

WRF-Var Overview

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Outline of Talk

- 1) Introduction to data assimilation.
- 2) Basics of modern data assimilation.
- 3) Demonstration with a simple system.
- 4) WRF-Var.
- 5) Important issues.



1. Introduction to data assimilation



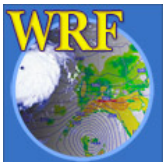
Modern weather forecast (Bjerknes, 1904)

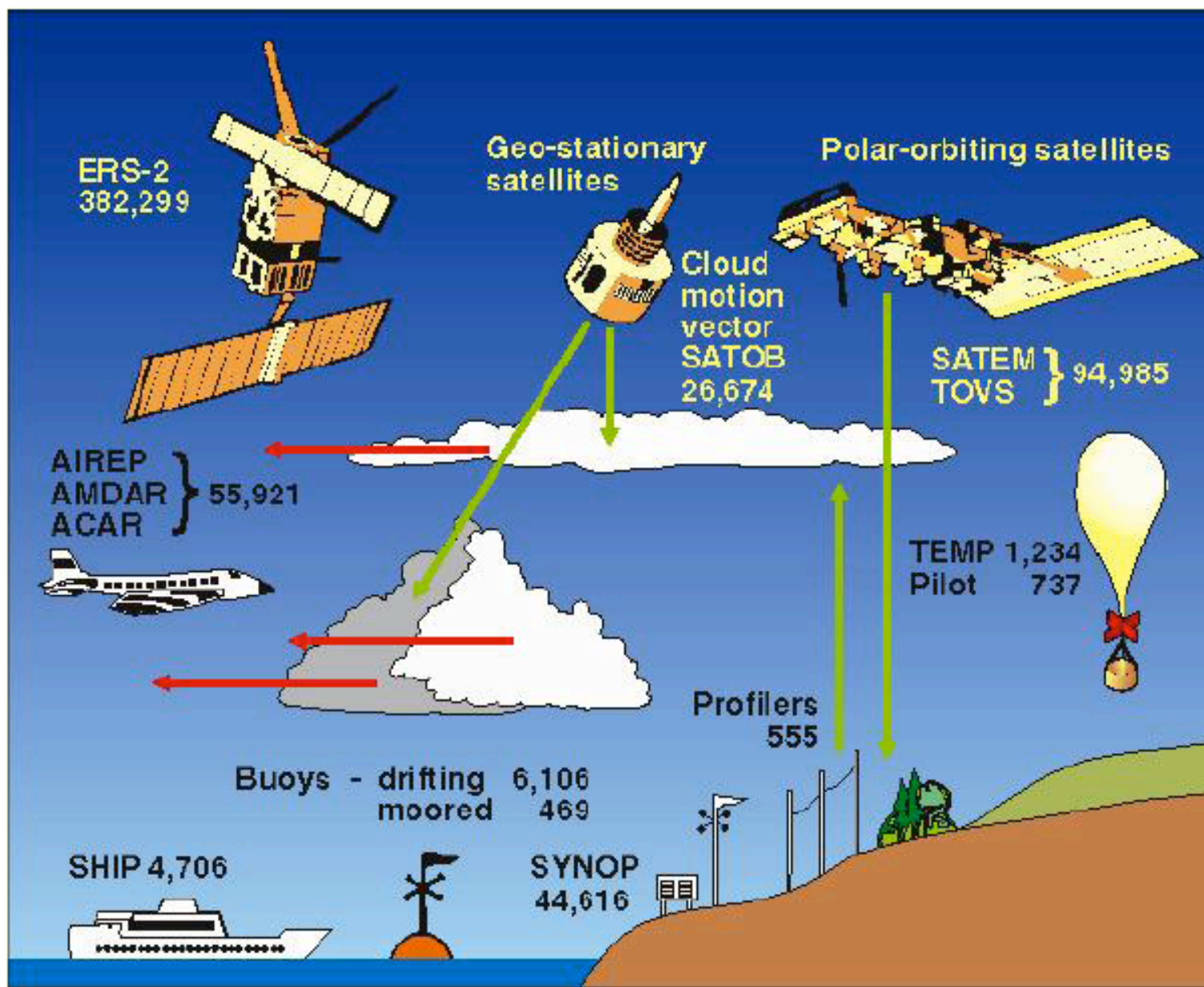
- A sufficiently accurate knowledge of the state of the atmosphere at the initial time
- A sufficiently accurate knowledge of the laws according to which one state of the atmosphere develops from another.

