# Numerical Prediction of Mesoscale Weather

Kazuo Saito
ksaito@mri-jma.go.jp

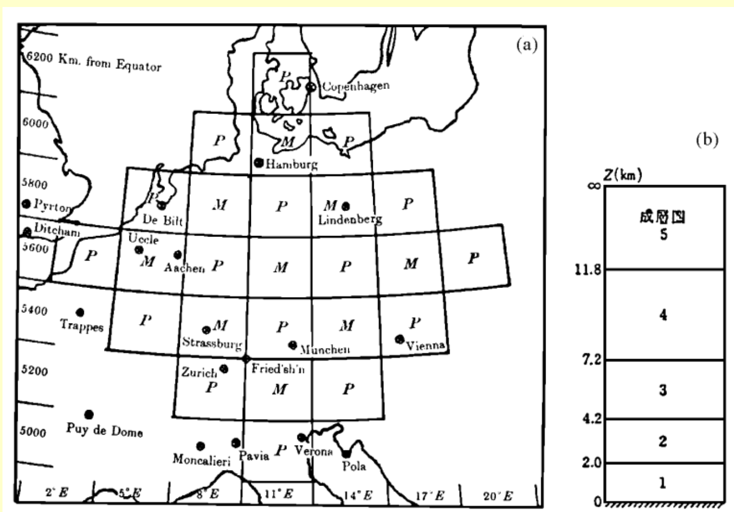
Meteorological Research Institute (MRI)

1. History of numerical weather prediction
2. Fundamental equations for atmosphere
3. Importance of the initial condition
4. Ensemble prediction
5. The K-computer project

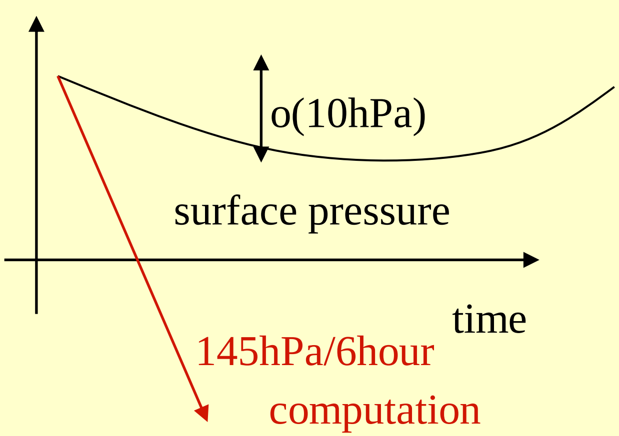
# 1. History of Numerical Weather Prediction

Numerical Weather Prediction (NWP)
.. predicts future state of the atmosphere quantitatively by time-integrating laws of physics
.. regarded as one of the best application fields of computational physics from the earliest period

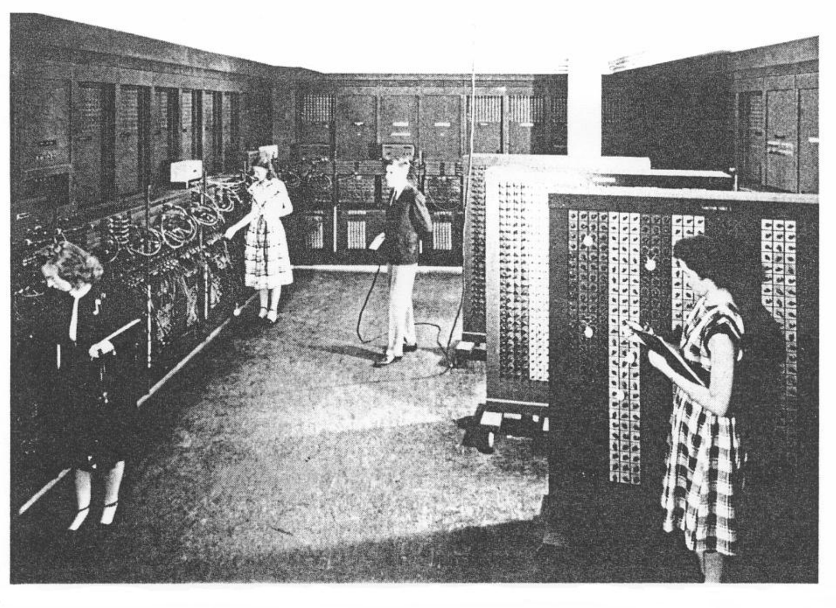
Bjerknes (1904) pointed out possibility of weather prediction based on dynamics and physics
Richardson (1922) tried weather prediction by solving the equations of fluid with hand calculation but failed by overwhelming of noises



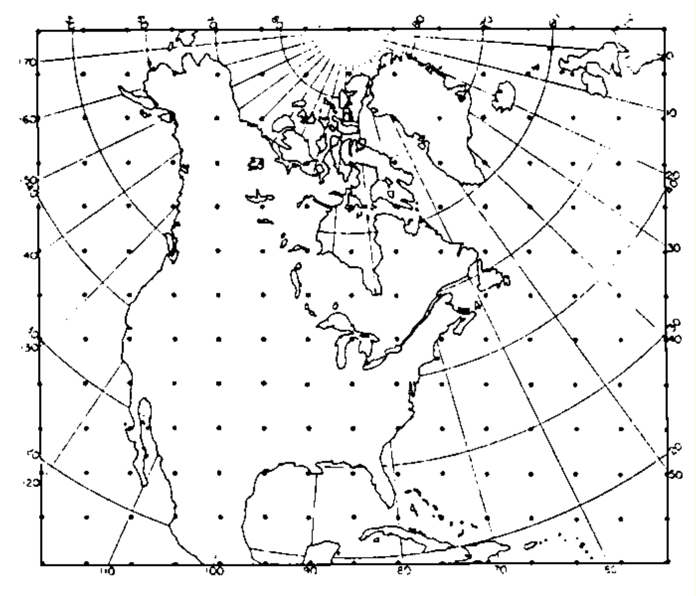

Horizontal and vertical grid taken by Richardson (1922)



# Dawn of numerical weather prediction



1946 Pennsylvania Univ. Developed the first digital computer (ENIAC)
23 word memories, 18,800 tubes (300FLOPS)
Von Neumann of Institute for Advanced Study, Princeton Univ. proposed application to weather prediction



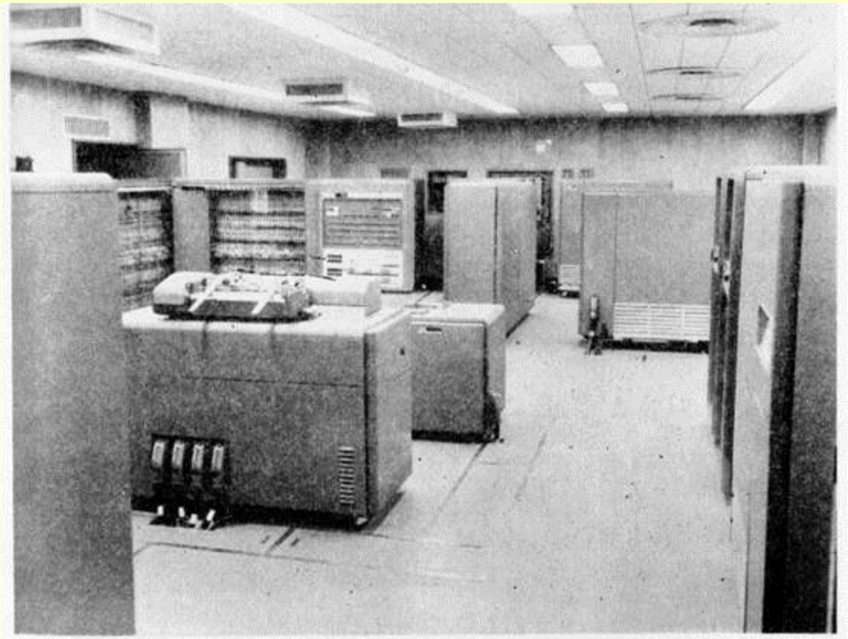
1950 First success of 24 hour forecast using ENIAC by Charney et al.
Grid distance 736 km at 45N
Number of grid points 15×18
One level (500hPa)
2-dimensional barotropic model which predicts the absolute vorticity preservation law

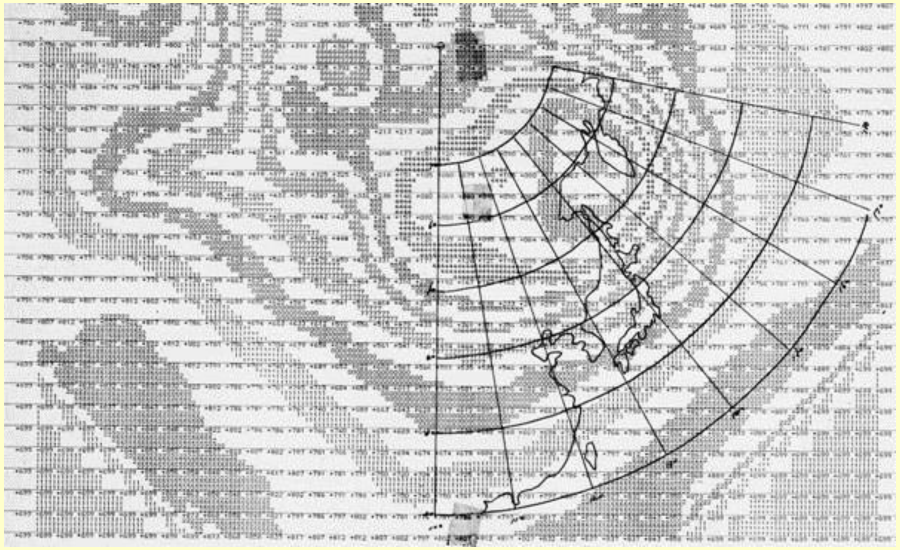
$$d/dt(f+\zeta) = 0$$

35 days for two 24 hour computations

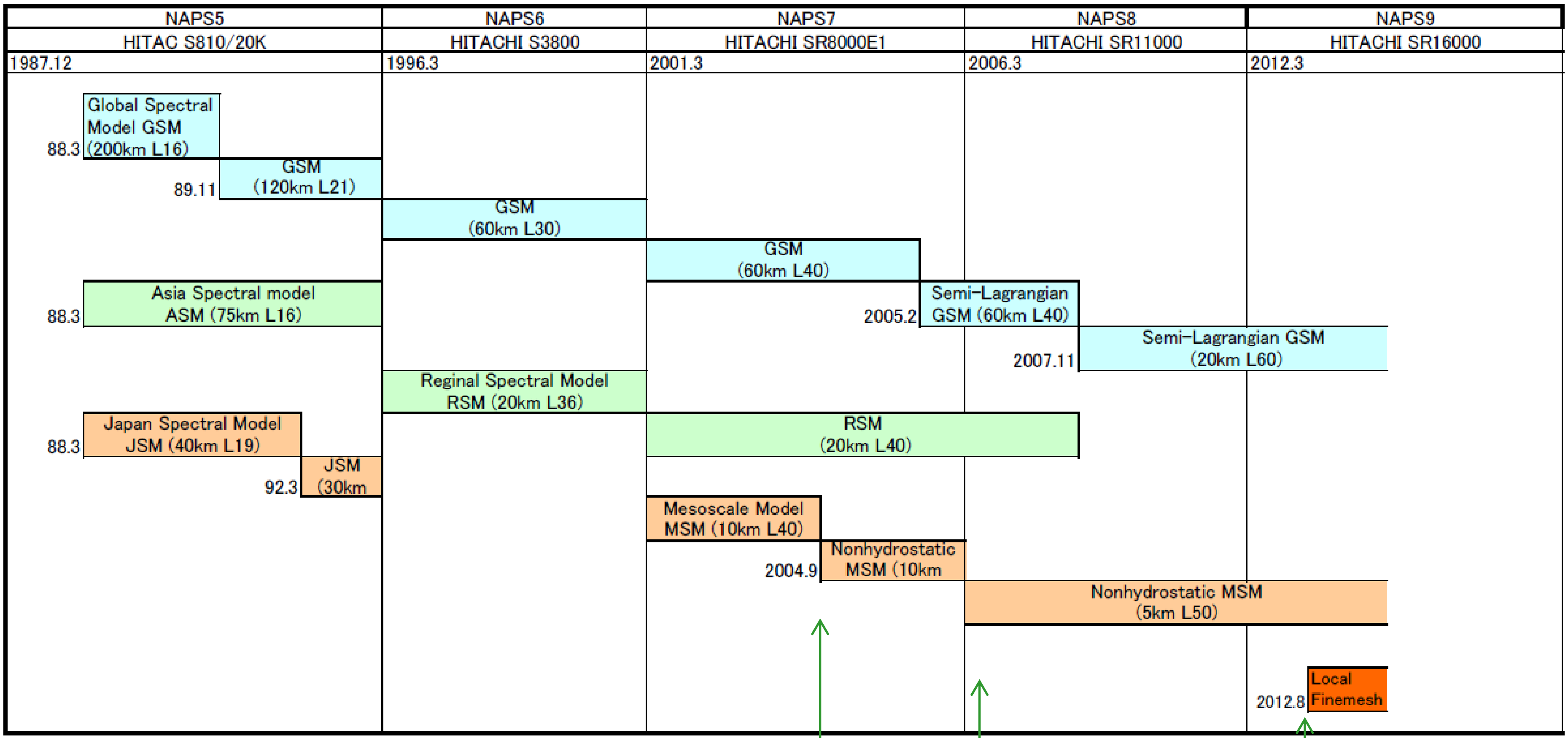
# NWP in Japan

1959 Japan Meteorological Agency implemented IBM704
core Memory of 8 K words (36 bit)
1960 Operation started with a northern hemispheric barotropic model
(381 km, one level)





# NWP models at JMA (1988-)




Operation of JMA-NHM (10km)

(5km)

(2km)

# 2. Fundamental equations for atmosphere

Six variables which describe the state of dry atmosphere:
three velocity components, pressure, temperature and density

**Prognostic equations**

- Momentum equation（three wind components: $u$, $v$ and $w$ ）
- Continuity equation（pressure: $p$）
- Thermodynamic equation (temperature: $T$)

**Diagnostic equation**

- State equation (density: $\rho$)

In the case of moist atmosphere, preservation of water substances and the phase change must be considered (cloud micro-physics).

# Momentum equation

- Momentum equation（three components）

$$\frac{du}{dt}+\frac{1}{\rho}\frac{\partial p}{\partial x}=dif.u$$

$$\frac{dv}{dt}+\frac{1}{\rho}\frac{\partial p}{\partial y}=dif.v$$

$$\frac{dw}{dt}+\frac{1}{\rho}\frac{\partial p}{\partial z}+g=dif.w$$

$\partial$: partial derivative symbol

・Nwton's law of motion: （Force）=（mass × acceleration）

→

Navier-Sokes' equation for fluid：

（acceleration）=（pressure gradient force per unit mass）

（+diffusion+gravity force for vertical direction ）

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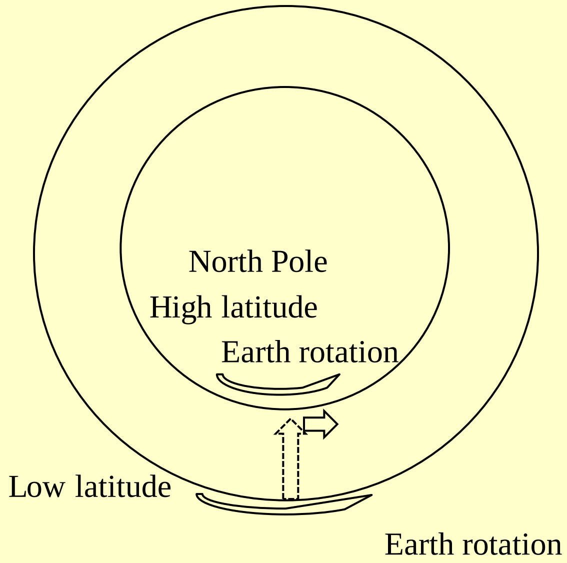
# Coriolis' force

Effect of Coriolis' force is added on the earth




Northward motion shifts eastward in Northern hemisphere due to the difference of speeds of earth rotation.

In vector formulation, Coriolis' force is vector product of angular velocity of the earth rotation $\Omega$ and wind vector $V$:

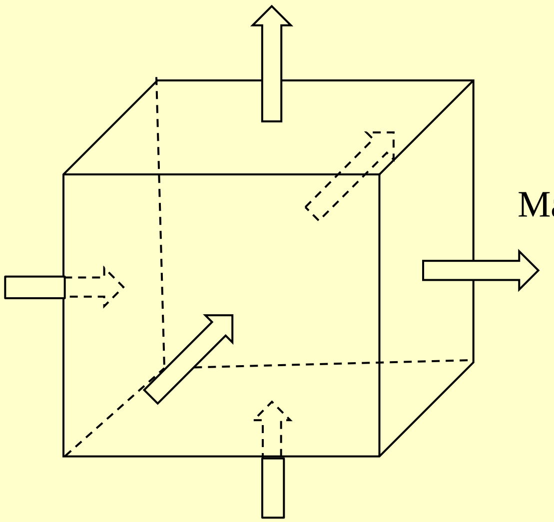
$$\frac{d\vec{V}}{dt} = (-2\vec{\Omega} \times \vec{V}) - \frac{1}{\rho}\nabla p + \vec{g} + \vec{F},$$

# Continuity equation

Continuity equation（law of mass preservation）

$$\frac{\partial \rho}{\partial t} + \frac{\partial \rho u}{\partial x} + \frac{\partial \rho v}{\partial y} + \frac{\partial \rho w}{\partial z} = 0$$

・・local time tendency of density=differences of mass flux through surrounding boundaries



Mass flux (density x wind speed)

# State equation for ideal gasses

Boyle-Charles's combined law for ideal gas with a molecular weight of $m$

$$p = \rho \frac{R^*}{m} T = \frac{M}{m} \frac{R^*}{V} T$$

$R^*$ : universal gas constant (=8.314J/mol/K)

In case of dry air (represented by subscript $d$),

by Dalton's law for partial pressure,

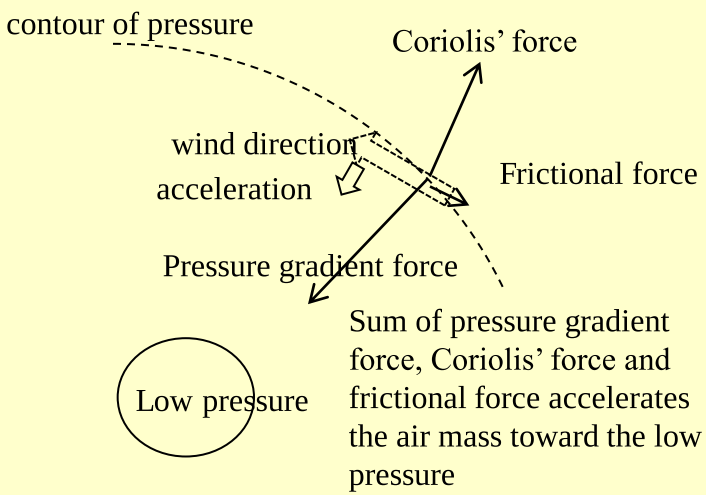
$$p_d = \sum_i p_i = \frac{R^*}{V} T \sum_i \frac{M_i}{m_i} = \frac{R^*}{V} T \frac{\sum_i M_i}{m_d} = \rho_d RT$$

