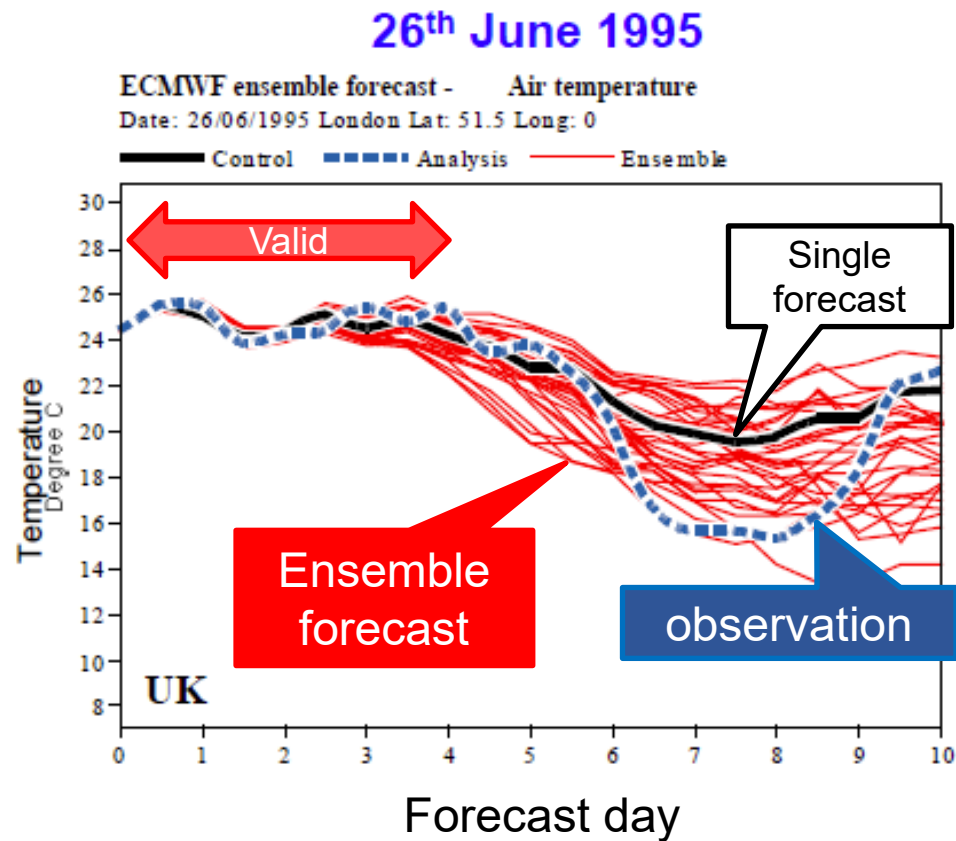
Weather system is governed by chaotic nature.

Ensemble forecast is a group of multiple forecast (20 – 50) from slightly different initial conditions.



(From JMA web site)