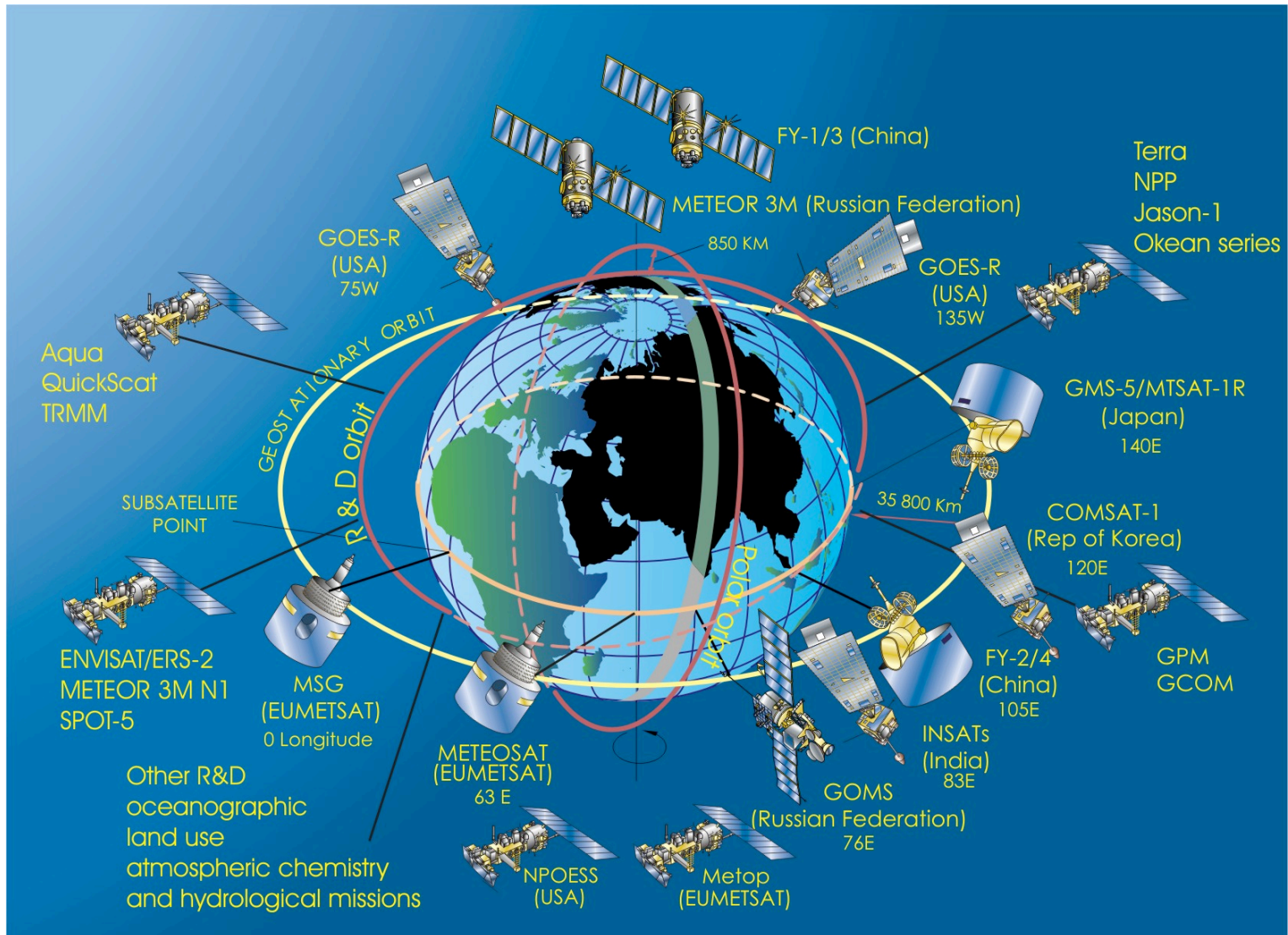


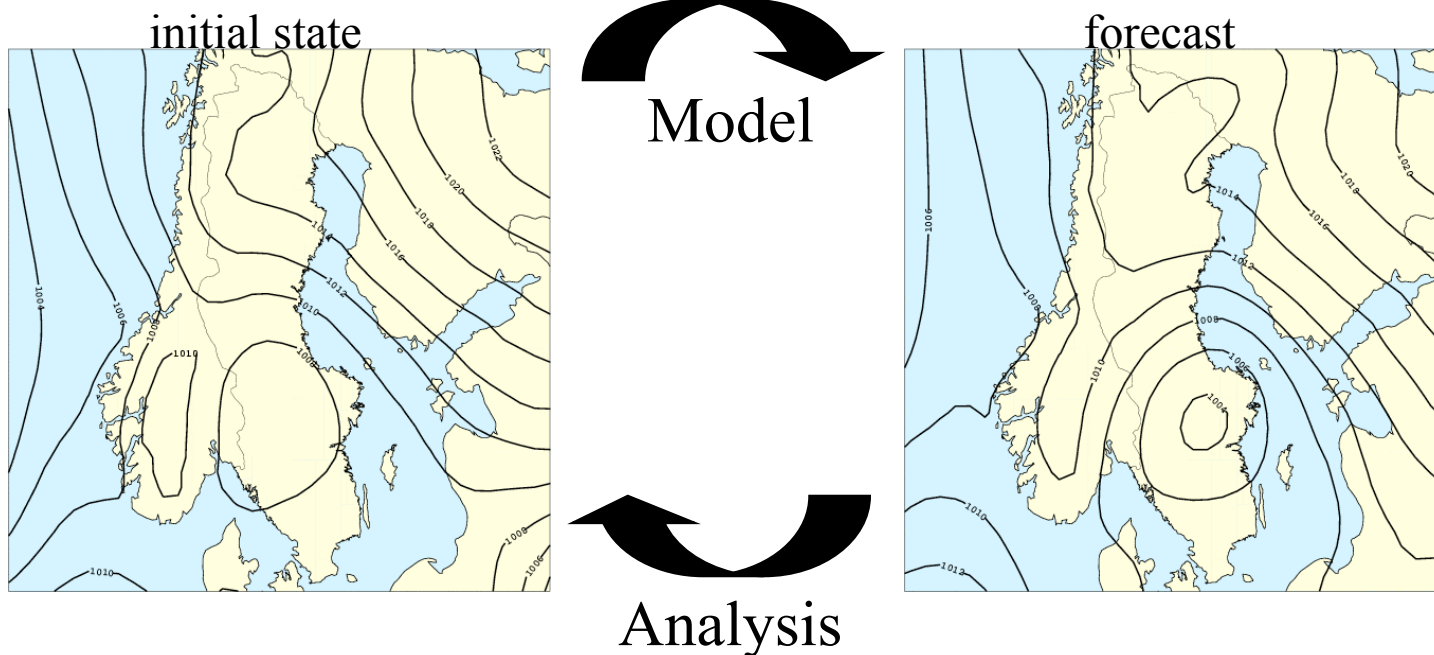
Vilhelm Bjerknes (1862–1951)