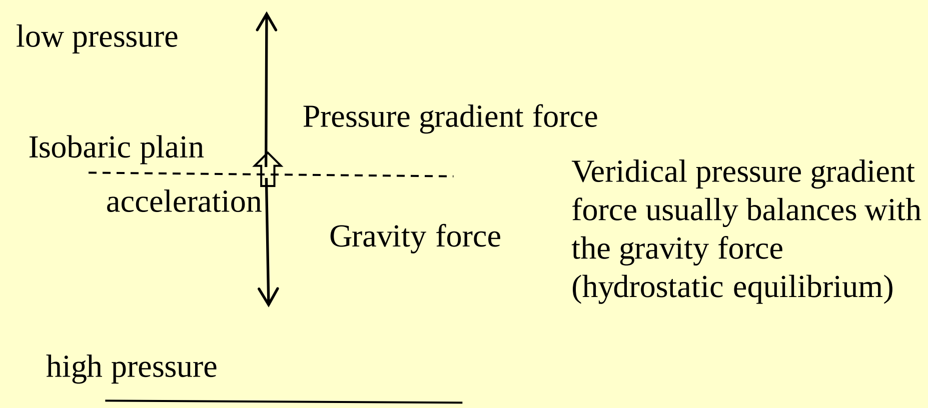
$i$ is index to represent gas component such as nitrogen, oxygen, and argon, and $m_d$ the weigh-average molecular of dry air (28.966 g/mol)

$$m_d = \frac{\sum_i M_i}{\sum_i \frac{M_i}{m_i}}$$

$R$ (=$R^*/m_d$) : gas constant for dry air (=287.05 J/Kg/K)

# Forces on air and acceleration




hydrostatic equilibrium $\frac{1}{\rho}\frac{dp}{dz}+g=0$

$$\rightarrow \frac{1}{p}\frac{dp}{dz}=-\frac{g}{RT} \quad \rightarrow \frac{d}{dz}(\log p)=-\frac{g}{RT}$$

$$\rightarrow \quad p=p_0 e^{-\frac{gz}{RT_m}}$$

… well-known barometric height formula (pressure-height equation)

# Thermodynamic equation

First law of the thermodynamics

$$dQ = dI + pd\alpha$$

$\because$ heating to air mass is the sum of internal energy increase and mechanical work by pressure. Here, $Q$ is the adiabatic heating rate and $\alpha$ is specific volume (inverse of density).

$$Qdt = C_v dT + pd\alpha = C_v dT + d(p\alpha) - \alpha dp$$
$$= (C_v + R)dT - \alpha dp = C_p dT - \alpha dp$$

Here $C_v$ is the specific heat of air at constant volume (=5R/2), and $C_p$ the specific heat of air at constant pressure

# Finite discretization

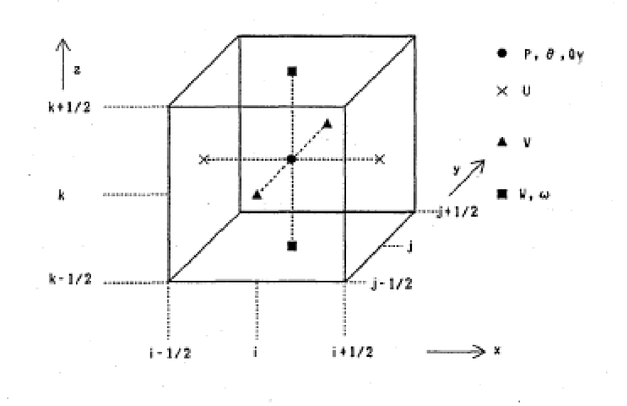
In the numerical model, differential equation is discretized by finite difference, based on the Taylor series expansion:

$$f(x+\Delta x) = f(x) + \Delta x f'(x) + \frac{(\Delta x)^2}{2} f''(x) + ..$$

$$f(x-\Delta x) = f(x) - \Delta x f'(x) + \frac{(\Delta x)^2}{2} f''(x) - ..$$

Here, *f'* (*f''*) is the first (second) derivative of the function *f*.
The second order centered difference can be obtained as :

$$\frac{\partial f}{\partial x} = \frac{f(x+\Delta x) - f(x-\Delta x)}{2\Delta x} + O(\Delta x)^2$$




or, in staggered grid,

$$\frac{\partial f}{\partial x} = \frac{f(x+\frac{\Delta x}{2}) - f(x-\frac{\Delta x}{2})}{\Delta x} + O(\frac{\Delta x}{2})^2$$

For advection term in momentum equations, higher order schemes are used e.g.,

$$\frac{\partial f}{\partial x} = \frac{9}{8}\frac{f(x+\frac{\Delta x}{2}) - f(x-\frac{\Delta x}{2})}{\Delta x} - \frac{1}{8}\frac{f(x+\frac{3\Delta x}{2}) - f(x-\frac{3\Delta x}{2})}{3\Delta x} + O(\frac{\Delta x}{2})^4$$

# Pressure equation and implicit treatment

Pressure equation is obtained from the continuity equation and the state equation:

$$\frac{\partial p}{\partial t} + C_s^{\ 2}\left(\frac{\partial \rho u}{\partial x} + \frac{\partial \rho v}{\partial y} + \frac{\partial \rho w}{\partial z}\right) = FP$$

Here, $C_s$ is the sound wave speed ($=(C_p/C_v \times RT)^{1/2}$) and FP represents forcing term such as the time tendency of (potential) temperature. Solutions of above equations include sound waves due to the elasticity of air. In atmospheric models for weather predication, pressure is treated implicitly in the vertical direction. The following 1-dimensional elliptic (Helmholtz-type) pressure equation is obtained:

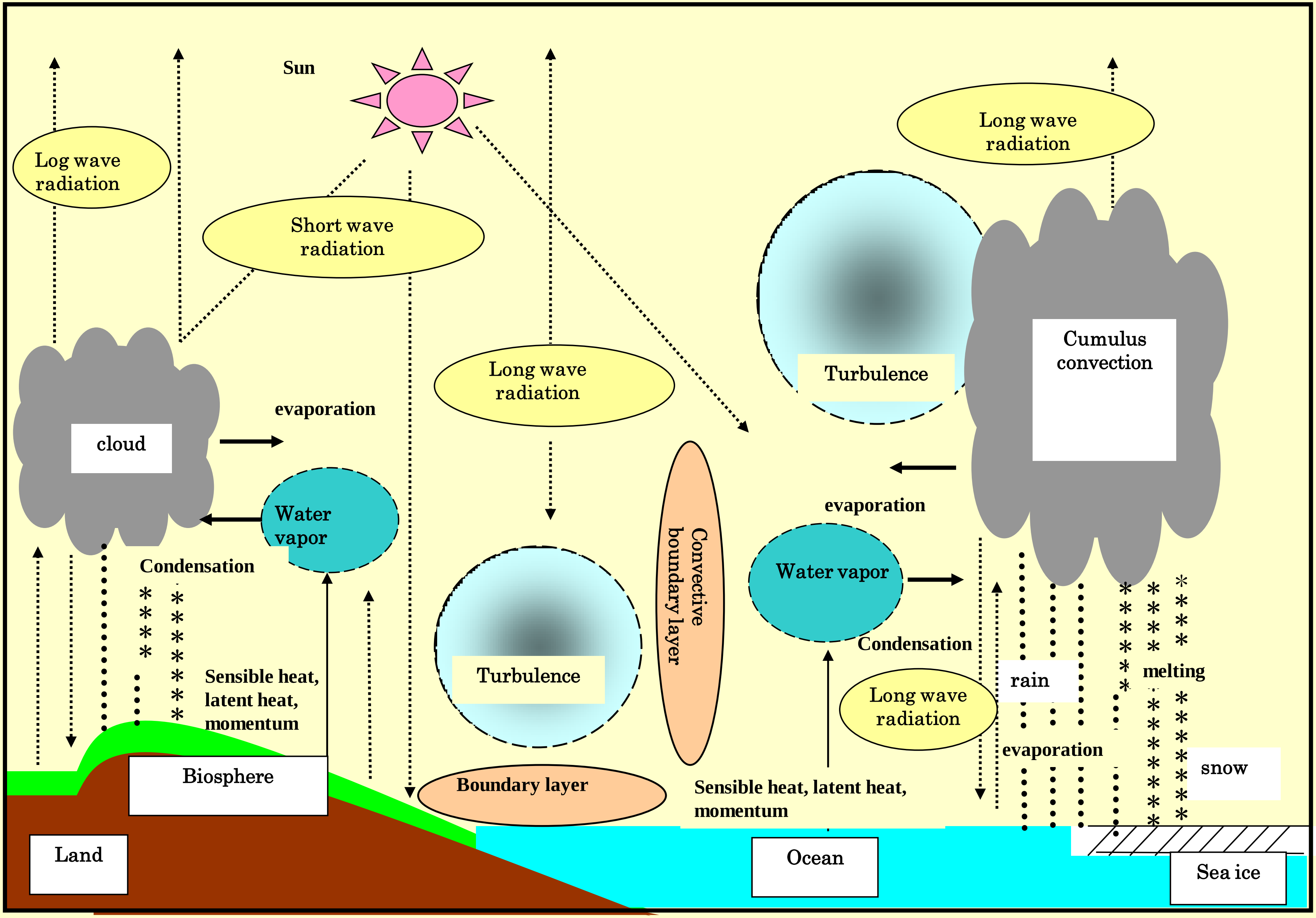
$$\frac{\partial^2 \overline{P^\tau}}{\partial z^2} + \frac{\partial}{\partial z}(h\overline{P^\tau}) + e'\overline{P^\tau} = FP.HE$$

$$\frac{\partial A}{\partial t} = \frac{A^{\tau+\Delta\tau} - A^\tau}{\Delta\tau}, \quad e' = -\left\{\frac{2}{(1+\beta)\Delta\tau C_s}\right\}^2,$$

$$FP.HE = -\frac{2}{(1+\beta)\Delta\tau}\frac{FP}{C_s^{\ 2}} + \frac{\partial}{\partial z}FW + \frac{2}{(1+\beta)\Delta\tau}\left\{\left(\frac{\partial \overline{\rho u^\tau}}{\partial x} + \frac{\partial \overline{\rho v^\tau}}{\partial y}\right) + \frac{\partial \rho w^\tau}{\partial z}\right\} + e' P^\tau.$$

Gaussian sweep-out elimination method is used to solve above equation.

# Physical processes in NWP model

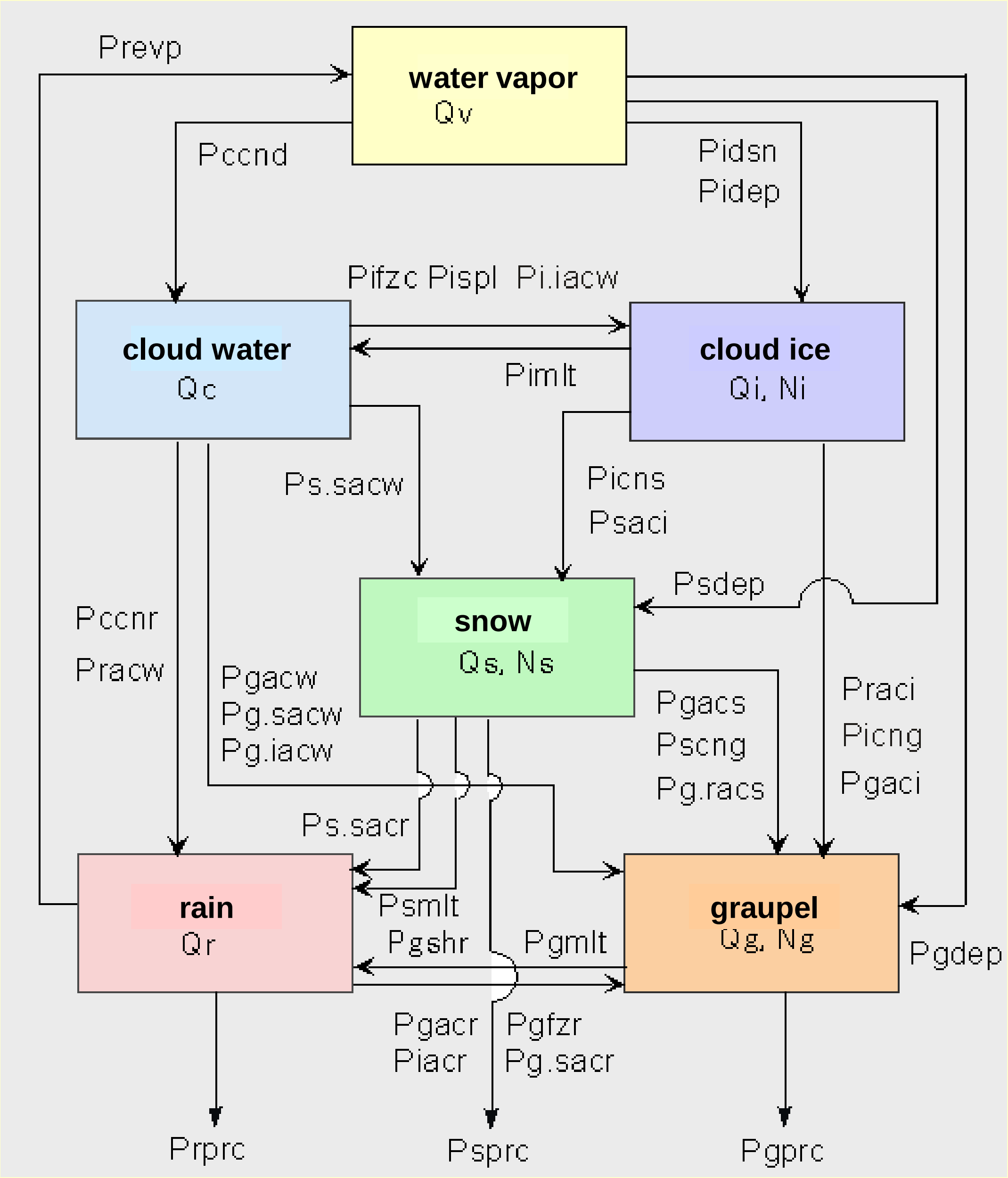


# *Cloud Microphysics*

- Typical prognostic variables
  - water vapor, cloud water, rain, cloud ice, and graupel (Qv, Qc, Qr, Qi, Qs, Qg)
  - number density of cloud ice, snow and graupel (Ni, Ns, Ng)

Tetens' formula for
saturated vapor pressure [hPa]

$$e_s = 6.11 \times 10^{\frac{7.5 \times t}{237.7 + t}}$$



# Bulk cloud microphysics

In bulk method, the size distribution function of water substance is expressed by the inverse exponential function of the particle diameter *D*.

$$N(D) = N_0 e^{-\lambda D}$$

Fall-out terminal velocity of particle is given as a power function of *D* by the Stokes' law in the form of

$$V(D) = aD^b$$

| Variable $Qx$(kg/kg) $Nx$(m$^{-3}$) | Size distribution $Nx(D)$ (m$^{-4}$) | Fall velocity $Udx$(m/s) | Density $\rho_x$(kg/m$^3$) |
|---|---|---|---|
| $Qr$ | $Nr(D) = Nr_0 \exp(-\lambda D)$ <br> $Nr_0 = 8 \times 10^6$ | $a_r D r^{b_r} \left(\frac{\rho_0}{\rho}\right)^{1/2}$ <br> $a_r = 842$ <br> $b_r = 0.8$ | $\rho_w = 1 \times 10^3$ |
| $Qs$ <br> $Ns$ | $Ns(D) = Ns_0 \exp(-\lambda D)$ <br> $(Ns_0 = 1.8 \times 10^6)$ | $a_s D s^{b_s} \left(\frac{\rho_0}{\rho}\right)^{1/2}$ <br> $a_s = 17$ <br> $b_s = 0.5$ | $\rho_s = 8.4 \times 10$ <br> $r_{s0} = r_0 = 75\,\mu$m <br> $m_{s0} = (4\pi/3)\rho_s r_{0s}^3$ |
| $Qg$ <br> $Ng$ | $Ng(D) = Ng_0 \exp(-\lambda D)$ <br> $(Ng_0 = 1.1 \times 10^6)$ | $a_g D g^{bg} \left(\frac{\rho_0}{\rho}\right)^{1/2}$ <br> $a_g = 124$ <br> $b_g = 0.64$ | $\rho_g = 3 \times 10^2$ <br> $r_{g0} = r_0 = 75\,\mu$m <br> $m_{g0} = (4\pi/3)\rho_g r_{0g}^3$ |
| $Qc$ | mono <br> $Di = \left(\frac{6\rho Qc}{\pi \rho_w Nc}\right)^{1/3}$ <br> $Nc = 1 \times 10^8$m$^{-3}$ | $a_c D c^{bc}$ <br> $a_c = 3 \times 10^7$ <br> $b_c = 2.0$ | $\rho_c = 1.0 \times 10^3$ |
| $Qi$ <br> $Ni$ | mono <br> $Di = \left(\frac{6\rho Qi}{\pi \rho_i Ni}\right)^{1/3}$ | $a_i D i^{bi} \left(\frac{\rho_0}{\rho}\right)^{0.35}$ <br> $a_i = 7 \times 10^2$ <br> $b_i = 1.0$ | $\rho_i = 1.5 \times 10^2$ <br> $m_{i0} = 1 \times 10^{-12}$kg |

# Bulk cloud microphysics

The mass-weighted mean velocity is obtained by

$$\overline{V} = \frac{\int \frac{\pi}{6}\rho_w D^3 V(D) N(D) dD}{\int \frac{\pi}{6}\rho_w D^3 N(D) dD} = \frac{\int D^3 a D^b e^{-\lambda D} dD}{\int D^3 e^{-\lambda D} dD} = \frac{a\Gamma(4+b)}{6\lambda^b}$$

Here Γ(x) is the Gamma function

$$\Gamma(z) = \int_0^\infty t^{z-1} e^{-t} dt$$

By Euler's partial integration, the Gamma function has the following characteristic

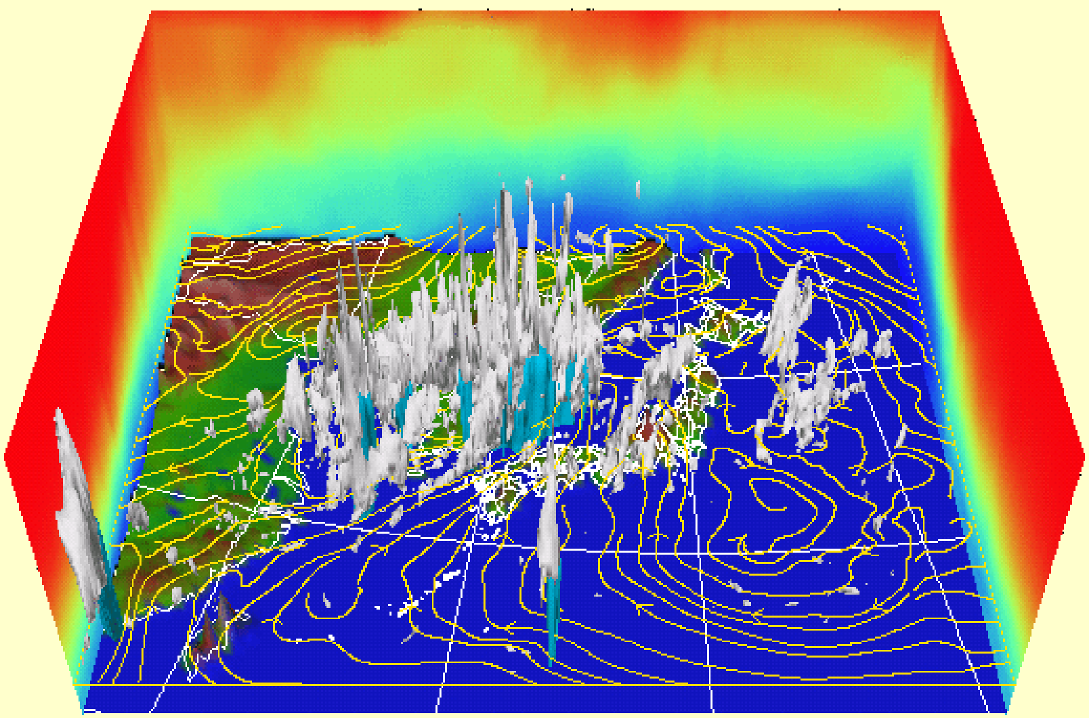
$$\Gamma(z) = \int_0^\infty t^{z-1}(-e^{-t})' dt = \left[-t^{z-1}e^{-t}\right]_0^\infty + (z-1)\int_0^\infty t^{z-2} e^{-t} dt$$

$$= (z-1)\Gamma(z-1)$$

# JMA nonhydrostatic model (Sep. 2004)

Mesoscale model of JMA which does not use approximation of the hydrostatic equilibrium

- *Fully compressible numerics developed by MRI and NPD*
- *3 ice bulk cloud microphysics with the Kain-Fritsch convective parameterization scheme*
- *Non-local boundary layer scheme*



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## The Operational JMA Nonhydrostatic Mesoscale Model

KAZUO SAITO
*Meteorological Research Institute, Tsukuba, Japan*

TSUKASA FUJITA, YOSHINORI YAMADA, JUN-ICHI ISHIDA, YUKIHIRO KUMAGAI, KOHEI ARANAMI, SHIRO OHMORI, RYOJI NAGASAWA, AND SAORI KUMAGAI
*Japan Meteorological Agency, Tokyo, Japan*

CHIASHI MUROI, TERUYUKI KATO, AND HISAKI EITO
*Meteorological Research Institute, Tsukuba, Japan*

YOSUKE YAMAZAKI
*Advanced Earth Science and Technology Organization, Tokyo, Japan*

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ABSTRACT

An operational nonhydrostatic mesoscale model has been developed by the Numerical Prediction Division (NPD) of the Japan Meteorological Agency (JMA) in partnership with the Meteorological Research Institute (MRI). The model is based on the MRI/NPD unified nonhydrostatic model (MRI/NPD-NHM), while several modifications have been made for operational numerical weather prediction with a horizontal resolution of 10 km. A fourth-order advection scheme considering staggered grid configuration is implemented. The buoyancy term is directly evaluated from density perturbation. A time-splitting scheme for advection has been developed, where the low-order (second order) part of advection is modified in the latter half of the leapfrog time integration. Physical processes have also been revised, especially in the convective parameterization and PBL schemes. A turbulent kinetic energy (TKE) diagnostic scheme has been developed to overcome problems that arise to predict TKE. The model performance for mesoscale NWP has been verified by comparison with a former operational hydrostatic mesoscale model of JMA. It is found that the new nonhydrostatic mesoscale model outperforms the hydrostatic model in the prediction of synoptic fields and quantitative precipitation forecasts.

