The Abdus Salam
International Centre for Theoretical Physics

United Nations
Educational, Scientific and
Cultural Organization

IAEA
International Atomic Energy Agency

1956-8

Targeted Training Activity: Seasonal Predictability in Tropical Regions to be followed by Workshop on Multi-scale Predictions of the Asian and African Summer Monsoon

4 - 15 August 2008

Initialization Issues of Coupled Ocean-atmosphere Prediction System.

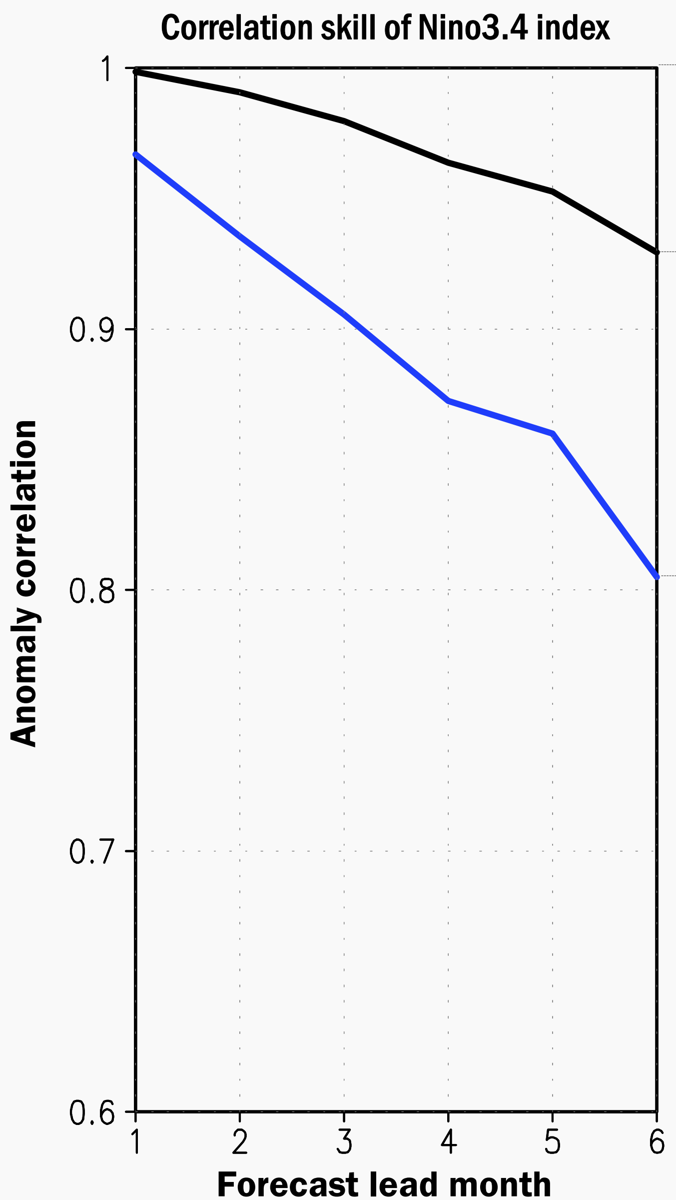
Kang In Sik
Seoul National University
School of Earth and Environmental Sciences
Division of Atmospheric Sciences
San 56-1 Shillim-dong, Kwanak-ku, Seoul 151-742
REPUBLIC OF KOREA