- **Analysis:** using observations and other information, we can specify the atmospheric state at a given initial time: “Today’s Weather”
- **Forecast:** using the equations, we can calculate how this state will change over time: “Tomorrow’s Weather”



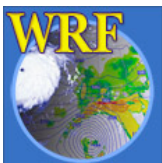
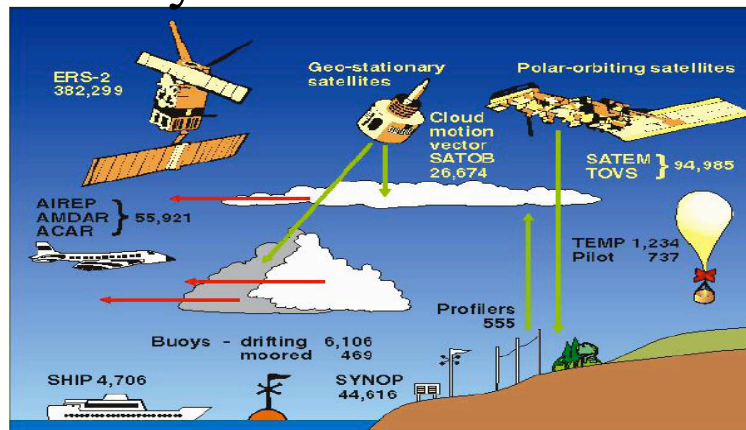






Model state
 $x, \sim 10^7$

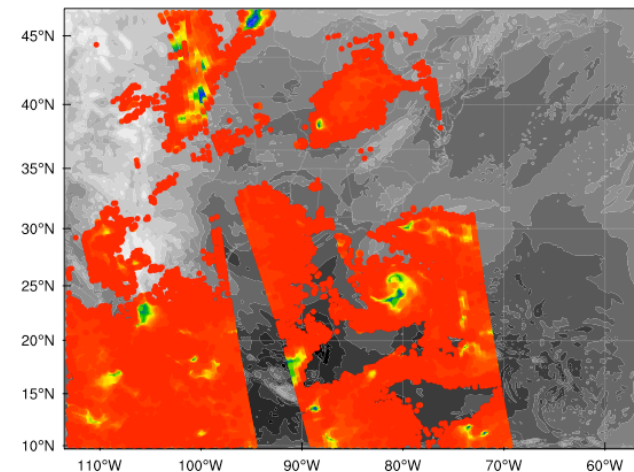
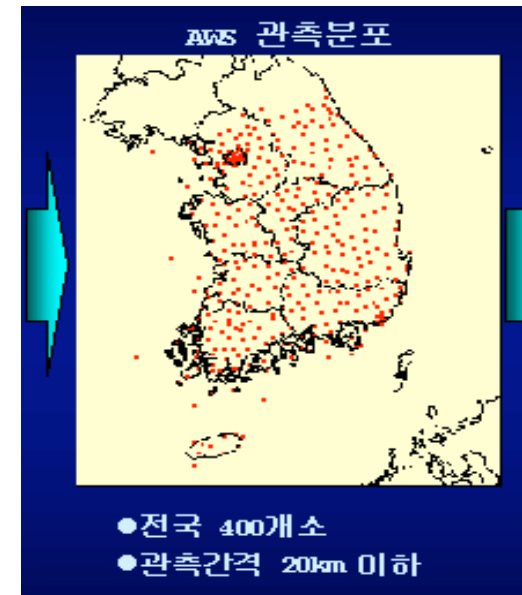
Observations
 $y^o, \sim 10^5 - 10^6$



Need For Data Assimilation in NWP

Fact: There are never enough good observations!!

- Consider NWP model:
 - Typical global model – $425 * 325 * 50 = 7$ million gridpts.
 - Minimum number of variables = 6 (u, v, w, T, p, q).
 - Number of degrees of freedom = 41.4 million.
- Typical number of observations = few $\times 10^6$ but:
 - Inhomogeneous distribution of data.
 - Observations not always in sensitive areas.
 - Observations have errors.
- Solutions:
 - Use sophisticated (variational/ensemble) techniques.
 - Use previous forecast to propagate past observations.
 - Use approximate physical balance relationships.
 - More/better observations!



Assimilation methods

- Empirical methods
 - Successive Correction Method (SCM)
 - Nudging
 - Physical Initialisation (PI), Latent Heat Nudging (LHN)
- Statistical methods
 - Optimal Interpolation (OI)
 - 3-Dimensional VARiational data assimilation (3DVAR)
 - 4-Dimensional VARiational data assimilation (4DVAR)
- Advanced methods
 - Extended Kalman Filter (EKF)
 - Ensemble Kalman Filter (EnFK)



2. Basics of modern data assimilation



The analysis problem for a given time

Consider a scalar x .

The background (normally a short-range forecast):

$$x^b = x^t + b.$$

The observation:

$$x^r = x^t + r.$$

The error statistics are assumed to be known:

$$\begin{aligned} \langle b \rangle &= 0, & \text{mean error (unbiased),} \\ \langle r \rangle &= 0, & \text{mean error (unbiased),} \\ \langle b^2 \rangle &= B, & \text{background error variance,} \\ \langle r^2 \rangle &= R, & \text{observation error variance,} \\ \langle br \rangle &= 0, & \text{nocorrelation between } b \text{ and } r, \end{aligned}$$

where $\langle . \rangle$ is ensemble average.