### 1. Introduction

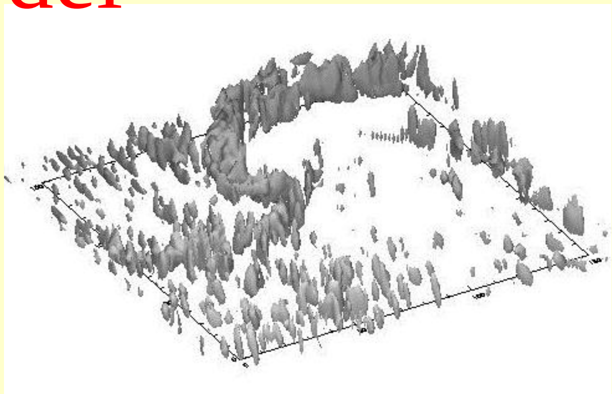
Rapid progress of the computer facilities in recent years enables us to use higher-resolution models in numerical weather prediction (NWP). The horizontal resolution of operational regional/mesoscale models in world main forecast centers is becoming higher and higher and is about 10 km, the limit of validity of the hydrostatic approximation. The Deutscher Wetterdienst (DWD) developed a regional nonhydrostatic model (the Lokall-Model; Doms and Schaettler 1997) and started its operational run with a horizontal resolution of 7 km in 1999. The Met Office introduced nonhydrostatic new dynamics (Davies et al. 2005) in the Unified Model in 2002. The Meteorological Service of Canada, the National Centers for Environmental Prediction of the United States, and other national forecast centers have also been developing or testing their nonhydrostatic NWP models for operation.

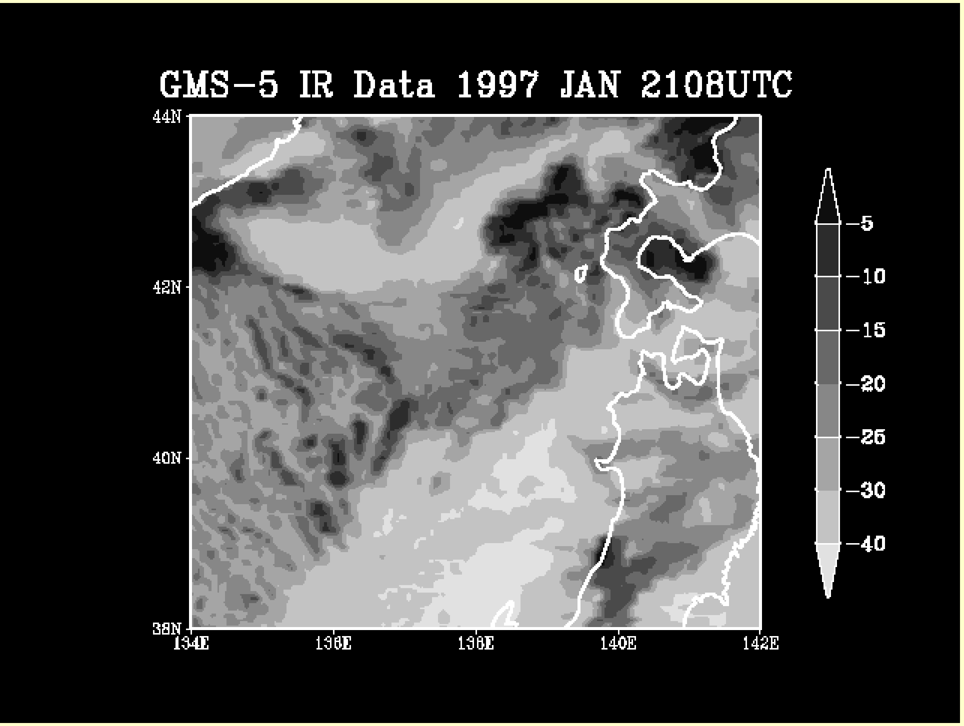
In Japan, the Japan Meteorological Agency (JMA) started operational run of a 10-km-resolution mesoscale model in March 2001, and 18-h time integration has been carried out 4 times a day. This model, MSM, was introduced to support information for disaster prevention and is also used for the very short range fore-

*Corresponding author address:* Dr. Kazuo Saito, Second Laboratory, Forecast Research Department, Meteorological Research Institute, 1-1 Nagamine, Tsukuba, Ibaraki 305-0052, Japan.
E-mail: ksaito@mri-jma.go.jp

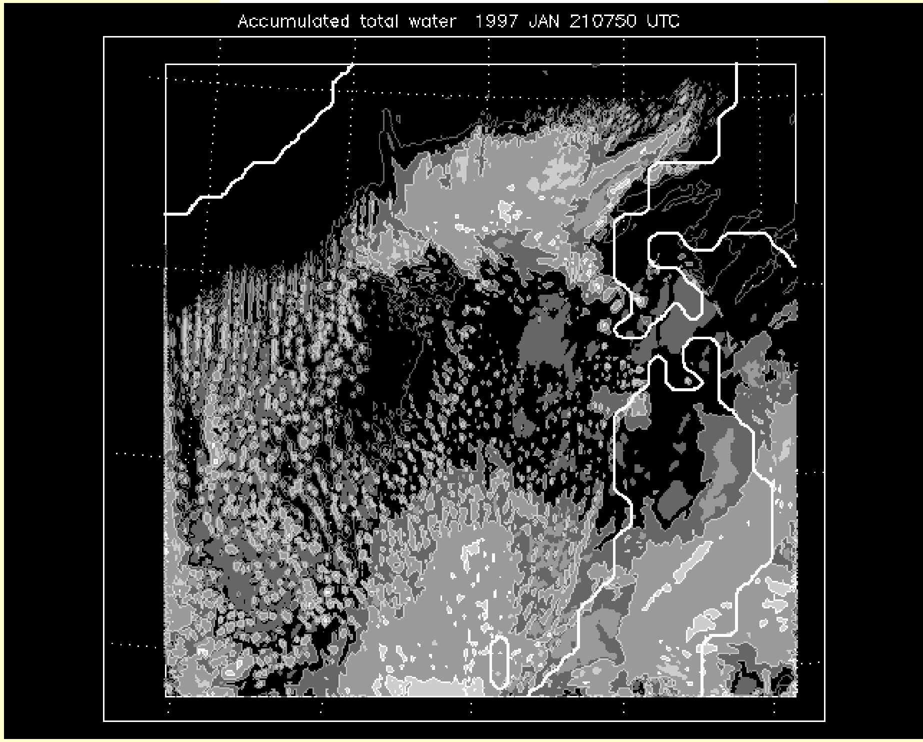
# Cloud resolving model

Polar low simulation with JMA NHM
Horizontal resolution 2km
Initial time 15UTC 21 January 1997



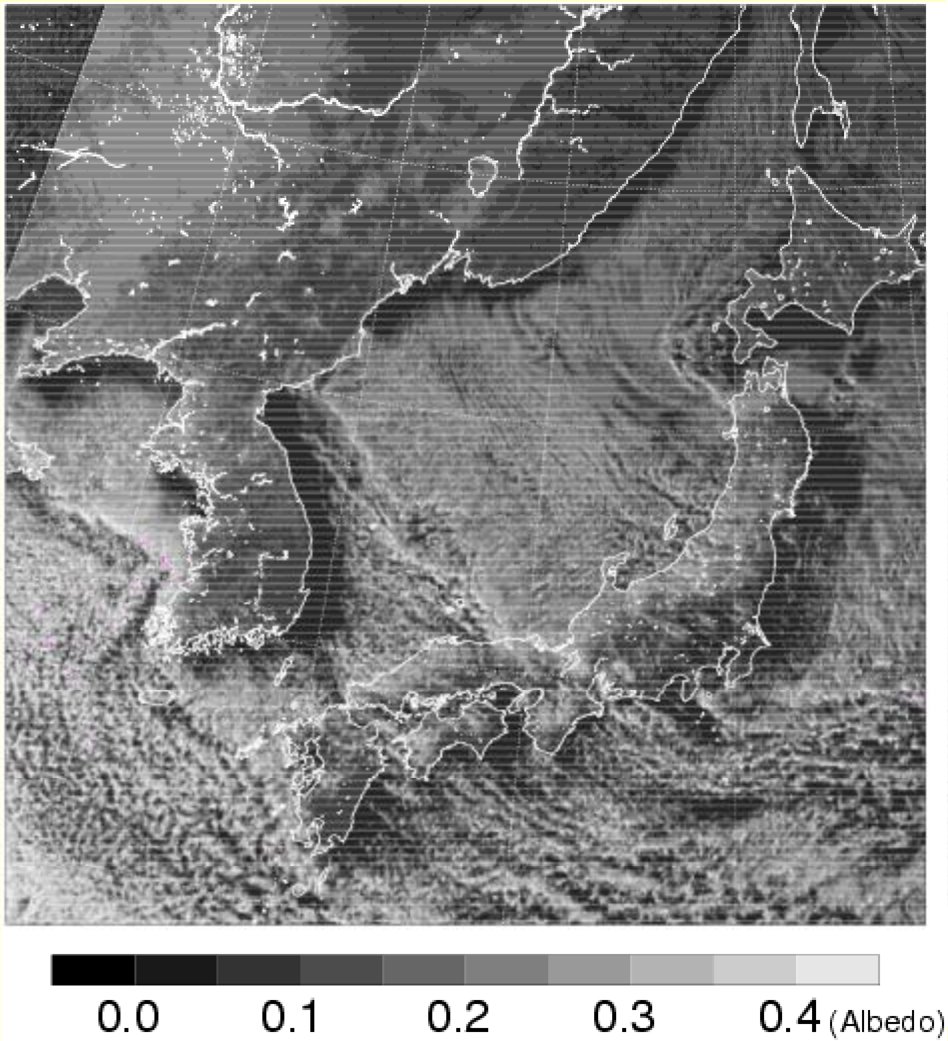


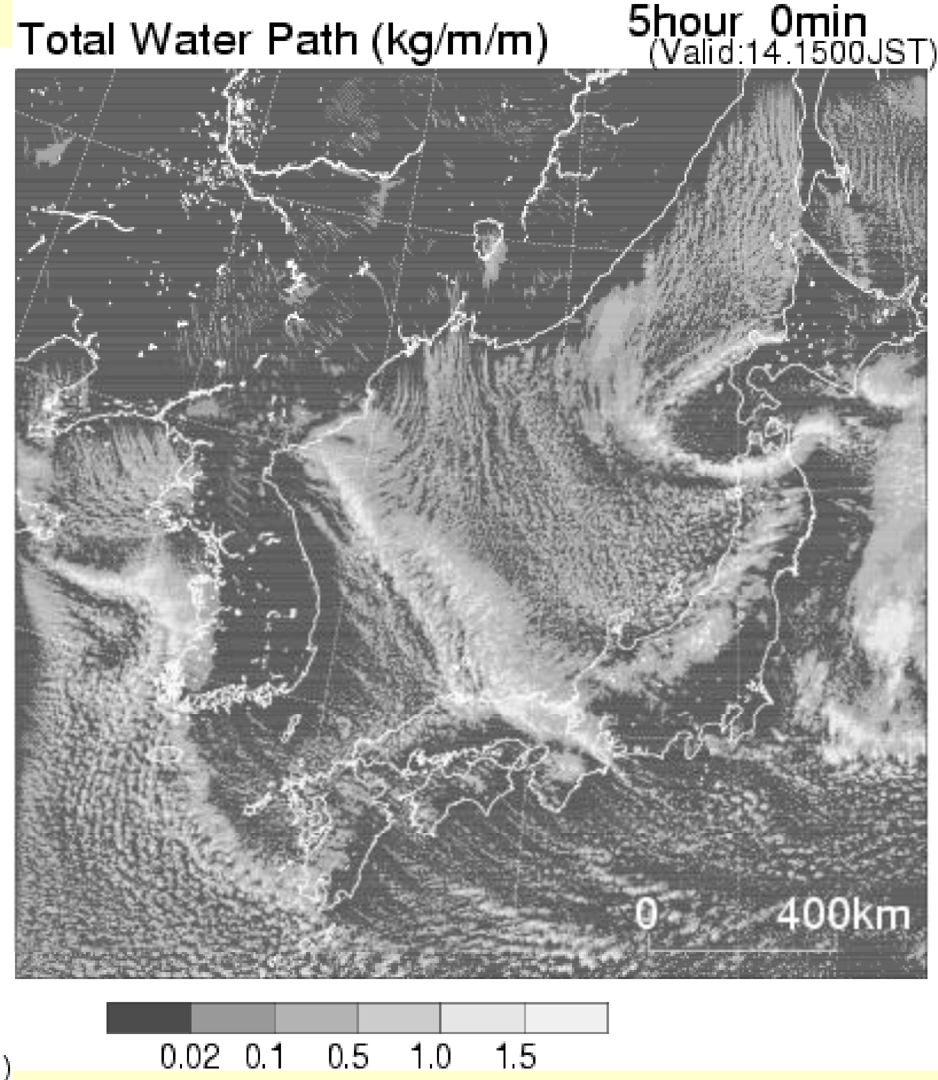

GMS satellite IR image




Cloud resolving simulation of a polar low (Yanase et al., 2002; GRL)

# Cloud resoling simulation of winter monsoon clouds over the Sea of Japan using Earth Simulator




Left) GMS satellite visible-Image at 15JST 14 January 2001
Right) Total water simulated by NHM with a horizontal resolution of 1 km

Eito et al. (2010; JMSJ)

# 3. Importance of the initial condition

## Major difference between climate projection and NWP

▪**the same point**

predict future state of the atmosphere quantitatively by time-integrating laws of physics.

▪**major difference**

**Climate projection**

**・・projects climate response to change of global environment such as $CO_2$, SST**

**⇒boundary condition and radiation-convection equilibrium are important**

**NWP**

**・・predicts weather of a specific day in short time range**

**⇒initial condition and time evolution are important**

# Maximum likelihood estimation in data assimilation

| | | |
|---|---|---|
| $x$ | : | analysis variable |
| $x_b$ | : | first guess of x |
| $y_o$ | : | observation data |
| $p(\cdot \mid \cdot)$ | : | conditional probabilistic density function (PDF) |

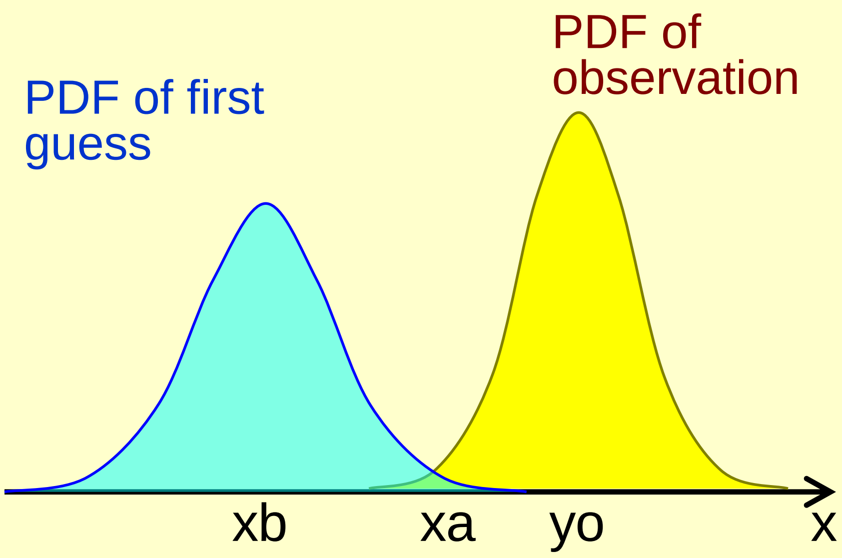
## Bayesian theorem

(if $\mathbf{x}_b$ and $\mathbf{y}_o$ are independent,

$$p(\mathbf{x} \mid \mathbf{x}_b, \mathbf{y}_o) = \frac{p_b(\mathbf{x}_b)\, p_o(\mathbf{y}_o)}{\int p_b(\mathbf{x}_b)\, p_o(\mathbf{y}_o)\, d\mathbf{x}}$$

## Baysian estimation

$$\hat{\mathbf{x}} = \max_{\mathbf{x}} [\, p_b(\mathbf{x}_b)\, p_o(\mathbf{y}_o)]$$



If PDFs of the first guess and observation are Gaussian normal distribution as

$$p_b(\mathbf{x}_b) = \frac{1}{\sqrt{2\pi\sigma_b^2}} \exp\{-\frac{(x-x_b)^2}{2\sigma_b^2}\}$$

$$p_o(y_o) = \frac{1}{\sqrt{2\pi\sigma_o^2}} \exp\{-\frac{(y-y_o)^2}{2\sigma_o^2}\}$$

The conditional PDF of $x$ with background $x_b$ and observation $y_o$ is normal as