Example of Ensemble forecasting

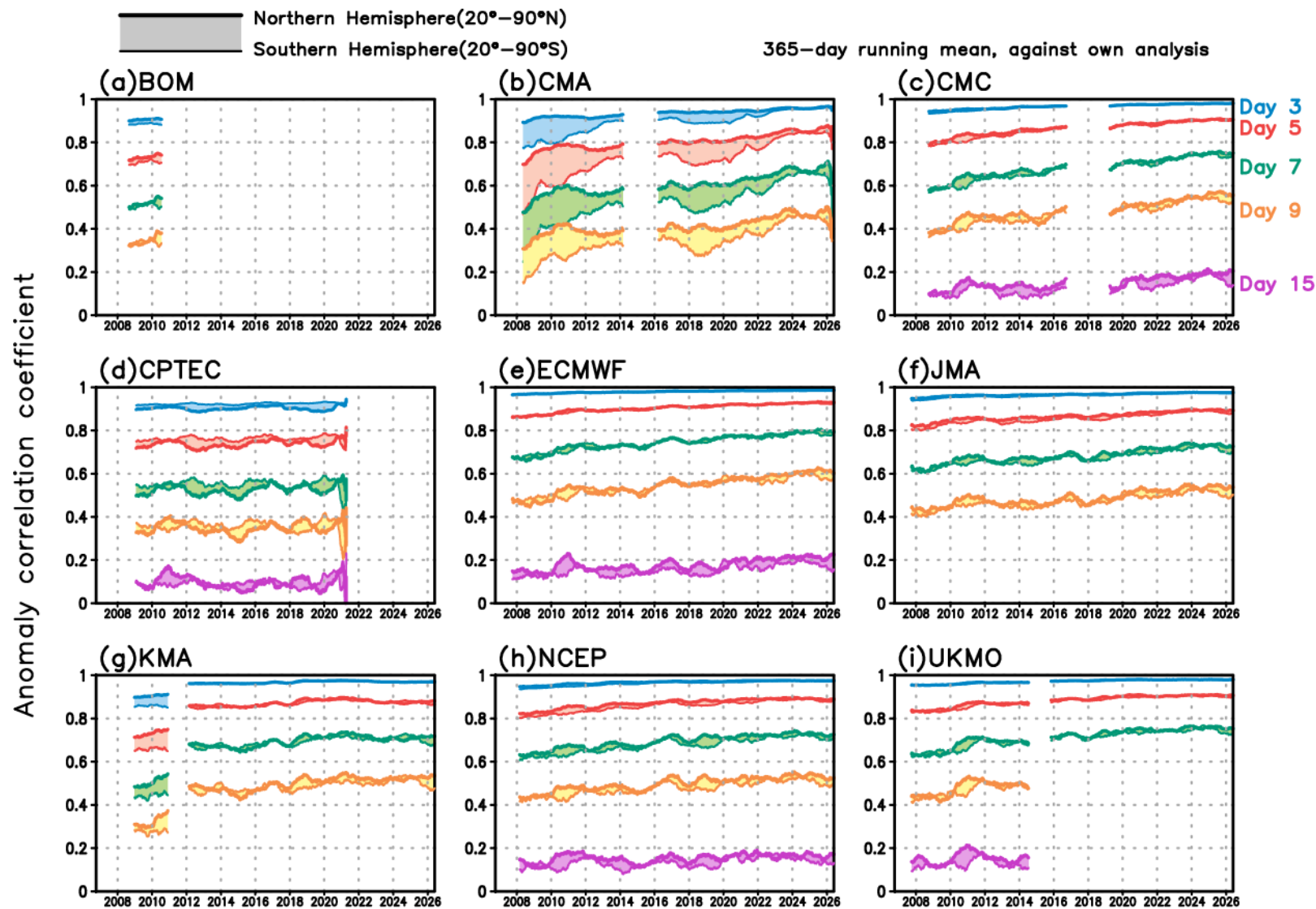


- ◆ Ensemble forecast (simultaneous multiple forecasts) can predict its reliability of forecasts.
- ◆ This increases forecast accuracy.



Accuracy of Global EPS

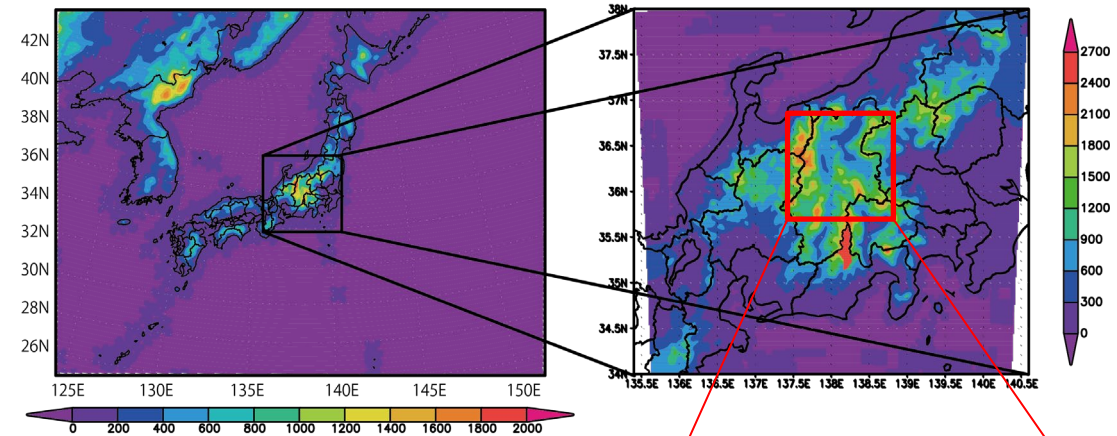
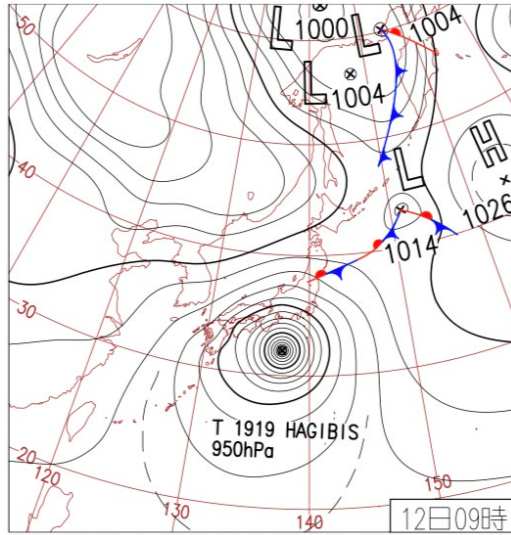
Skill comparison of TIGGE medium-range ensemble forecasts
ACC Z500 control run (OCT2006–MAY2026)