BLUE: the Best Linear Unbiased Estimate

The analysis: $x^a = x^t + a$.

Search for the best estimate: $x^a = \alpha x^b + \beta x^r$

Substitute the definitions, we have:

$$\alpha + \beta = 1.$$

$$\langle a \rangle = 0$$

The variance:

$$A = \langle a^2 \rangle = B - 2\beta B + \beta^2(B + R)$$

To determine β : $\frac{dA}{d\beta} = -2B + 2\beta(B + R) = 0$
we have

$$\beta = \frac{B}{B + R}.$$

$$A^{-1} = B^{-1} + R^{-1}$$

The analysis: $x^a = x^b + \frac{B}{B+R} (x^r - x^b)$.

“3DVAR”

The analysis is obtained by minimizing the cost function J , defined as:

$$J = \frac{1}{2} (x - x^b)^T B^{-1} (x - x^b) + \frac{1}{2} (x - x^r)^T R^{-1} (x - x^r) .$$

The gradient of J with respect to x :

$$J' = B^{-1} (x - x^b) + R^{-1} (x - x^r) .$$

At the minimum, $J' = 0$, we have:

$$x^a = x^b + \frac{B}{B + R} (x^r - x^b) ,$$

the same as BLUE.

Sequential data assimilation (I)

True states : $\dots, x_{i-1}^t, x_i^t, x_{i+1}^t, \dots$

Observations : $\dots, x_{i-1}^r, x_i^r, x_{i+1}^r, \dots$

Forecasts : $\dots, x_{i-1}^f, x_i^f, x_{i+1}^f, \dots$

Analyses : $\dots, x_{i-1}^a, x_i^a, x_{i+1}^a, \dots$

Sequential data assimilation (II)

Forecast model:

$$x_{i+1}^t = M(x_i^t) + q_i,$$

where q_i is the model error.

As q_i is unknown and x_i^a is the best estimate of x_i^t , the forecast model usually takes the form:

$$x_{i+1}^f = M(x_i^a).$$

OI (and 3DVAR):

$$x_i^a = x_i^f + \frac{B}{B + R} (x_i^r - x_i^f).$$

Sequential data assimilation (III)

4DVAR

4DVAR analysis is obtained by minimizing the cost function J , defined as:

$$J(x_i) = \frac{1}{2} (x_i - x_i^f)^T B^{-1} (x_i - x_i^f) \\ + \frac{1}{2} \sum_{k=0}^K [M_{k-1}(x_i) - x_{i+k}^r]^T R^{-1} [M_{k-1}(x_i) - x_{i+k}^r]$$

where, K is the assimilation window and

$$\begin{aligned} M_{-1}(x_i) &= x_i \\ M_0(x_i) &= M(x_i) \\ M_{k-1}(x_i) &= \underbrace{M(M(\dots M(x_i) \dots))}_k \end{aligned}$$

Sequential data assimilation (IV)

4DVAR (continue)

The gradient of J with respect to x :

$$J' = B^{-1} (x_i - x_i^f) + \sum_{k=0}^K \prod_{j=0}^{k-1} \mathbf{M}_{i+j}^T R^{-1} [M_{k-1}(x_i) - x_{i+k}^r]$$

where, \mathbf{M}_{i+j}^T is the adjoint model of M at time step $i + j$.

Sequential data assimilation (V)

Extended Kalman Filters:

True states: $x_{i+1}^t = M(x_i^t) + q_i$

Model states: $x_{i+1}^f = M(x_i^a)$

Forecast error: $x_{i+1}^f - x_{i+1}^t = M(x_i^a) - M(x_i^t) - q_i$

A major assumption in KF:

$$M(x_i^a) - M(x_i^t) \approx \mathbf{M}_i(x_i^a - x_i^t)$$

Sequential data assimilation (VI)

Extended Kalman Filters (continue):

Forecast error covariance matrix:

$$\begin{aligned} P_{i+1}^f &= \left\langle \left(x_{i+1}^f - x_{i+1}^t \right) \left(x_{i+1}^f - x_{i+1}^t \right)^T \right\rangle \\ &\approx \mathbf{M}_i \left\langle \left(x_i^a - x_i^t \right) \left(x_i^a - x_i^t \right)^T \right\rangle \mathbf{M}_i^T + \left\langle q_i q_i^T \right\rangle \\ &= \mathbf{M}_i P_i^a \mathbf{M}_i^T + Q_i \end{aligned}$$

Sequential data assimilation (VII)

Extended Kalman Filters (continue):

For the analysis step:

$$K_i = P_i^f (P_i^f + R)^{-1}$$

$$x_i^a = x_i^f + K_i(x_i^r - x_i^f)$$

$$P_i^a = (I - K_i)P_i^f$$

For the forecast step:

$$x_{i+1}^f = M(x_i^a)$$

$$P_{i+1}^f = M_i P_i^a M_i^T + Q_i$$

Sequential data assimilation (VIII)

From scalar to vector:

Number of grid points $\approx 10^7$:

$$x \rightarrow \mathbf{x}$$

$$x^b \rightarrow \mathbf{x}^b$$

Dimension of \mathbf{B} , $\mathbf{P} \approx 10^7 \times 10^7$.

Number of observations, 10^6 :

$$x^r \rightarrow \mathbf{y}^o$$

$$x - x^r \rightarrow H(\mathbf{x}) - \mathbf{y}^o$$

Dimension of $\mathbf{R} \approx 10^6 \times 10^6$.