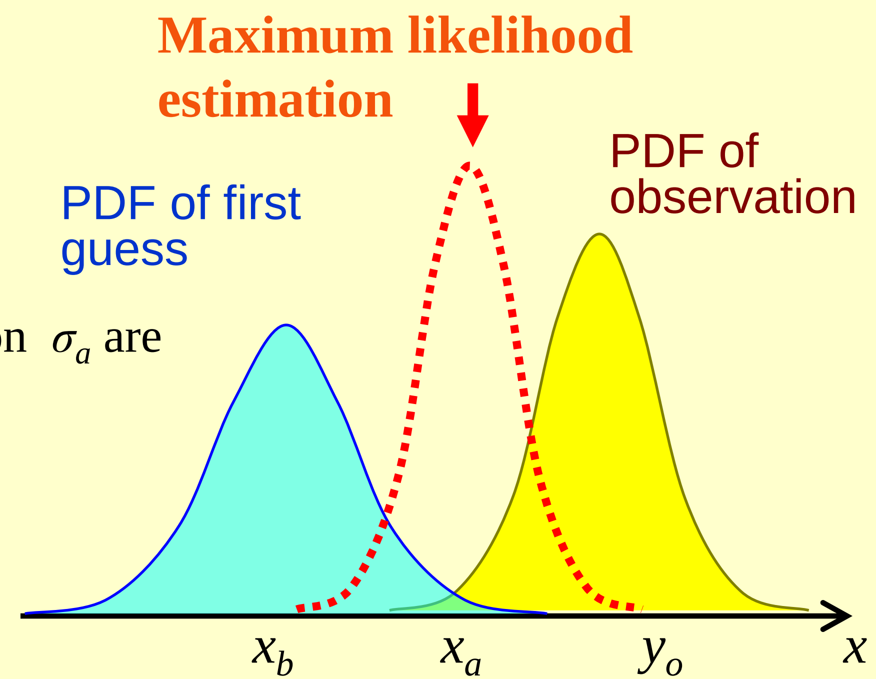
$$p(\mathbf{x} \mid \mathbf{x}_b, \mathbf{y}_o) = \frac{p_b(\mathbf{x}_b) p_o(\mathbf{y}_o)}{\int p_b(\mathbf{x}_b) p_o(\mathbf{y}_o) d\mathbf{x}}$$

$$= \frac{1}{\sqrt{2\pi\sigma_a^2}} \exp\{-\frac{(x-x_a)^2}{2\sigma_a^2}\}$$

Where analysis $x_a$ and its standard deviation $\sigma_a$ are

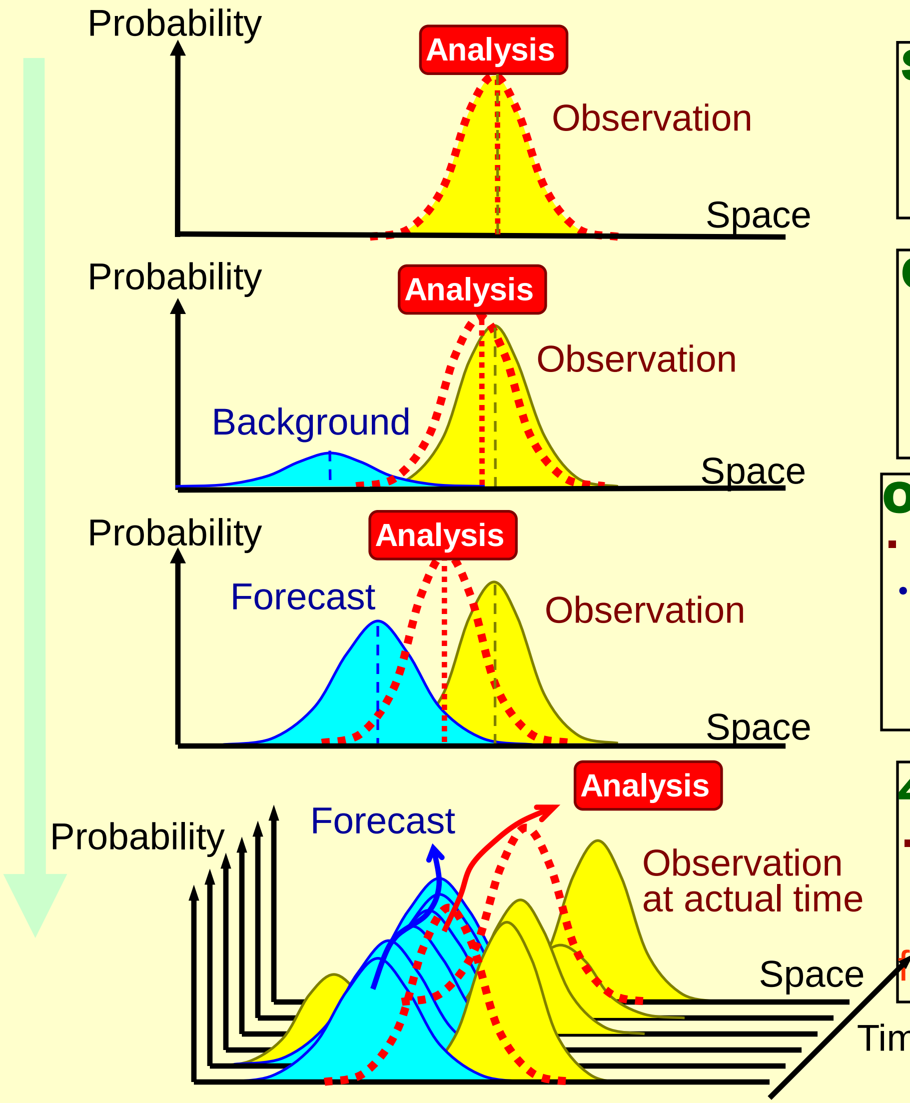
$$\frac{x_a}{\sigma_a^2} = \frac{x_b}{\sigma_b^2} + \frac{y_o}{\sigma_o^2}$$

$$\frac{1}{\sigma_a^2} = \frac{1}{\sigma_b^2} + \frac{1}{\sigma_o^2} \quad \longrightarrow \quad x_a = \frac{\sigma_o^2 x_b + \sigma_a^2 y_o}{(\sigma_a^2 + \sigma_o^2)}$$




Analysis is weighted mean of first guess and observation, and analysis error becomes smaller than the errors of first guess and observation.

# Relation between 1st guess, observation and analysis




**Simple fitting**

- Use observation data only

**Correction method**

- Use observation data
- Use low quality background information

**Optimal interpolation／3D-VAR**

- Use observation data
- Use forecast as the 1st guess
  background error is given by statistics

**4D-VAR**

- Use observation data
- Use forecast model and 1st guess
  Analysis is obtained by time evolution of forecast/adjoint models

# 4Dimensional –Variational method

Forecast model

**Cost function :**

$$J = J_b + J_o + J_c$$

$$= \frac{1}{2}\left(x_0 - x_0^b\right)^{\mathrm{T}} \mathrm{B}^{-1}\left(x_0 - x_0^b\right) + \frac{1}{2}\left(HMx_0 - y^o\right)^{\mathrm{T}} \mathrm{R}^{-1}\left(HMx_0 - y^o\right) + J_c$$

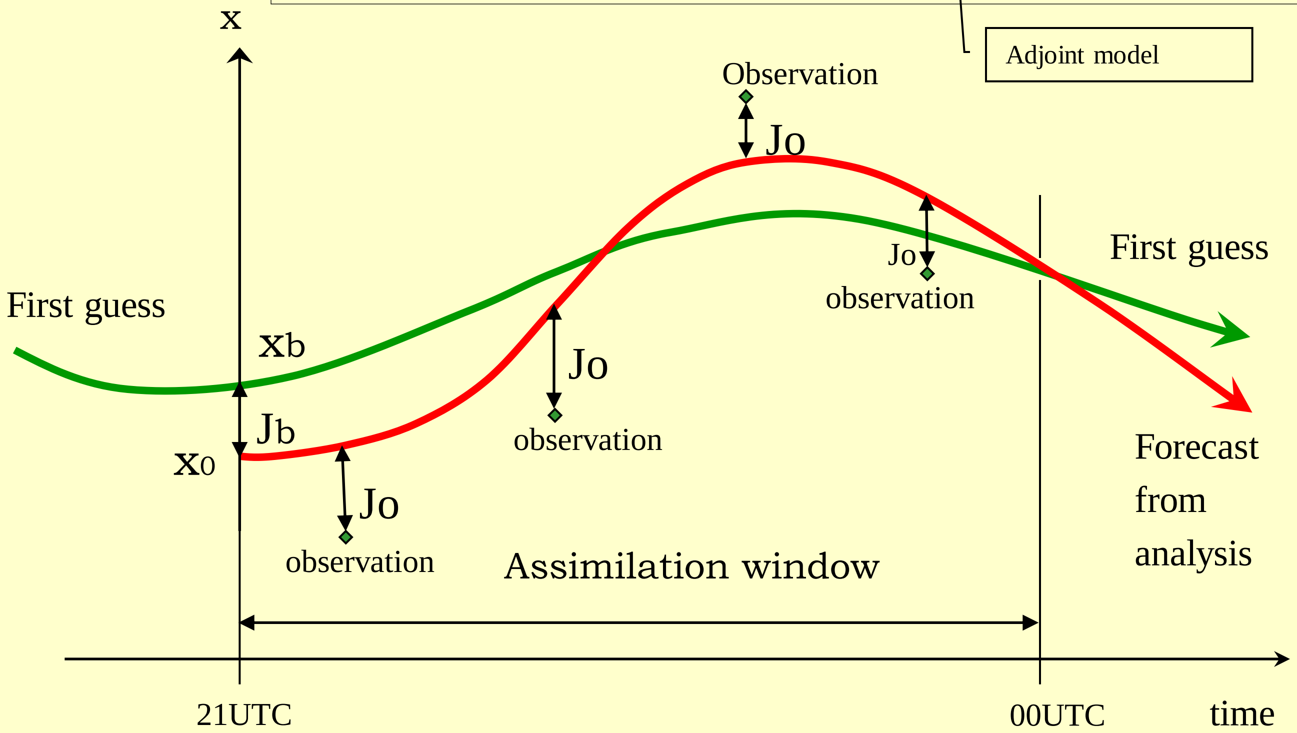
Penalty term

**Gradient of cost function:**

$$\nabla_{x0} J = \nabla_{x0} J_b + \nabla_{x0} J_o + \nabla_{x0} J_c$$

$$= \mathrm{B}^{-1}\left(x_0 - x_0^b\right) + \mathrm{M}^{\mathrm{T}}\mathrm{H}^{\mathrm{T}}\mathrm{R}^{-1}\left(HMx_0 - y^o\right) + \nabla_{x0} J_c$$

Adjoint model




Observation data can be assimilated at observation time

# 4Dimensional –Variational method

**Cost function :**

$$J = J_b + J_o + J_c$$

$$= \frac{1}{2}\boxed{\left(x_0 - x_0^b\right)^{\mathrm{T}} \mathrm{B}^{-1}\left(x_0 - x_0^b\right)} + \frac{1}{2}\boxed{\left(HMx_0 - y^o\right)^{\mathrm{T}} \mathrm{R}^{-1}\left(HMx_0 - y^o\right)} + J_c$$

Forecast model

Distant from the first guess

Penalty term

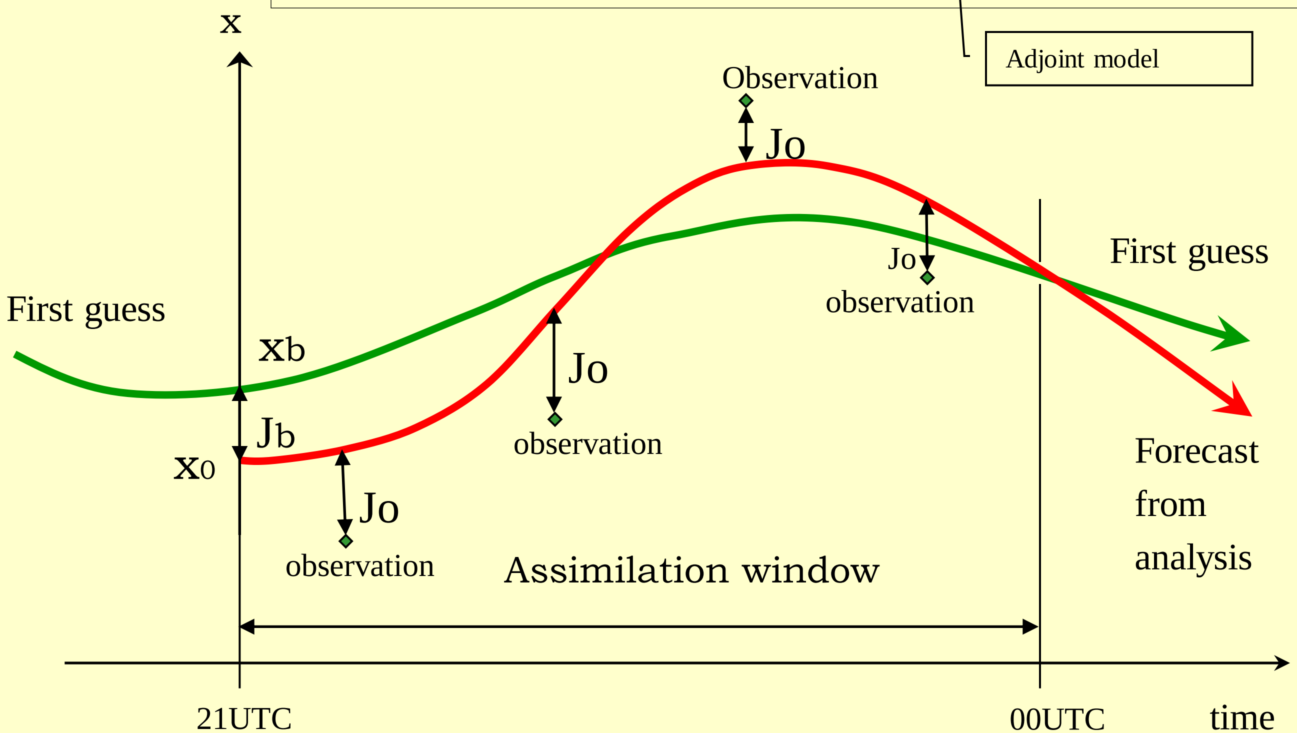
Distant from observations

**Gradient of cost function:**

$$\nabla_{x0} J = \nabla_{x0} J_b + \nabla_{x0} J_o + \nabla_{x0} J_c$$

$$= \mathrm{B}^{-1}\left(x_0 - x_0^b\right) + \mathrm{M}^{\mathrm{T}}\mathrm{H}^{\mathrm{T}}\mathrm{R}^{-1}\left(HMx_0 - y^o\right) + \nabla_{x0} J_c$$

Adjoint model

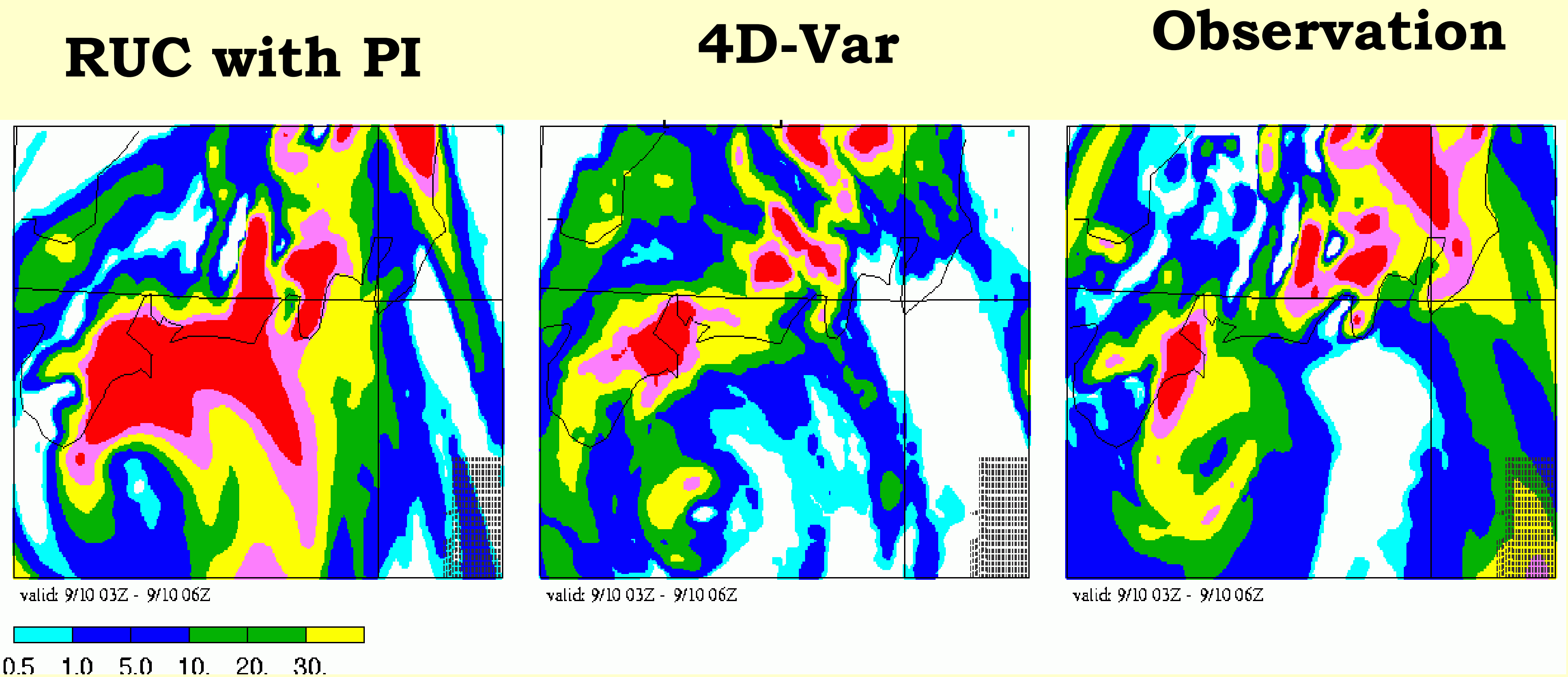



Observation data can be assimilated at observation time

# Meso 4DVAR (Mar. 2002)

## (Koizumi et al., 2005；SOLA)

**The world first implementation of regional 4DVAR for operation.**
LT and ADJ models based on MSM (a hydrostatic spectral model) of JMA.



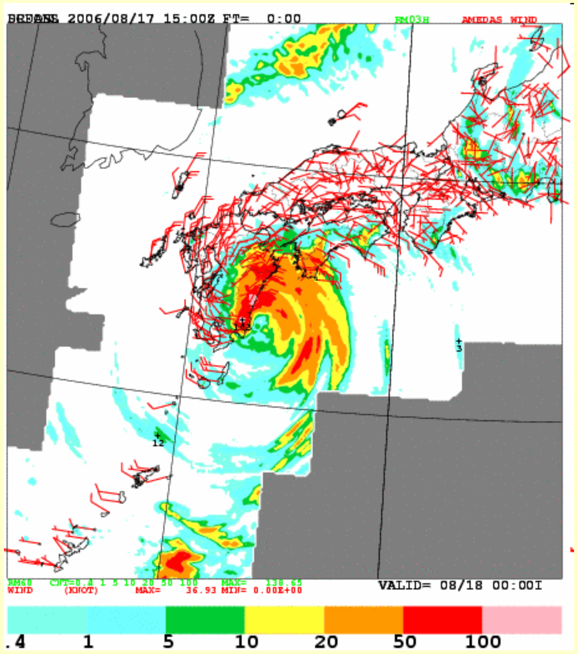

**FT=15-18**

3 hour accumulated rain for FT=18
Initial 12 UTC 9 September 2001

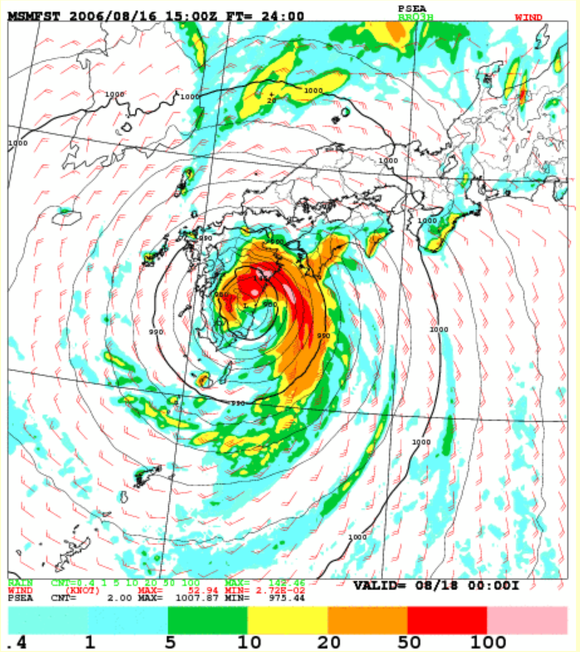
# Nonhydrostatic 4DVAR (Apr. 2009-)
## (JNoVA; Honda et al., 2009)

LT and ADJ models based on JMA-NHM

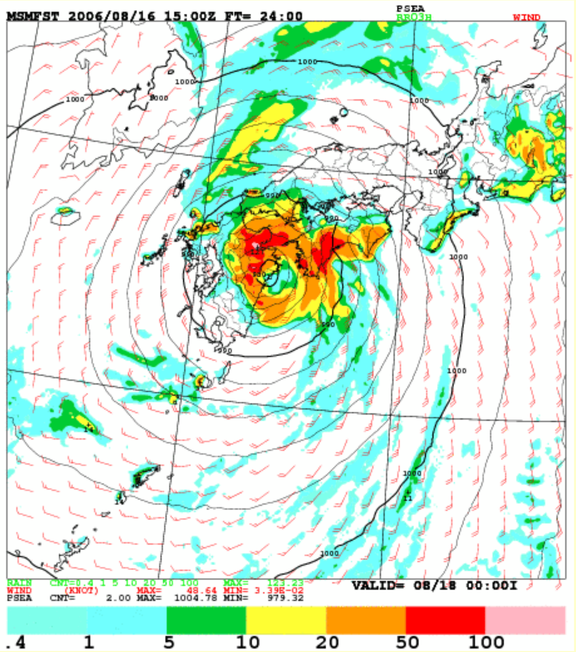
Radar-AMeDAS observation




JNoVA (nonhydrostatic)