© Mio Matsueda, TIGGE Museum

(After TIGGE Museum)

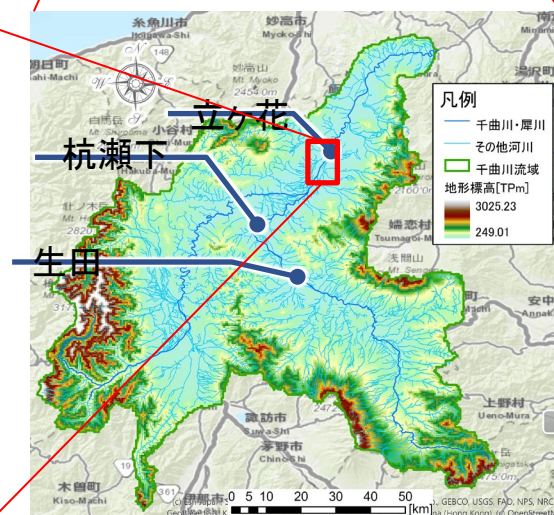
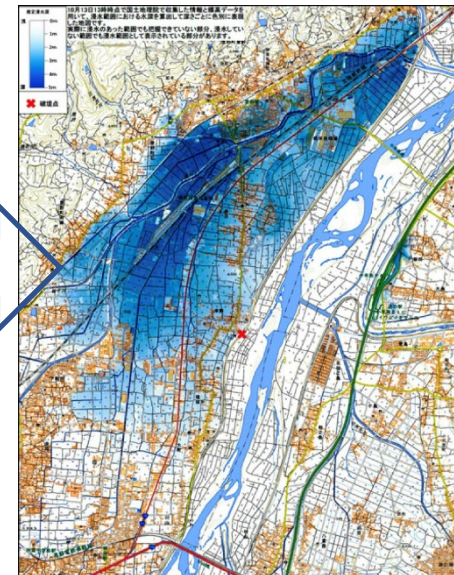
Example: Flood forecasting study for Typhoon Hagibis 2019