Sequential data assimilation (IX)

OI:

$$\mathbf{x}_i^a = \mathbf{x}_i^f + \mathbf{B}\mathbf{H}^T \left(\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R} \right)^{-1} \left[\mathbf{y}^o - H(\mathbf{x}_i^f) \right]$$

$$\mathbf{x}_{i+1}^f = M(\mathbf{x}_i^a)$$

4DVAR:

$$J(\mathbf{x}_i) = \frac{1}{2} \left(\mathbf{x}_i - \mathbf{x}_i^f \right)^T \mathbf{B}^{-1} \left(\mathbf{x}_i - \mathbf{x}_i^f \right) + \frac{1}{2} \sum_{k=0}^K \left[H \left(M_{k-1} (\mathbf{x}_i) \right) - \mathbf{y}^o_{i+k} \right]^T \mathbf{R}^{-1} \left[H \left(M_{k-1} (\mathbf{x}_i) \right) - \mathbf{y}^o_{i+k} \right]$$

$$J' = \mathbf{B}^{-1} \left(\mathbf{x}_i - \mathbf{x}_i^f \right) + \sum_{k=0}^K \prod_{j=0}^{k-1} \mathbf{M}_{i+j}^T \mathbf{H}^T \mathbf{R}^{-1} \left[H \left(M_{k-1} (\mathbf{x}_i) \right) - \mathbf{y}^o_{i+k} \right]$$

Sequential data assimilation (X)

The Extended Kalman Filter:

For the analysis step i :

$$\mathbf{K}_i = \mathbf{P}_i^f \mathbf{H}_i^T (\mathbf{H}_i \mathbf{P}_i^f \mathbf{H}_i^T + \mathbf{R})^{-1}$$

$$\mathbf{x}_i^a = \mathbf{x}_i^f + \mathbf{K}_i [\mathbf{y}^o - H(\mathbf{x}_i^f)]$$

$$\mathbf{P}_i^a = (\mathbf{I} - \mathbf{K}_i \mathbf{H}_i) \mathbf{P}_i^f$$

For the forecast step, from i to $i + 1$:

$$\mathbf{x}_{i+1}^f = M(\mathbf{x}_i^a)$$

$$\mathbf{P}_{i+1}^f = \mathbf{M}_i \mathbf{P}_i^a \mathbf{M}_i^T + \mathbf{Q}_i$$

Issues on data assimilation

- Observations \mathbf{y}^o
- Observation operator H
- Observation errors \mathbf{R}
- Background \mathbf{x}^b
- Size of \mathbf{B} : statistical model and tuning
- \mathbf{M} and \mathbf{M}^T : development and validity
- Minimization algorithm (Quasi-Newton; Conjugate Gradient; ...)
- Model errors \mathbf{Q}
- Size of \mathbf{P}^f and \mathbf{P}^a : simplifications

3. Demonstration with a simple system



The Lorenz 1964 equation

Nonlinear equation (NL):

$$x_{i+1} = ax_i - x_i^2 = M(x_i).$$

Depending on a , three types of solution are found: steady state; limited cycle; chaotic.

Tangent Linear equations (TL):

$$x_{i+1}^{tl} = (a - 2x_i^{bs}) x_i^{tl} = \mathbf{M}_i x_i^{tl}.$$

(linearized around basic state x_i^{bs})

Adjoint equation (AD):

$$x_i^{ad} = (a - 2x_i^{bs}) x_{i+1}^{ad} = \mathbf{M}_i^T x_{i+1}^{ad}.$$

Note here for this simple case we have

$$\mathbf{M}_i = \mathbf{M}_i^T = (a - 2x_i^{bs}).$$

Issues on data assimilation for the system based on the Lorenz 64 equation

- Observation operator $H = \mathbf{H} = \mathbf{H}^T = 1$
- Estimate of the true states - generated (with model error!)
- Observation error $x^o - x^t = \sigma_o G$
- Size of \mathbf{B} is 1, but $B = \sigma_b^2$ still needs attention
- Model errors \mathbf{Q} : $q_i = \sigma_m G$ when “true” states are generated; but we assume $Q = B/4$
- Size of \mathbf{P}^f or \mathbf{P}^a is 1.
- \mathbf{M} and \mathbf{M}^T : no effort in development but their validity is still a major problem
(model, assimilation window length, ...)
- Gaussian statistics

Too simple?

Try: Lorenz63 model

Try: 1-D advection equation

Try: 2-D shallow water equation

...

Try: ARW!!!