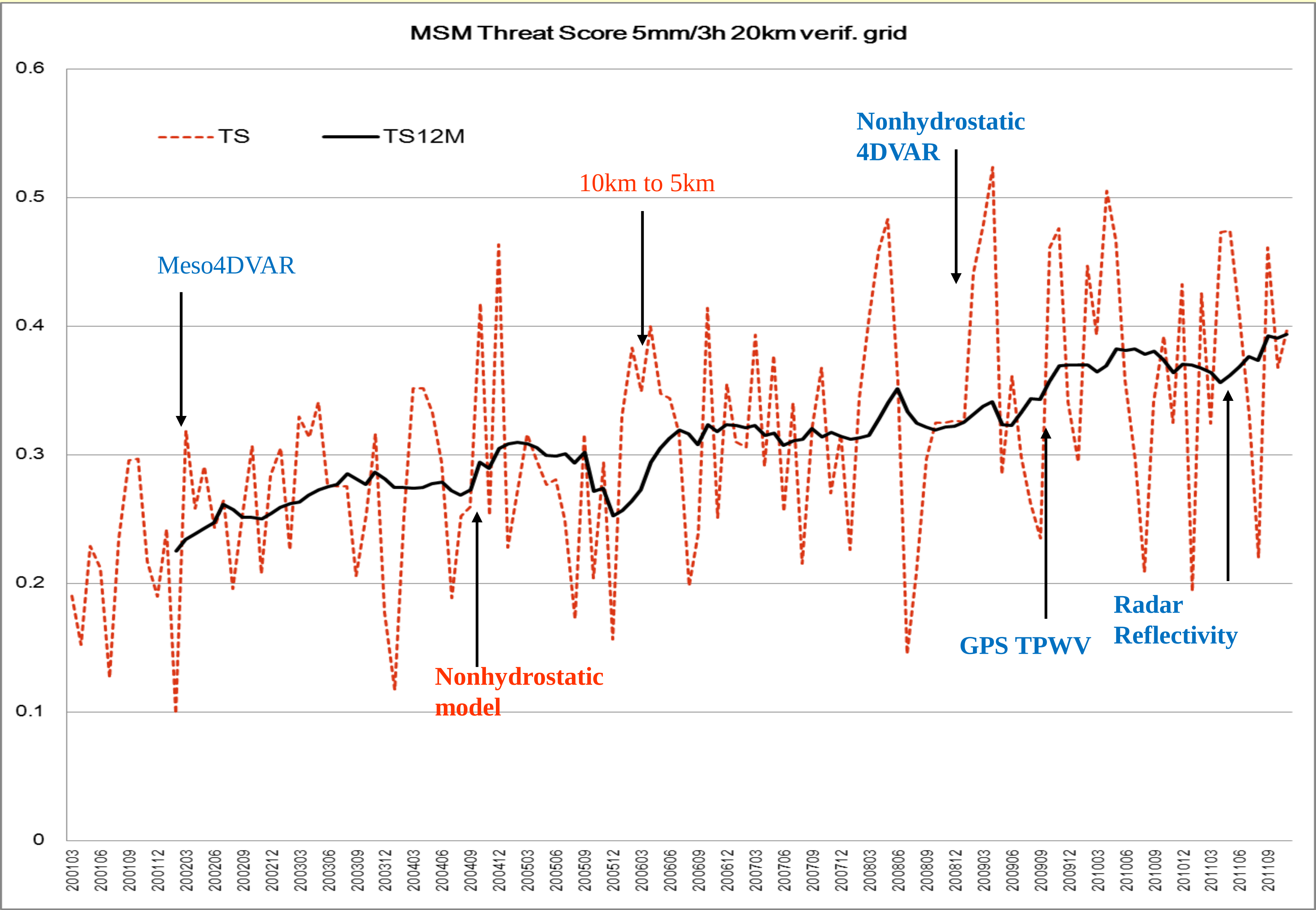

Meso 4DVAR (hydrostatic)



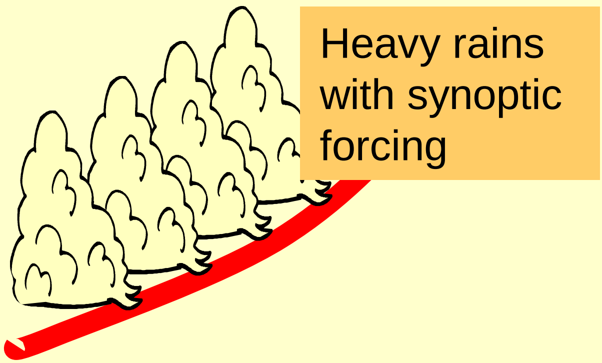

FT=24 from 2006 Aug 17 15UTC

Sawada and Honda (2009)

# Threat score of MSM Mar.2001-Nov.2011 (FT=0-15)

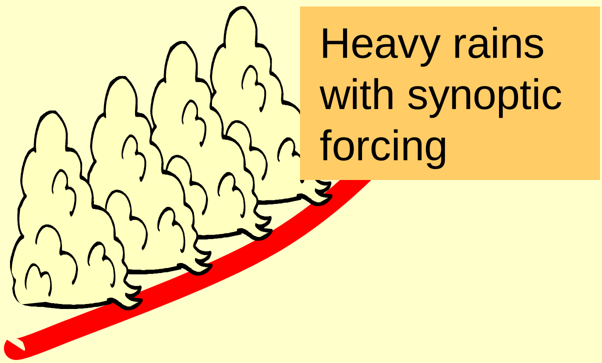


# Predictability of heavy rainfalls

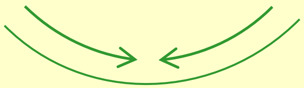




・・relatively predictable in the current mesoscale NWP up to a point

# Predictability of heavy rainfalls

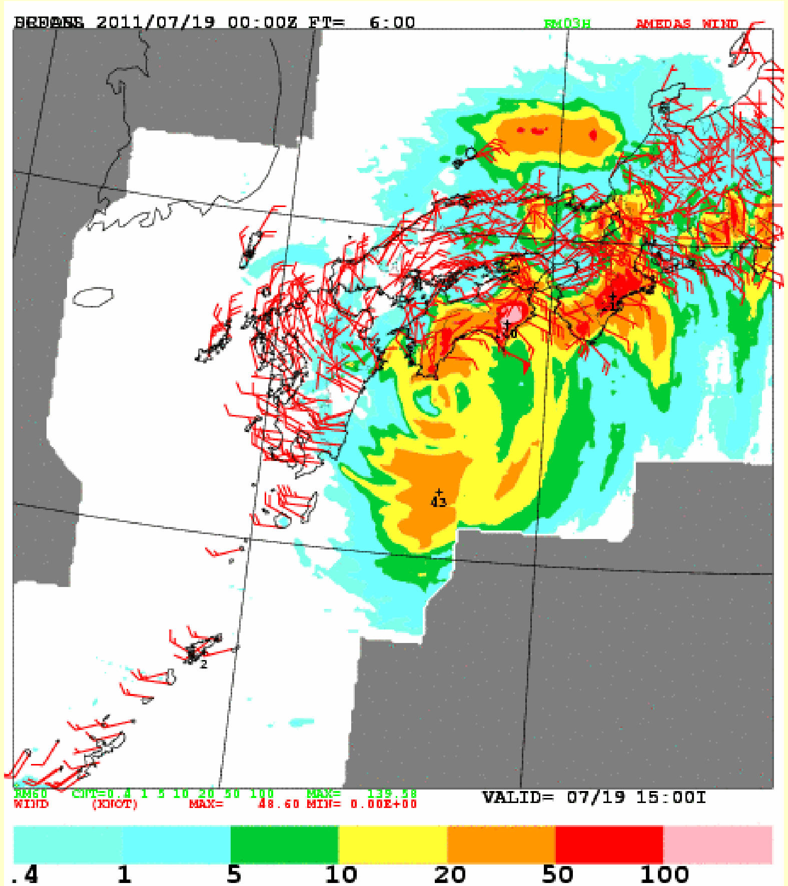




・・relatively predictable in the current mesoscale NWP up to a point

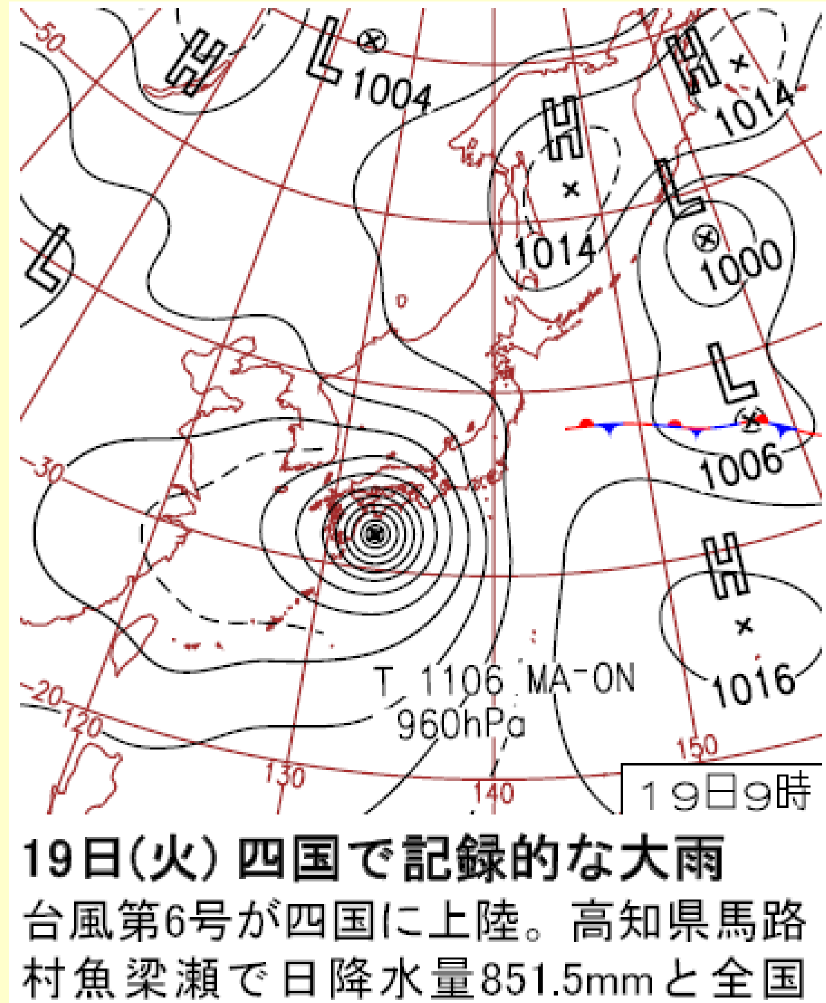


Position is fixed by forcing regardless the trivial errors in initial condition

# Example of orographic heavy rainfall




Radar-AMeDAS Observed rainfall
03-06 UTC, 19July 2011

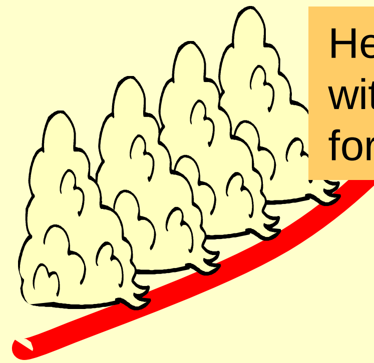



A strong typhoon (T201106 Ma-on) hit western Japan and a record breaking 851mm rainfall was observed in one day (19 July 2001).

MSM accurately predicted the orographically forced heavy rainfall.

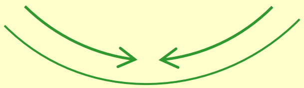
# Predictability of heavy rainfalls

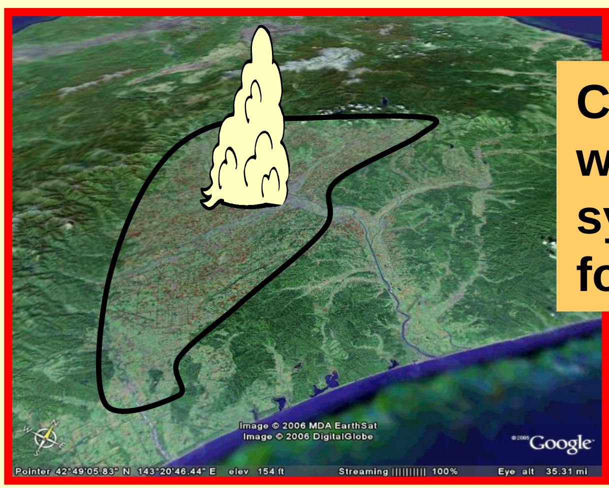
Heavy rains with orographic forcing



Heavy rains with synoptic forcing

・・relatively predictable in the current mesoscale NWP up to a point

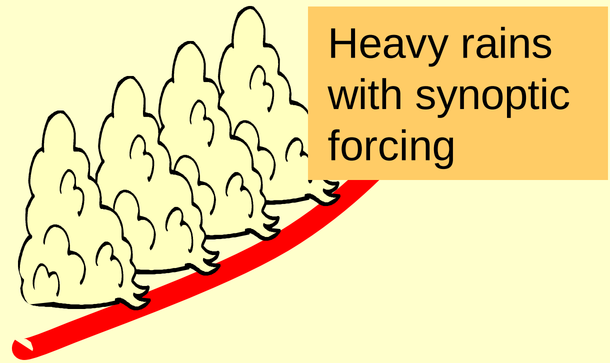




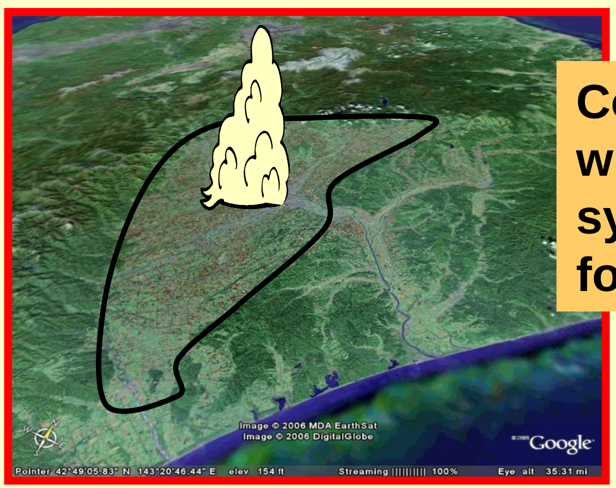

**Convective rains without strong synoptic/orographic forcing**

・・difficult to predict due to

# Predictability of heavy rainfalls


・・relatively predictable in the current mesoscale NWP up to a point



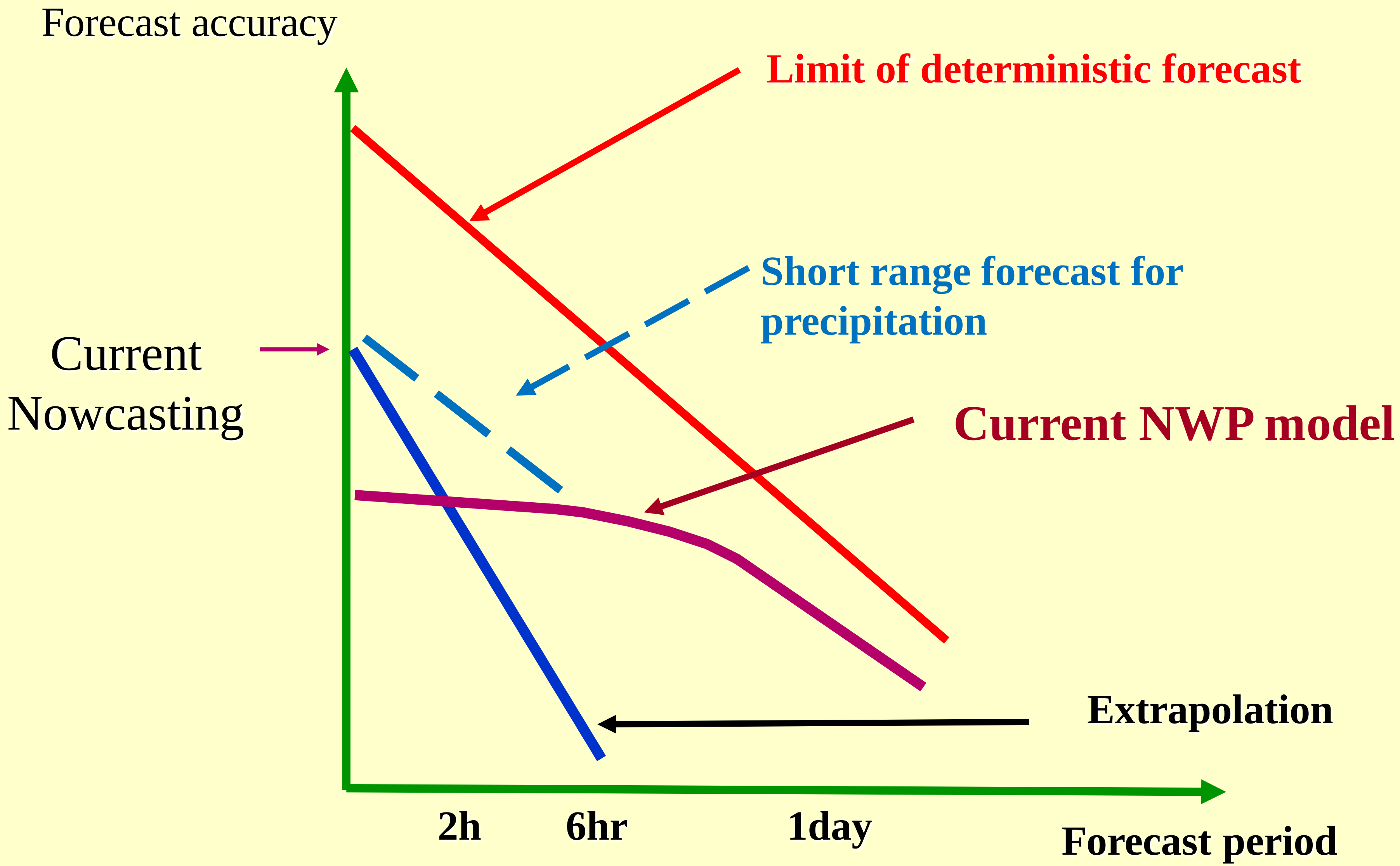

**Convective rains without strong synoptic/orographic forcing**

・・difficult to predict due to

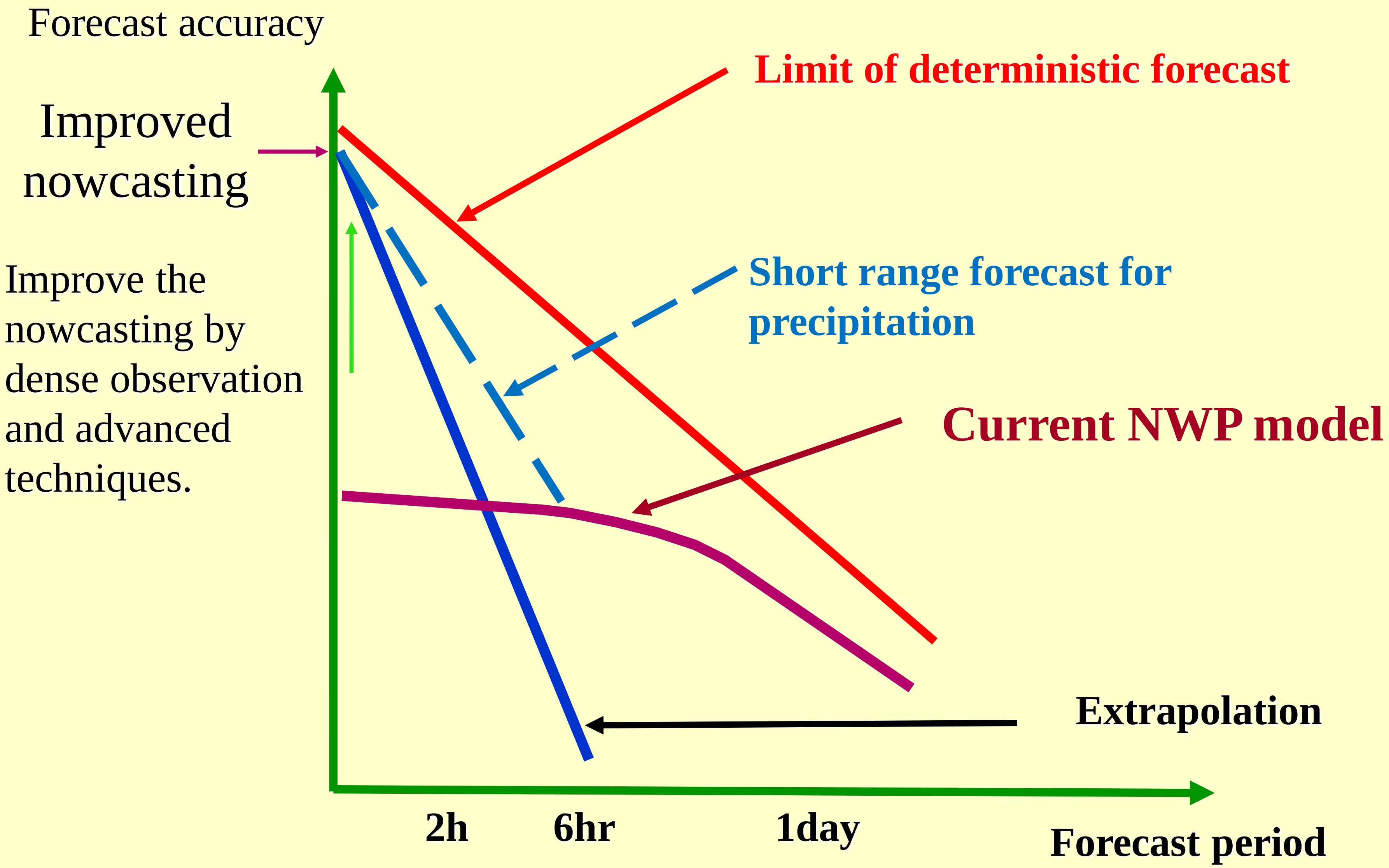
- small horizontal/temporal scales
- phenomena in unstable atmosphere