NWP model domain



Flood inundation at Nagano City

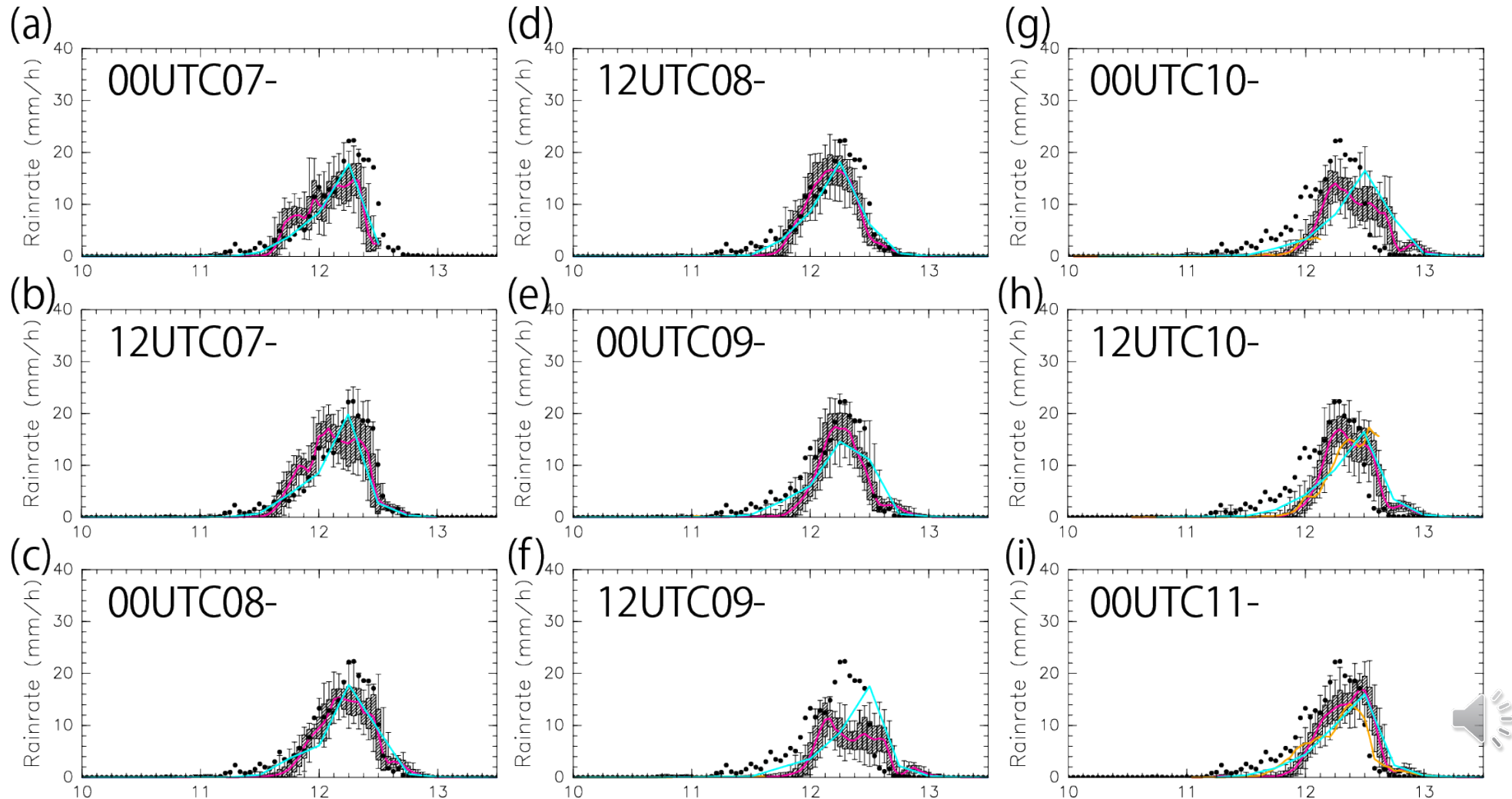


Chikuma River basin

Ensemble forecasting of rainfall

Ensemble mean Rainfall Analysis

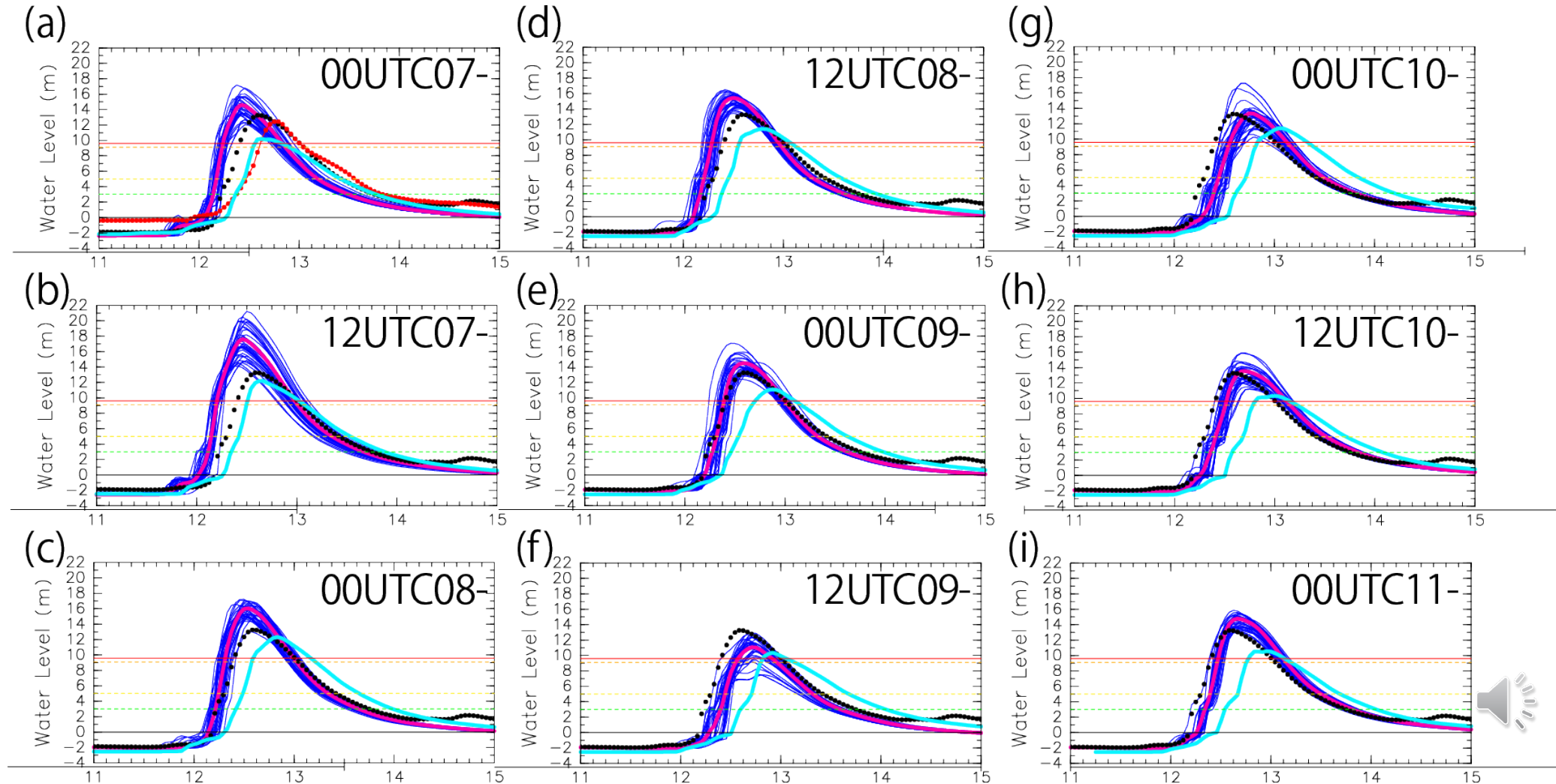