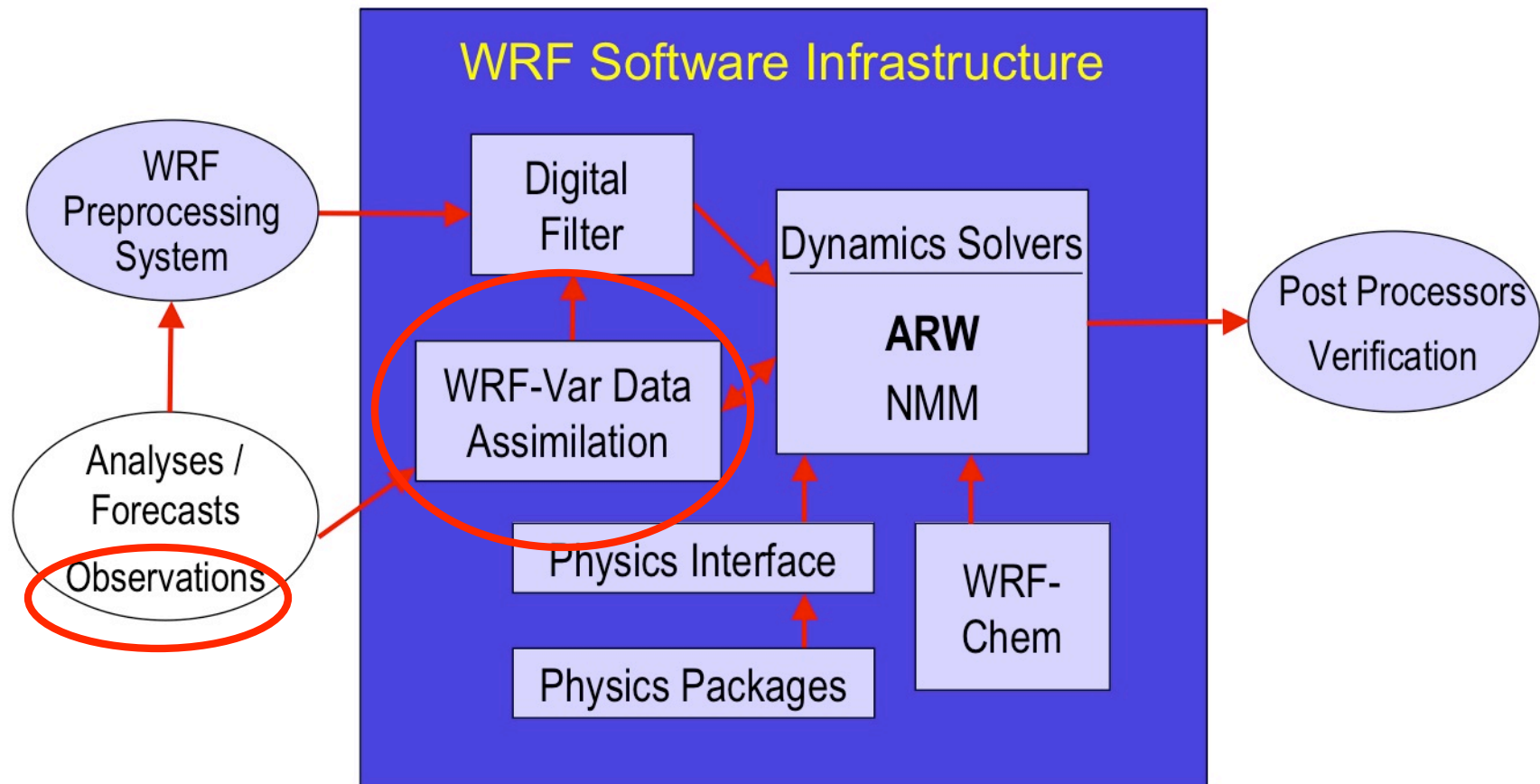


4. WRF-Var

...WRF-Var is a **V**ariational data assimilation system built within the software framework of **WRF**, used for application in both research and operational environments....



WRF Modeling System



ARW = Advanced Research WRF (NCAR) Core

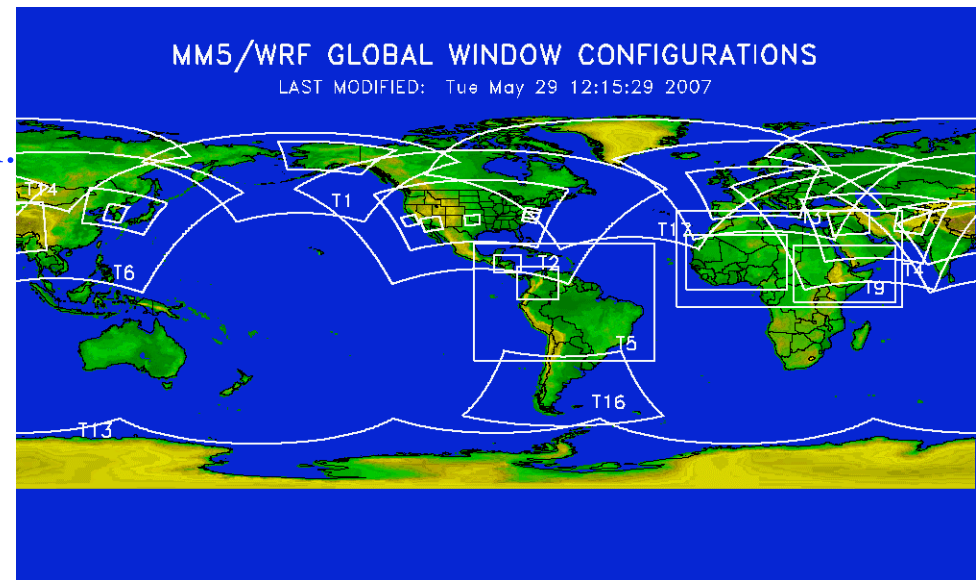
NMM = Nonhydrostatic Mesoscale Model (NCEP) Core