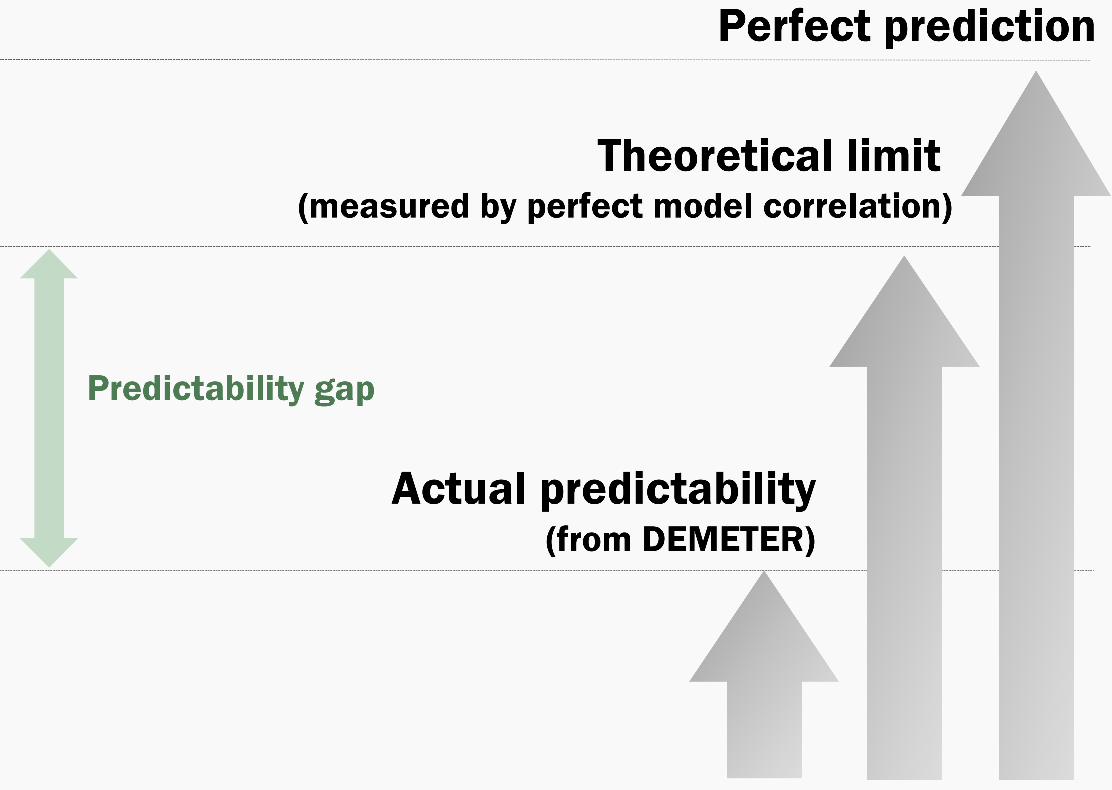
Initialization Issues of Coupled Ocean-atmosphere Prediction System