Result is very sensitive to small perturbations in initial conditions

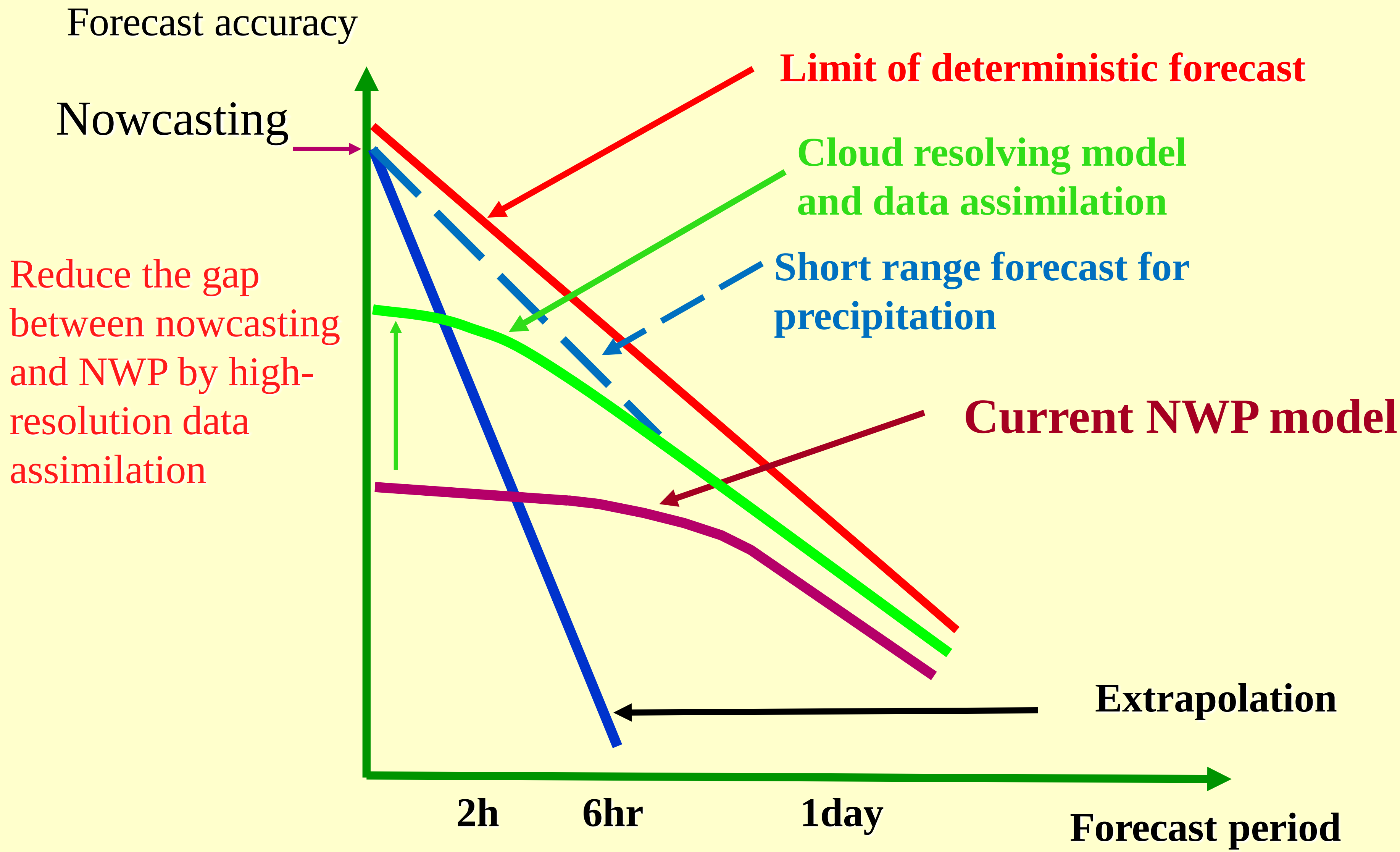
# Approaches to predict local heavy rain



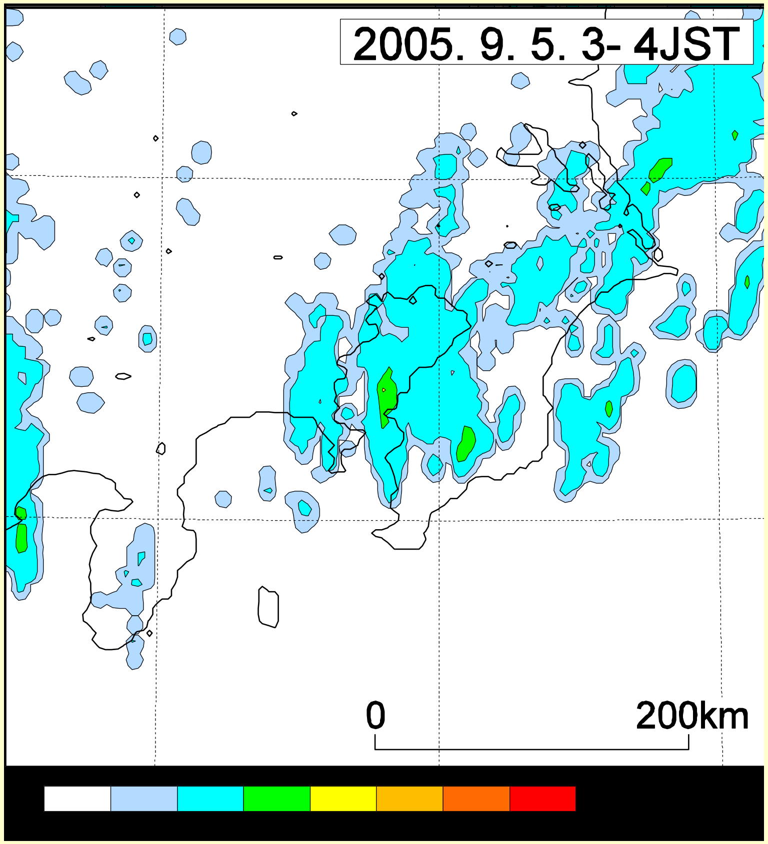
# Approaches to predict local heavy rain (1)

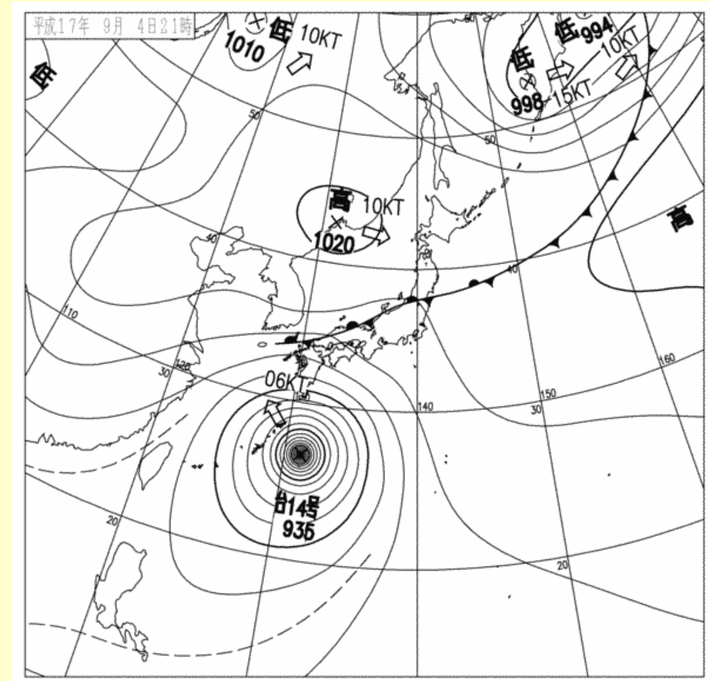


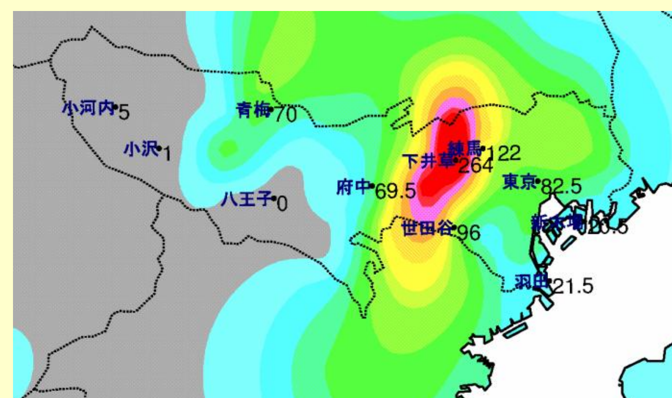
# Approaches to predict local heavy rain (2)



# Local Heavy rainfall on September 2005 in Tokyo



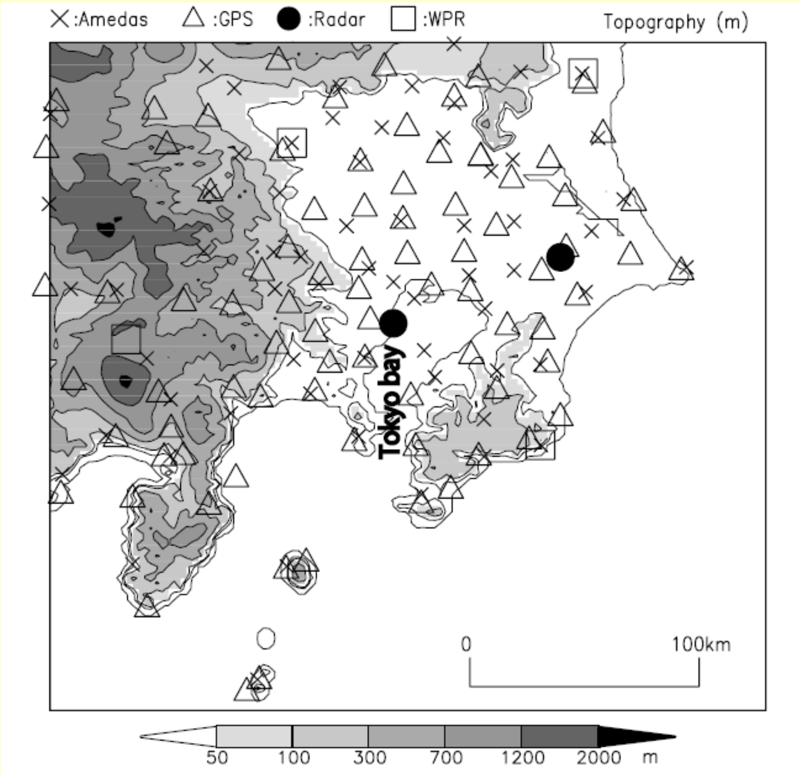




Local heavy rainfall on 4 September 2005

100mm precipitation in 1 hour was observed in Tokyo. No significant disturbances over Tokyo metropolitan area.

# Cloud resolving 4DVAR with cloud microphysics

(Kawabata et al., 2011; *Mon. Wea. Rev.)*




Kessler warm rain process was implemented in LT/ADJ models.

4DVAR assimilation of

- Doppler Radar's Radial Winds
- Radar Reflectivity
- GPS precipitable water vapor
- Surface observations (wind, temperature)

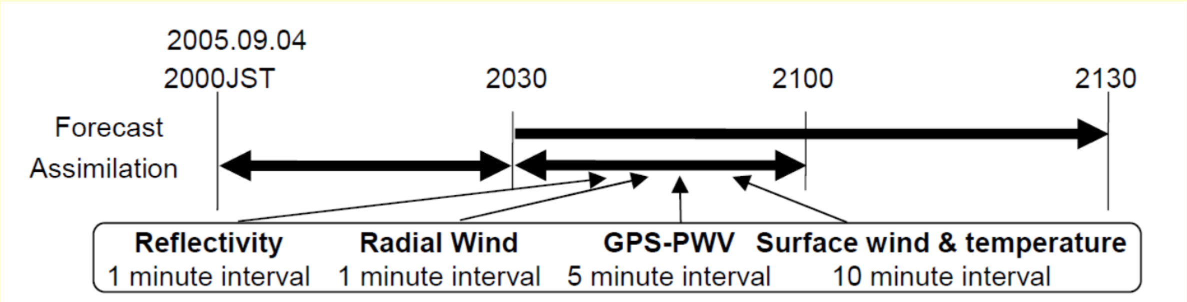
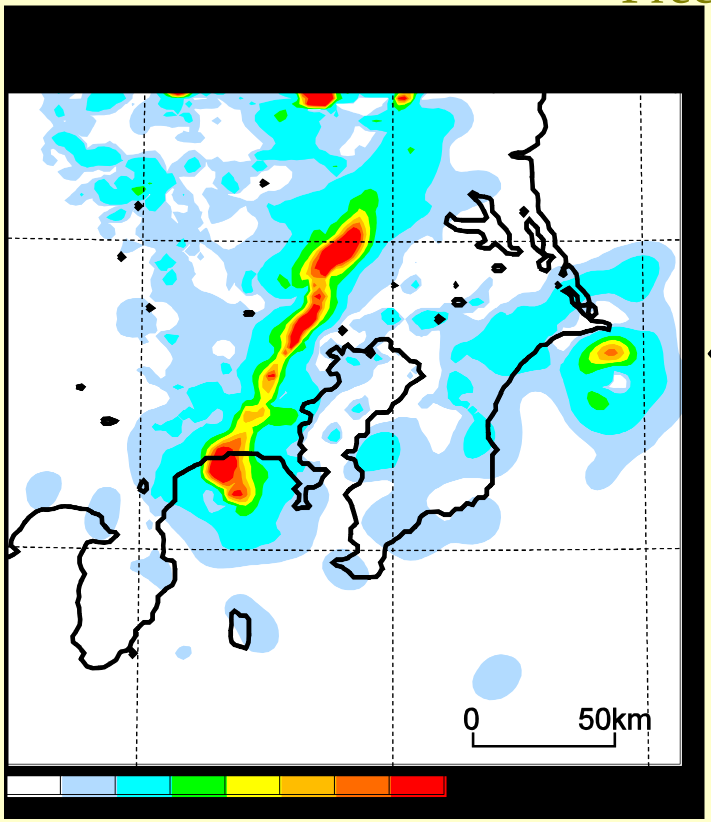


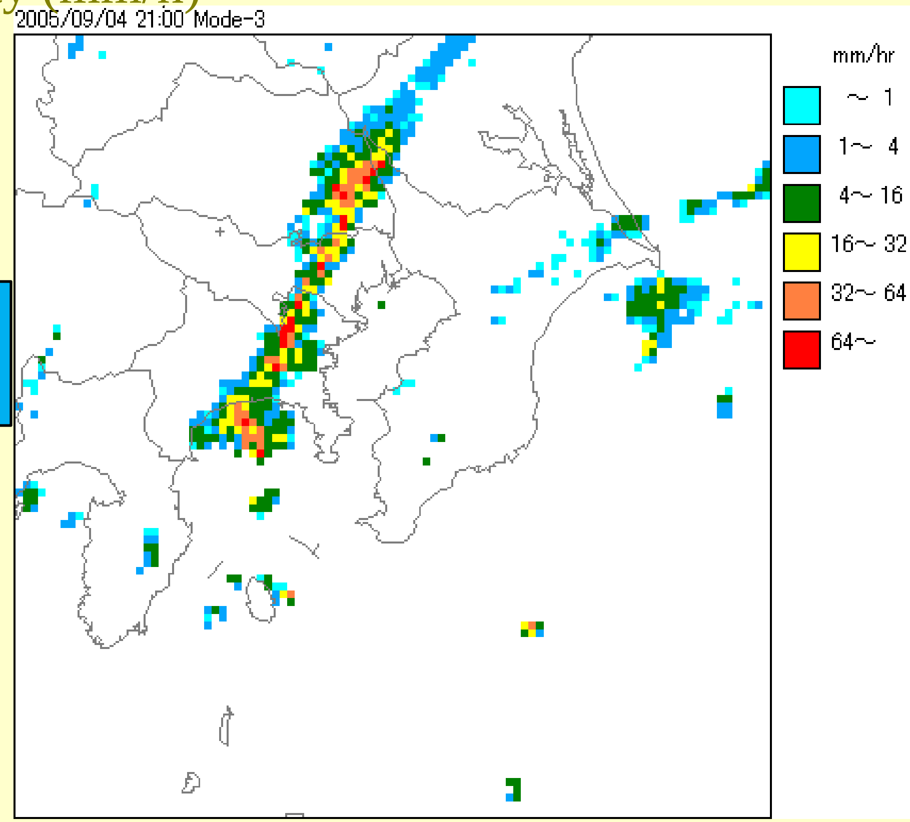

FIG. 9. Schematic diagram of assimilation experiment.