GSM(JMA Global forecast) MSM (JMA Mesoscale forecast)



(After Ushiyama et al.,2020)

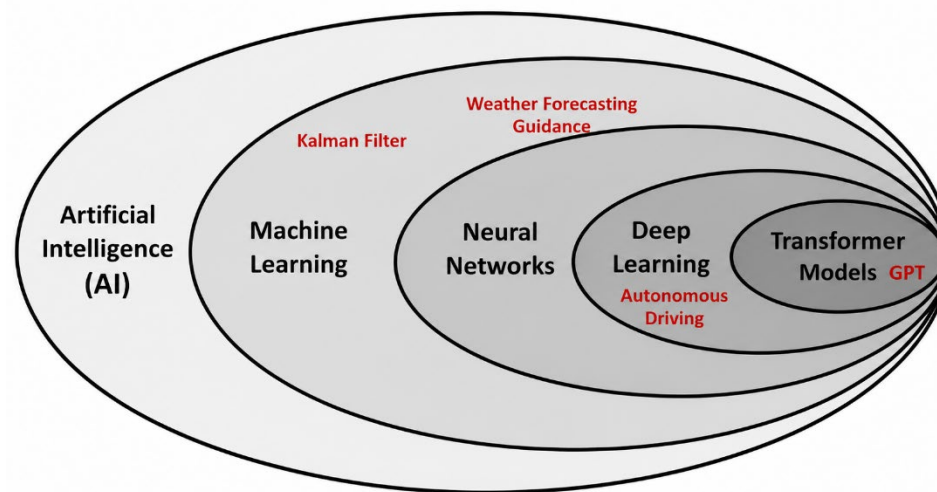
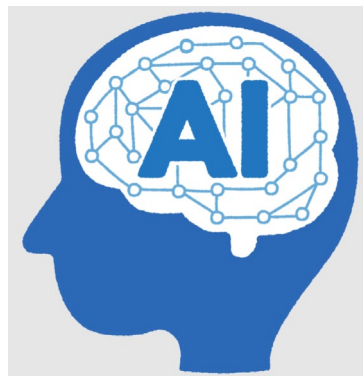
Ensemble flood forecasts