WRF-Var (WRFDA) Data Assimilation Overview

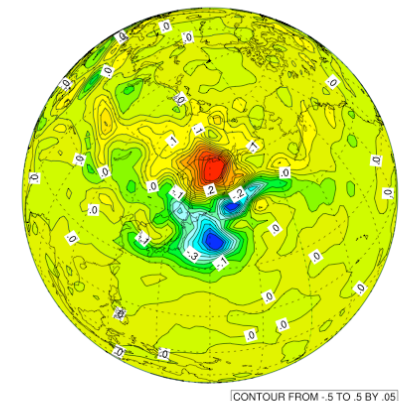
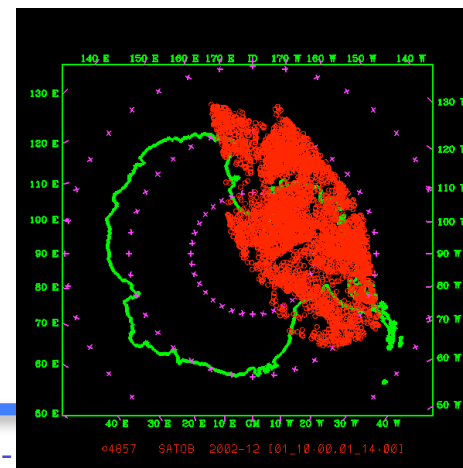
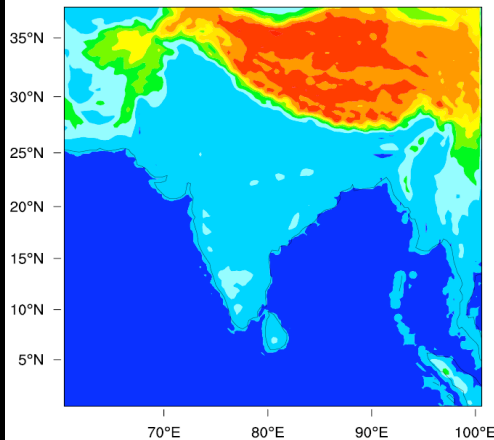
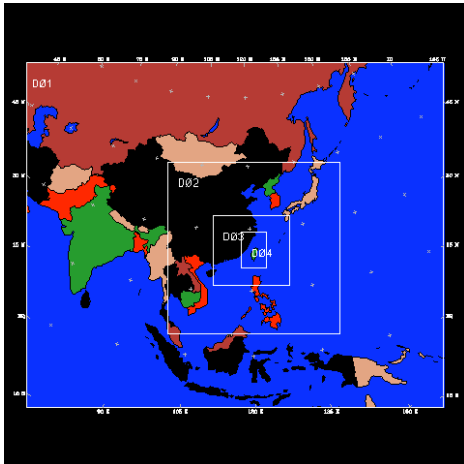
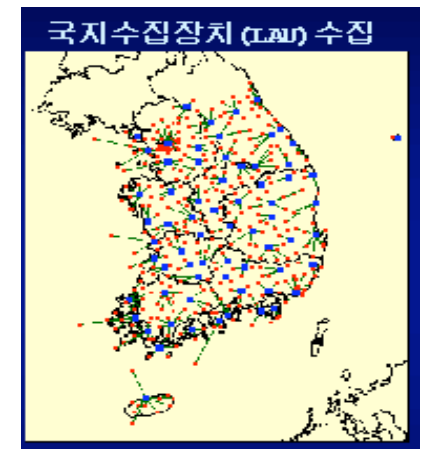
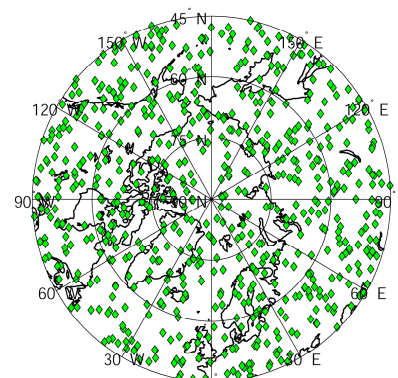
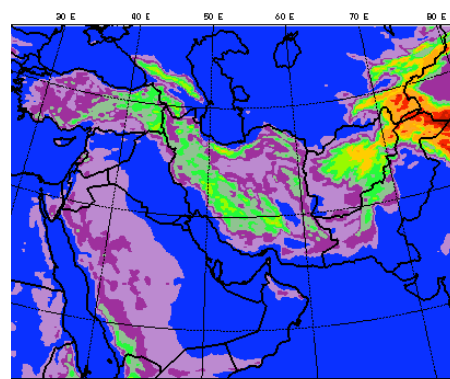
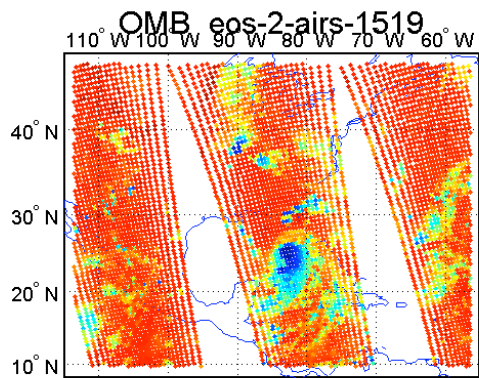
- **Goal:** Community WRF DA system for regional/global, research/operations, and deterministic/probabilistic applications.
- **Techniques:**
 - 3D-Var
 - 4D-Var (regional)
 - Ensemble DA,
 - Hybrid Variational/Ensemble DA.
- **Model:** WRF (ARW and NMM)
- **Support:**
 - NCAR/ESSL/MMM/DAG
 - NCAR/RAL/JNT/DATC
- **Observations:** Conv.+Sat.+Radar

AFWA Theaters:



The WRF-Var Program

- NCAR staff: 23FTE, ~12 projects.
- Non-NCAR collaborators (AFWA, KMA, CWB, BMB, etc): ~10FTE.
- Community users: ~30 (more in 4000 general WRF downloads?).



Future Plans

General Goals:

- Unified, multi-technique WRF DA system.
- Retain flexibility for research, multi-applications.
- Leverage international WRF community efforts.