4DVAR analysis

Precip. intensity (mm/h)

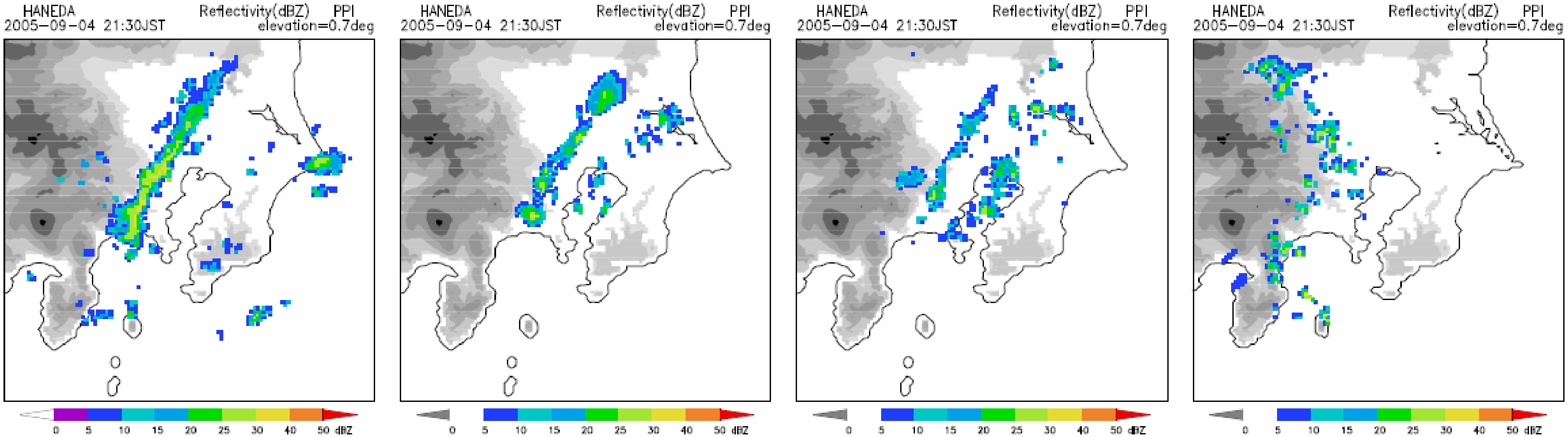
Observation




Assimilation of radar reflectivity 2030-2100JST

(Kawabata et al., 2011; *Mon. Wea. Rev.)*




2130 JST
Obs

4DVAR with
assimilation of
radar reflectivity

4DVAR without
radar reflectivity

$1^{st}$ guess

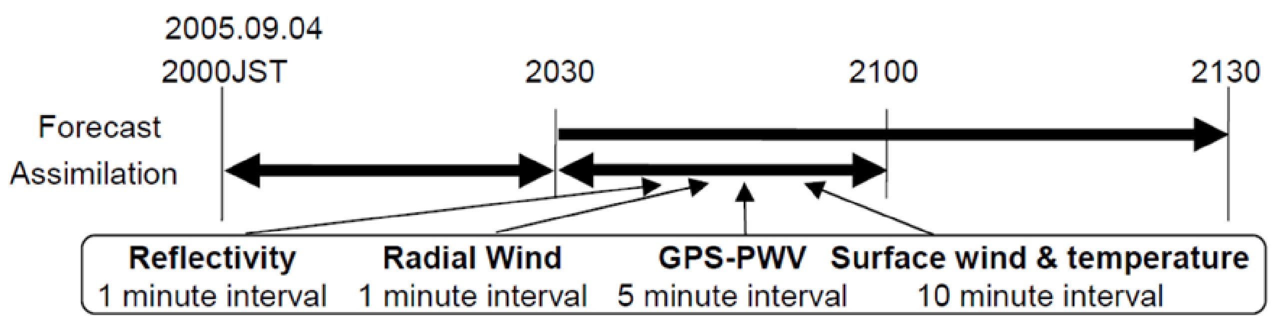
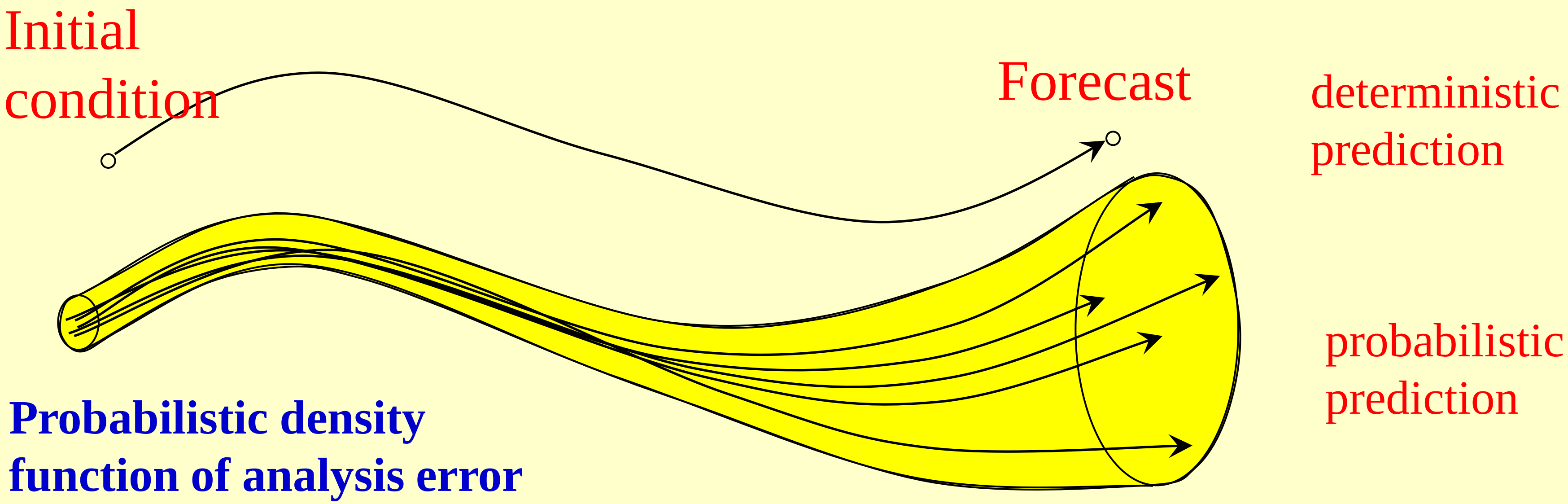



FIG. 9. Schematic diagram of assimilation experiment.

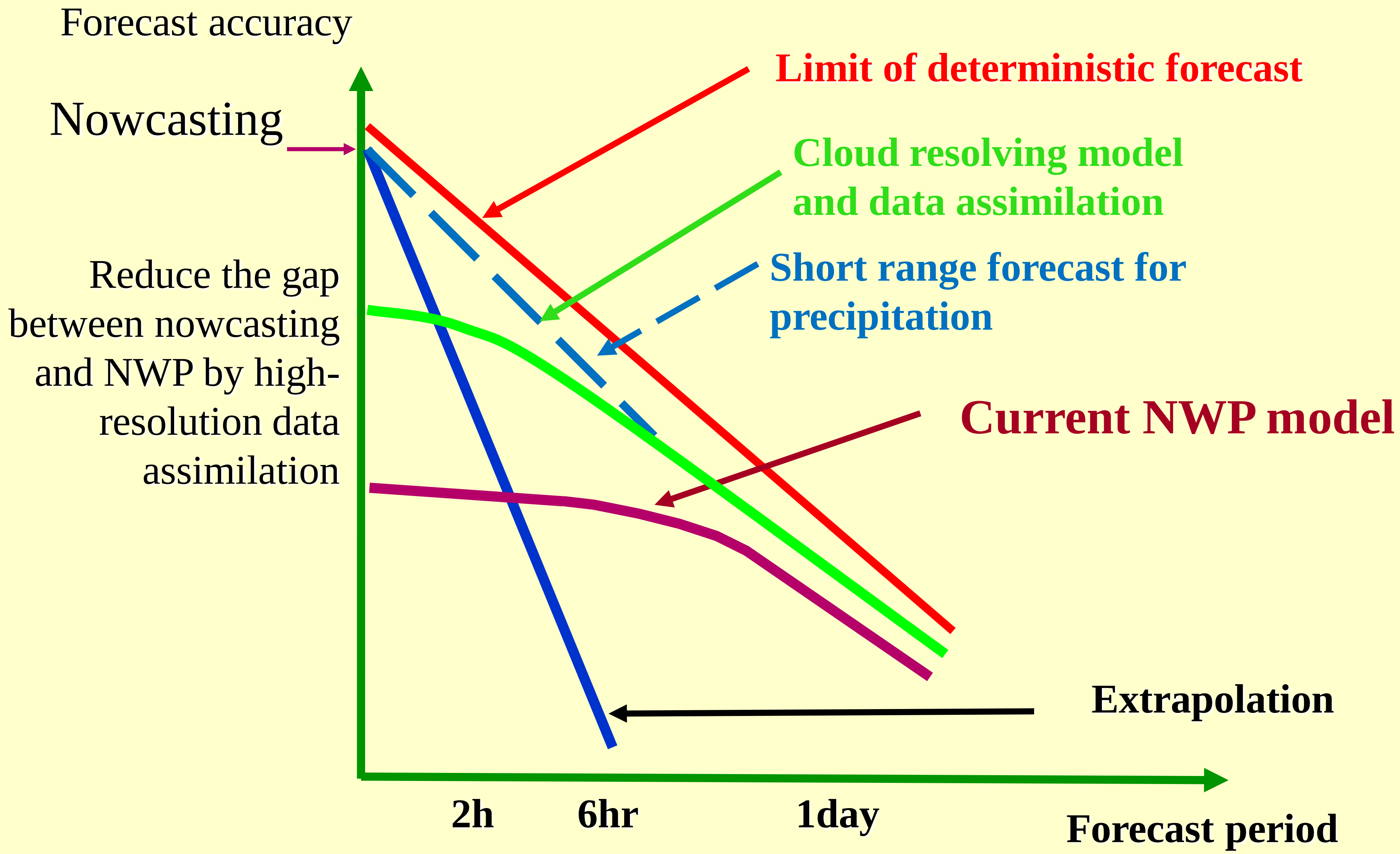
Kawabata, T., T. Kuroda, H. Seko, and K. Saito, 2011: A cloud-resolving 4D-Var assimilation experiment for a local heavy rainfall event in the Tokyo metropolitan area, *Mon. Wea. Rev.* **139**, 1911-1931.

# 4. Ensemble prediction

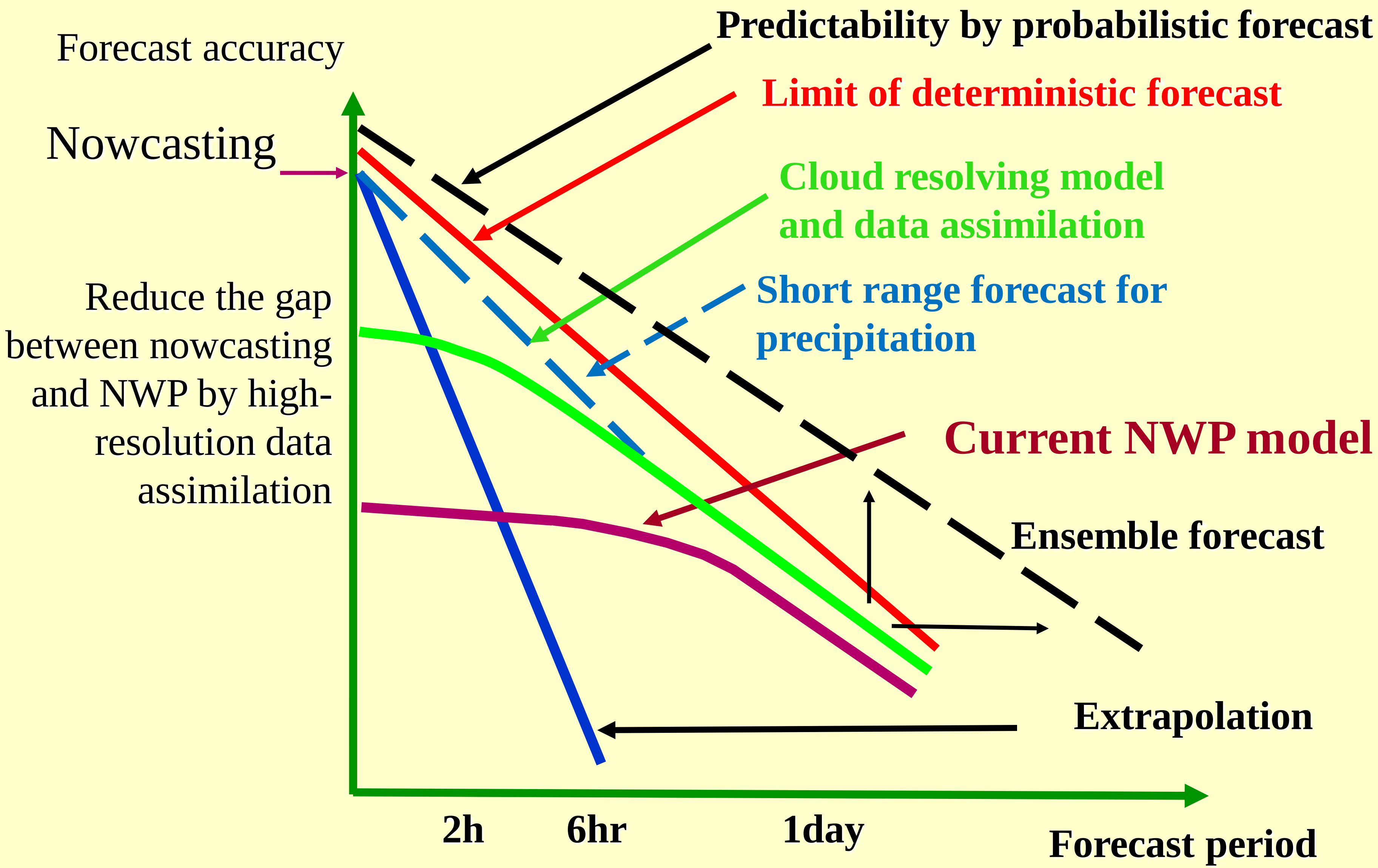



Time integration of the probabilistic density function is practically impossible. In the ensemble forecast, finite members approximate the features of probabilistic density function of atmospheric states.

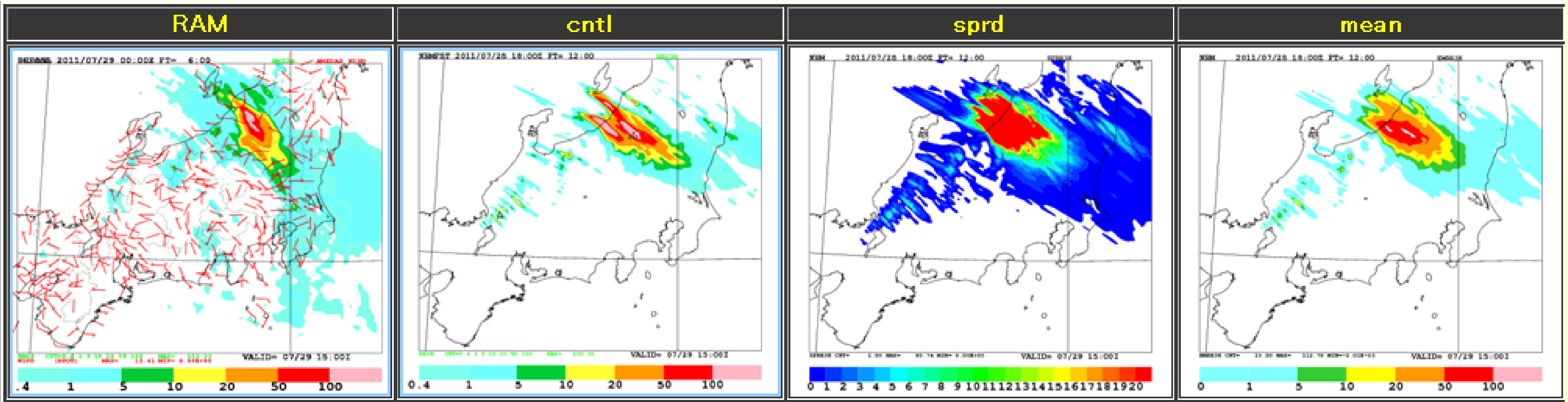
# Approaches to predict local heavy rain



# Approaches to predict local heavy rain (3)



# 2km ensemble prediction from JMA nonhydrostatic 4D-VAR analysis for 2011 Niigata-Fukushima heavy rainfall

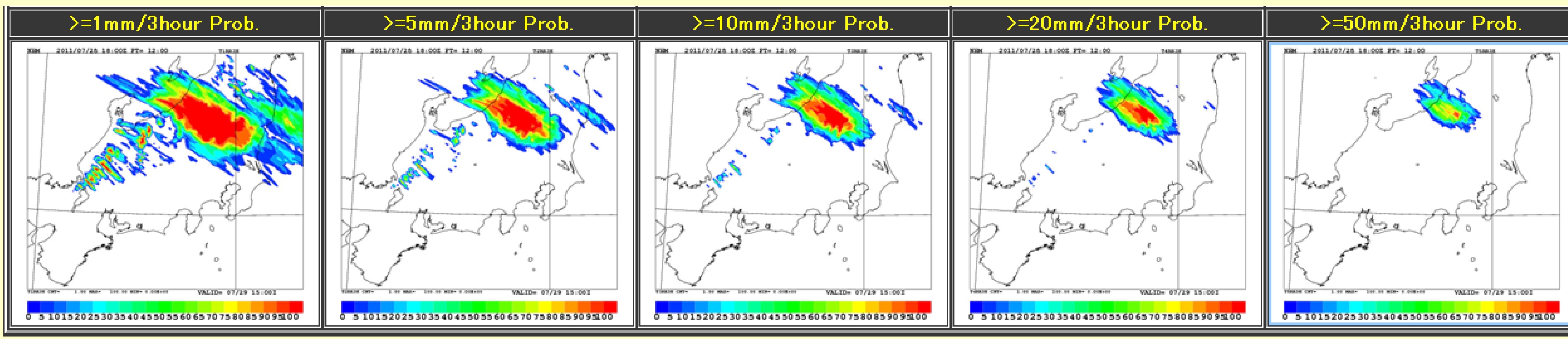



Observation
03-06 UTC, 29 July 2011

Control run

Ensemble spread

Ensemble mean

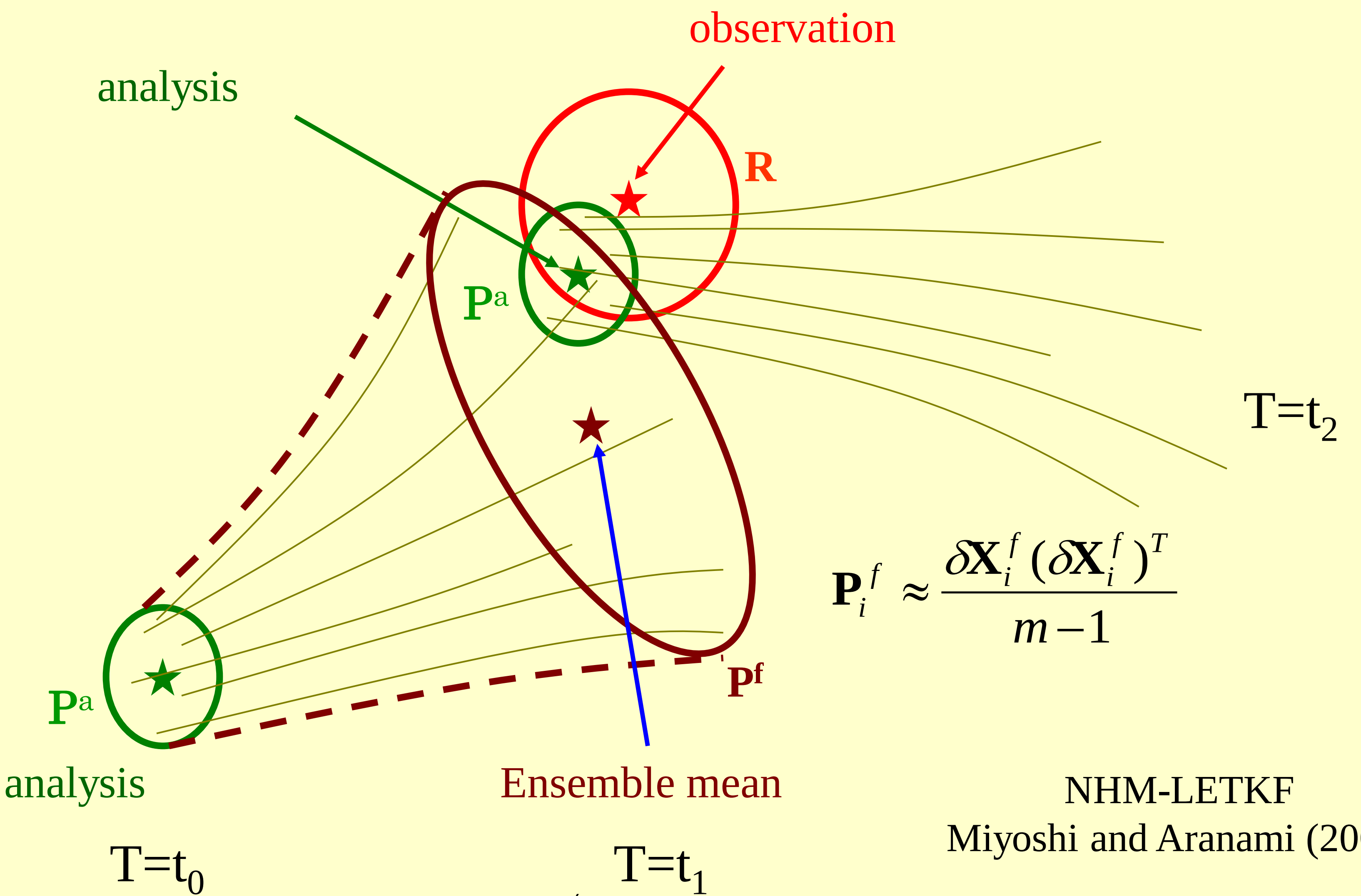



1mm/3h　　5mm/3h　　10mm/3h　　20mm/3h　　50mm/3h

Probability of precipitation at FT=18
Solid probability even for 50mm/3h

Saito et al. (2013)