Ensemble forecast Ensemble mean Simulation based on Rainfall analysis
Based on JMA Global forecast Observed water level

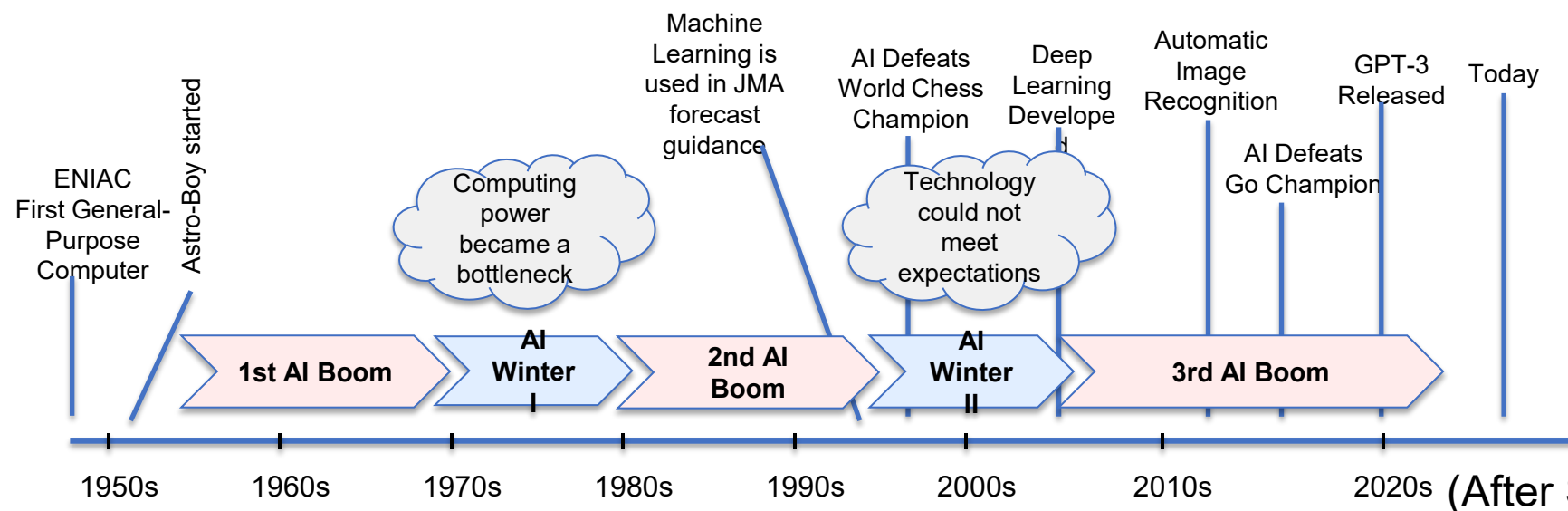


(After Ushiyama et al., 2020)