WRF-Var Development (MMM Division):

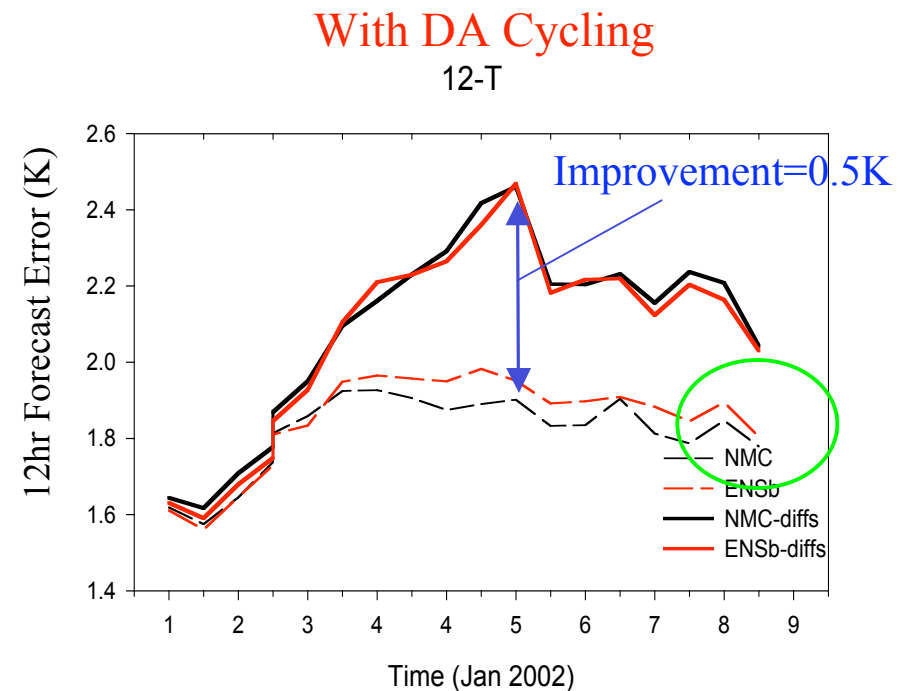
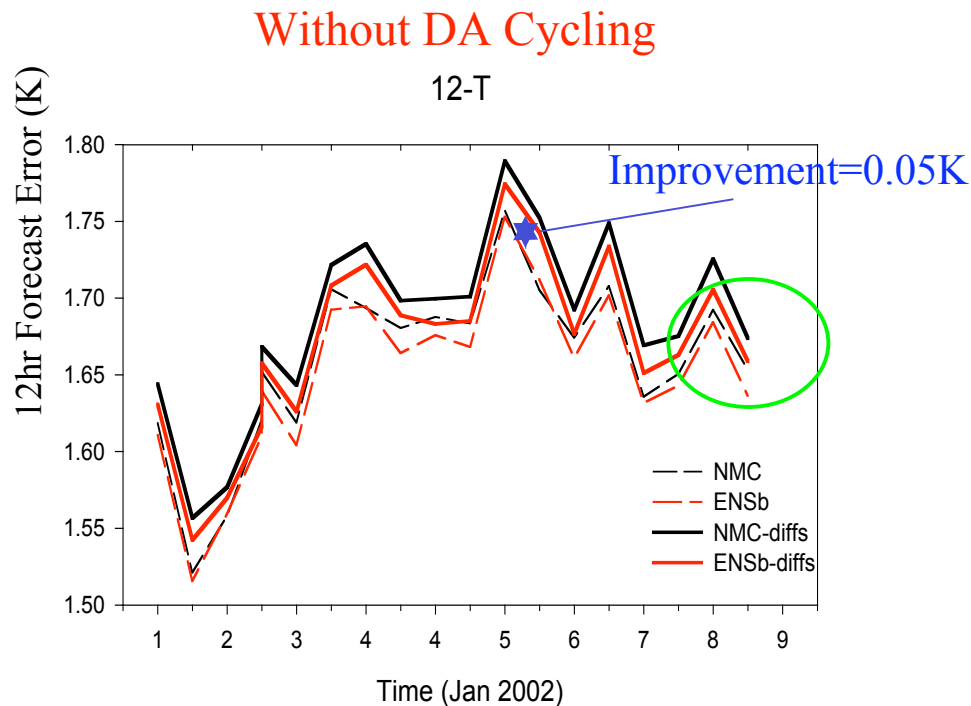
- 4D-Var (additional physics, optimization).
- Sensitivities tools (adjoint, ensemble, etc.).
- EnKF within WRF-Var -> **WRFDA**.
- Instrument-specific radiance QC, bias correction, etc.

Data Assimilation Testbed Center (DATC):

- Technique intercomparison: 3/4D-Var, EnKF, Hybrid
- Obs. impact: AIRS, TMI, SSMI/S, METOP.
- New Regional testbeds: US, India, Arctic, Tropics.



Importance of Data Assimilation For General WRF Development/Testing



Warning: Cycling with insufficient observations leads to degradation (1.8K vs. 1.7K)



Experiment (Mi-Seon Lee, KMA)

5. Important issues covered by this tutorial

- y^o observations - collection, quality control, bias correction, thinning, ...
- H observation operator, including the tangent linear operator \mathbf{H} and the adjoint operator \mathbf{H}^T .
- M forecast model, including the tangent linear model \mathbf{M} and adjoint model \mathbf{M}^T .
- \mathbf{B} background error covariance ($\sim 10^7 \times 10^7$).
- \mathbf{R} observation error covariance which includes the representative error ($10^6 \times 10^6$).
- Minimization algorithm
- \mathbf{P}^a and \mathbf{P}^f analysis and forecast error covariances