# Ensemble Kalman Filter




$$\mathbf{P}_i^f \approx \frac{\delta\mathbf{X}_i^f (\delta\mathbf{X}_i^f)^T}{m-1}$$

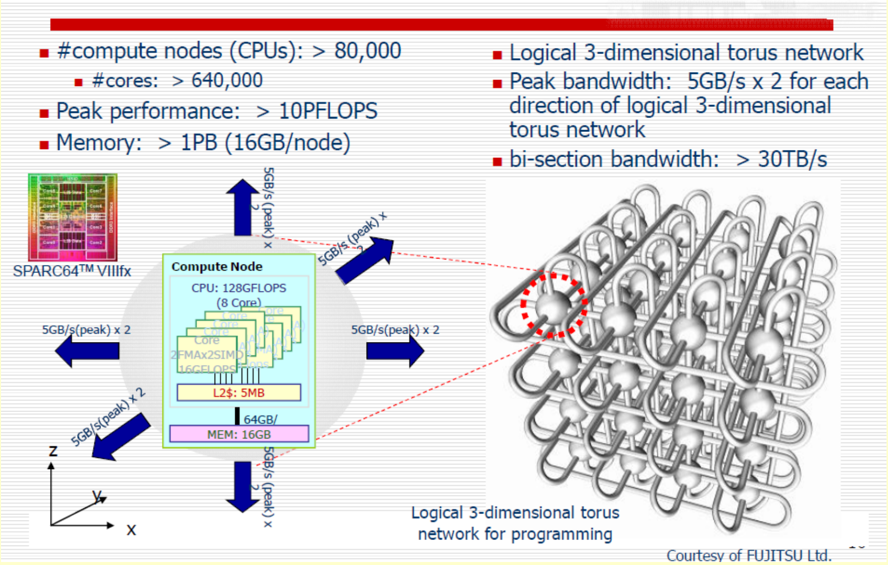
NHM-LETKF
Miyoshi and Aranami (2006)

$$\mathbf{X}^a = \bar{x}^f e + \delta\mathbf{X}^f \left( \tilde{\mathbf{P}}^a (\mathbf{H}\delta\mathbf{X})^T \mathbf{R}^{-1} (y^o - \overline{H(x^f)}) e + \sqrt{m-1}\,\mathbf{U}\mathbf{D}^{-1/2}\mathbf{U}^T \right)$$

$$= \bar{x}^f e + \delta\mathbf{X}^f \tilde{\mathbf{P}}^a (\mathbf{H}\delta\mathbf{X})^T \mathbf{R}^{-1} (y^o - \overline{H(x^f)}) e + \delta\mathbf{X}^f \mathbf{T}$$

# 4. The K-Computer project


450km (280miles)
west from Tokyo



"HPCI Strategic Programs for Innovative Research (SPIRE)" is being carried out by RIKEN, with partners in industry, universities, national institutes under an initiative by MEXT

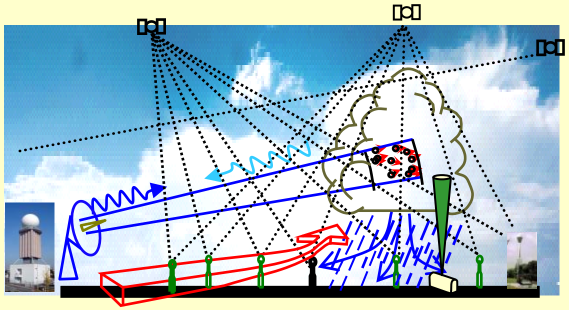
# The HPCI Strategic Programs for Innovative Research (2011.4-2016.3)
# Field 3: Weather, Climate and Environment Prediction for disaster prevention

## Sub theme ②：Super high performance mesoscale NWP

### a. Cloud resolving 4DDA

•feasibility of dynamical prediction of local heavy rainfall in very sort range forecast

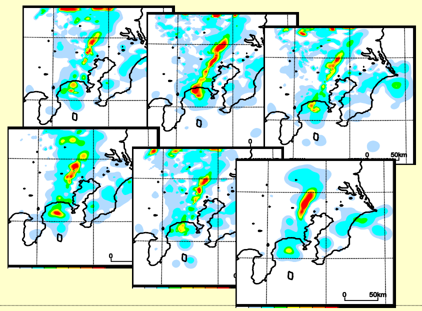
MRI, JMA, DPRI/Kyoto Univ., NIED, ISM



### b. Cloud Resolving ensemble NWP and its verification

•quantitative prediction of the probability of local heavy fall with a lead time to disaster prevention

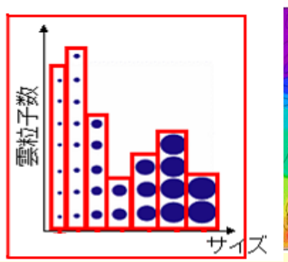
MRI, JMA, Tohoku Univ., DPRI/Kyoto Univ.



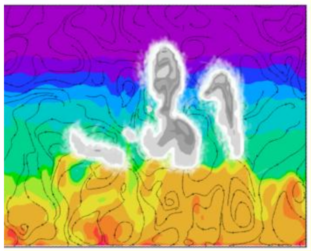
### c. High performance atmospheric model

• Evaluation of model’s uncertainty through super high resolution numerical experiments

JAMSTEC, MRI, Tokyo Univ., Nagoya Univ., etc.

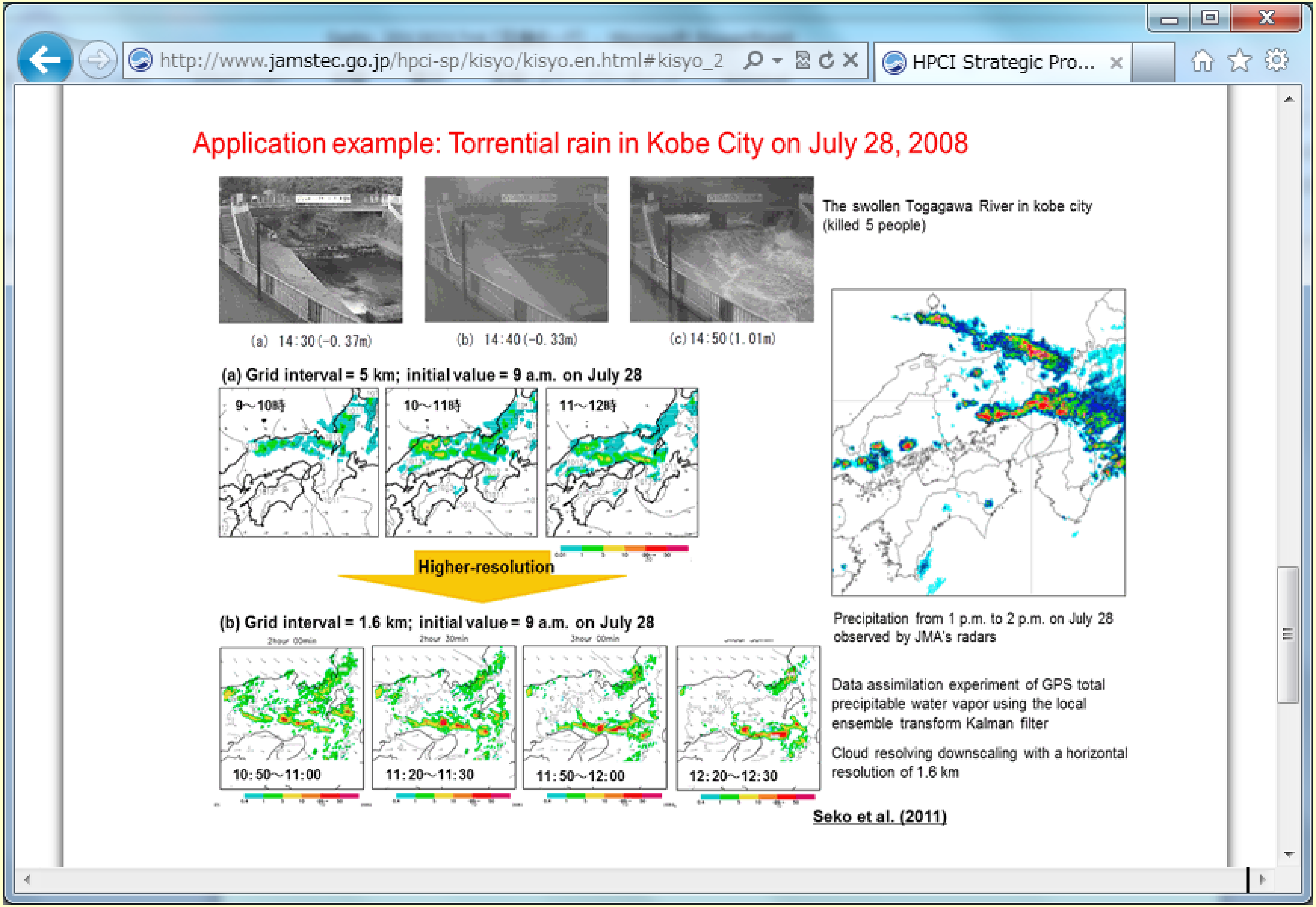



**Bin**

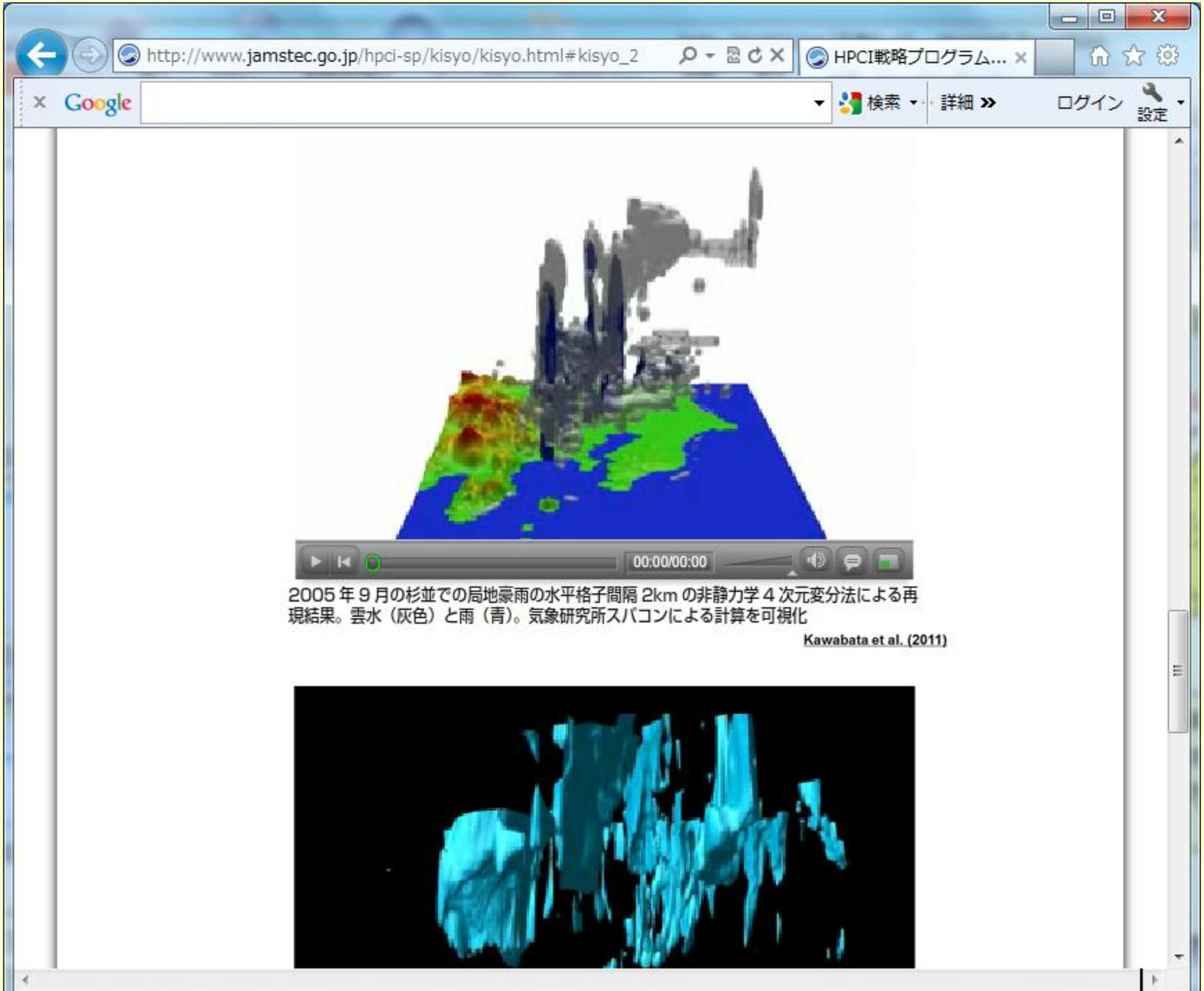


**LES**

http://www.jamstec.go.jp/hpci-sp/kisyo/kisyo.en.html#kisyo_2



http://www.jamstec.go.jp/hpci-sp/kisyo/kisyo.html#kisyo_2



The 3rd Research Meeting of Ultrahigh Precision Meso-Scale Weather Prediction - Windows Internet Exp...

http://www.jamstec.go.jp/hpci-sp/meso_sg2013/inde



# The 3rd Research Meeting of Ultrahigh Precision Meso-Scale Weather Prediction

## Date/Time

March 21, 2013 (Thu)　09:00～17:30

## Venue

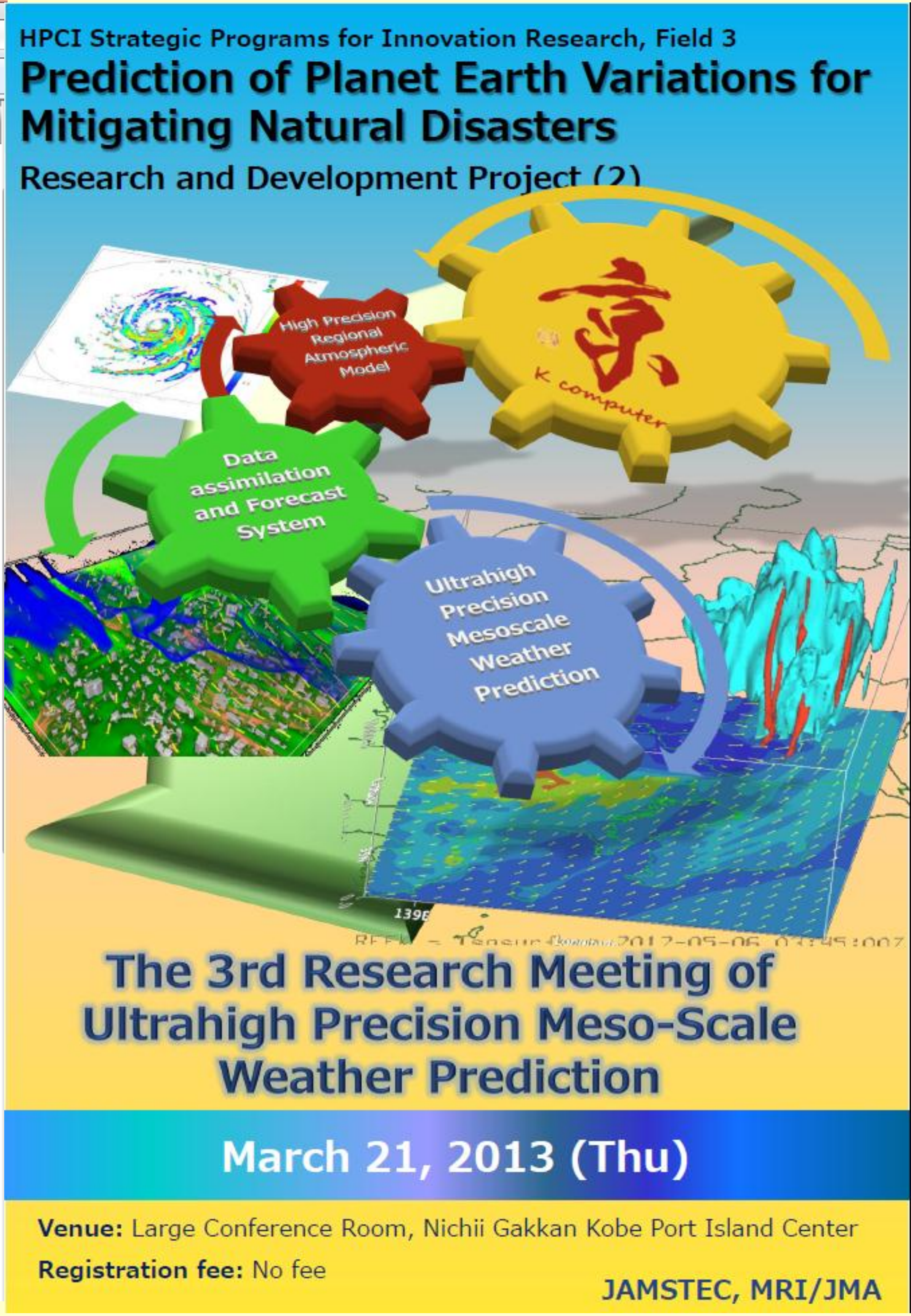
Large Conference Room, Nichii Gakkan Kobe Port Island Center
TEL : +81-78-304-5991
7-1-5, Minatojima-Minamimachi, Chuo-ku, Kobe 650-0047, Japan

## Program

| March 21 | | |
|---|---|---|
| 09:00-09:20 | Opening Address<br>Introduction | Akihide Segami (MRI)<br>Tatsushi Tokioka (JAMSTEC)<br>Kazuo Saito (MRI/JAMSTEC) |
| 09:20-10:40 | Development of cloud-resolving data assimilation systems | Chair: Tadashi Tsuyuki (MRI) |
| | Keynote Speech | Ming Xue (University of Oklahoma) |
| 11:10-12:30 | Development of a regional cloud-resolving ensemble analysis and forecasting system | Chair: Hiromu Seko (MRI/JAMSTEC) |
| 14:00-17:00 | Address<br>Development and basic research for the ultrahigh precision regional models<br>Keynote Speech | Tetsuyuki Muramatsu (MEXT)<br>Chair: Fujio Kimura (JAMSTEC)<br>Song-You Hong (Yonsei University) |
| 17:00-17:30 | General Discussion | |

## Registration: No fee required

Those who are interested in participating are required to send an email to the following address by March 3. Participants in the lunch and dinner also need to be registered in advance.



# Summary

- Prediction of weather is performed by numerical computation.
- Performance of sate of the art mesoscale NWP has been remarkably improved, but still storm scale prediction is challenging.
- High resolution data assimilation and ensemble prediction are necessary.  The K-computer will reduce compromise of resolutions and ensemble members and show a prototype of the future NWP system.

# Thank you

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