AI usage in Atmospheric Science

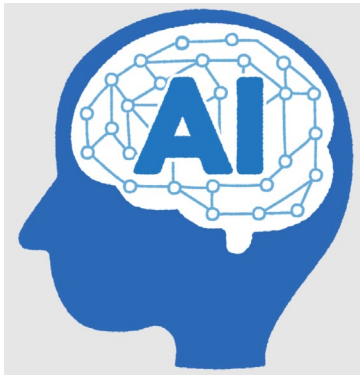


History of Artificial Intelligence



Weather Forecasting using AI/ML

- Physical NWP
 - Fluid dynamics
 - Thermodynamics
 - Radiation
 - Cloud microphysics
- ▶ Disadvantages
 - Extremely high computational costs
 - Difficulty in achieving high resolution
 - Inability to fully utilize observation data
 - Uncertainty in physical processes



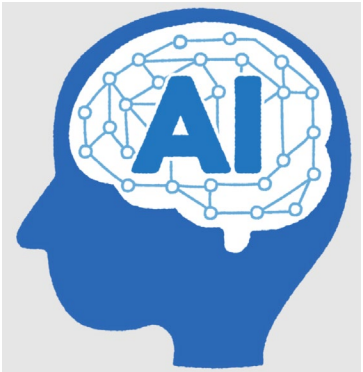
- ▶ Weather Forecasting using AI/ML
 - High speed computation
 - Low-cost computation
 - Several ML models outperformed physical NWP
- ▶ But, disadvantages are;
 - Explainability
 - Extreme weather events
 - Stability in long term, physical consistency
 - Training costs



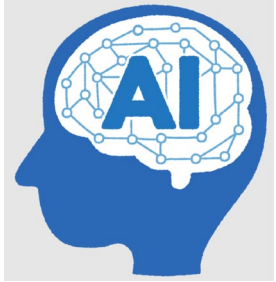
(After Zhang et al.,2025)

Weather Forecasting using AI/ML

- ▶ CNN (convolutional neural network)
 - Precipitation nowcasts
 - Temperature/Wind forecast
 - ▶ Specializes in spatial pattern extraction
- ▶ RNN/LSTM/ConvLSTM
 - Time-series weather forecasting
 - Precipitation nowcasts
 - ▶ Capable of handling time-series dependencies
- ▶ Transformer
 - **Pangu-Weather** (by Huawei) 2023
 - ▶ 3D Earth-Specific Transformer
 - ▶ Global forecast using ECMWF ERA5
 - ▶ Significantly faster than physical NWP
 - ▶ High accuracy even in extreme weather forecasts
 - **GraphCast** (Google Deepmind) 2023
 - ▶ 10 days forecast
 - ▶ Exceeds ECMWF HRES on many metrics
- ▶ GNN (Graph neural network)
 - **GraphCast, DGFormer**
 - ▶ Treating the Earth as a graph
 - ▶ Representing spatial relationships
 - ▶ Specializes in global interaction modeling
- ▶ Generative AI
 - GAN
 - Diffusion model
 - VAE
 - ▶ High-resolution modeling
 - ▶ Extreme precipitation simulation
 - ▶ Ensemble simulation
 - ▶ **GenCast, FuXi-ENS, NowcastNet**
 - ▶ In particular, **GenCast** outperformed the ECMWF ENS in over 97% of cases



Weather Forecasting using AI/ML



▶ CNN Integration with the Laws of Physics

- Physics-informed AI
 - ▶ Examples: **FourCastNet**, **NeuralGCM**, SFNO
 - ▶ Features: PDEs (Partial Differential Equations), Fluid Dynamics, Spherical Calculus are incorporated into neural networks.
- **FourCastNet (NVIDIA) 2022**
 - ▶ Utilizes the Fourier Neural Operator, Global Forecasts, Ultra-fast, High resolution

▶ 5. Datasets

- ERA5
 - ▶ ECMWF reanalysis data, 0.25° 1-hour intervals Global
Most widely used
 - ▶ Many AI weather models use ERA5.

▶ 6. Key Claims

- AI has already begun to partially outperform NWP
 - ▶ Computational speed,
 - ▶ Short- to medium-range forecasts,
 - ▶ Extreme weather detection
- However, it is not a complete replacement.
 - ▶ Lack of interpretability
 - ▶ Prediction of rare events
 - ▶ Long-term stability
 - ▶ Physical consistency
 - ▶ Training costs
- The future lies in the integration of “AI + physics”
- The paper emphasizes that AI integrated with physical laws—rather than pure AI—is crucial.



(After Zhang et al.,2025)