In-Sik Kang

Climate and Environment System Research Center
Seoul National University, Korea

Predictability of Seasonal Prediction



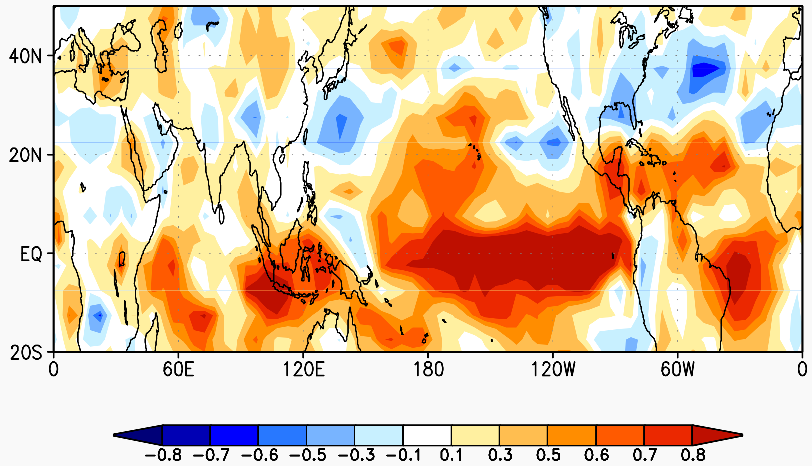


Gap between theoretical limit & actual predictability

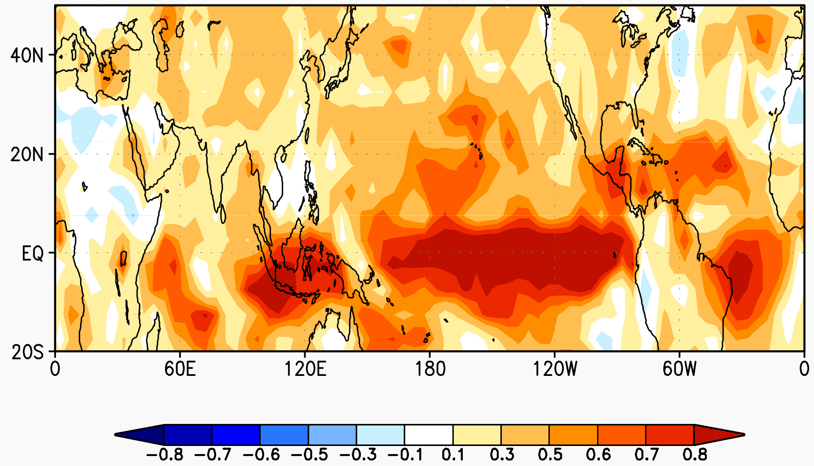
1. **Deficiency due to Initial conditions**
2. **Model imperfectness**

Statistical correction (SNU AGCM)

Before Bias correction



After Bias Correction



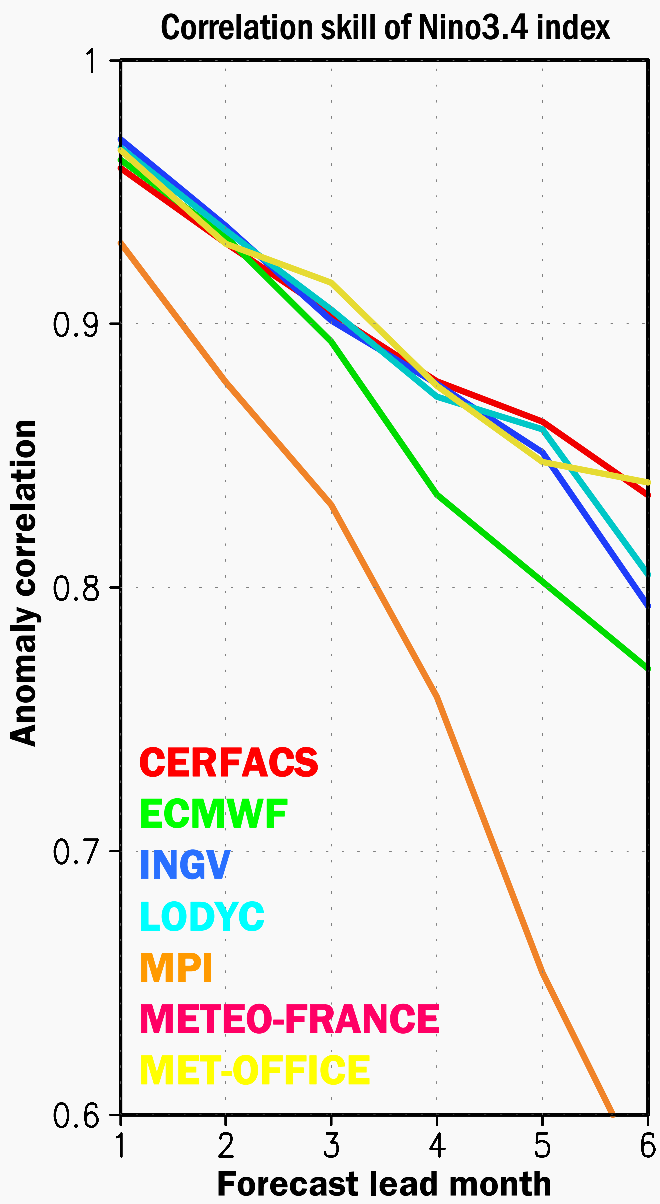
Predictability over equatorial region is not improved much

Is post-processing a fundamental solution?

Forecast error comes from (model imperfectness / poor initial conditions)

(**Model improvement** / **Good initialization process**) is essential to achieve to predictability limit

Impact of Initial condition



MPI : Poor initialization process compared to others

Initialization process

MPI

Observed SST

Surface flux from AGCM

Oceanic GCM

Surface flux is not enough to force the ocean

Other models

Subsurface Temperature

Observed SST Surface flux

Oceanic GCM

Temperature observations plays an important role to reflects observational states

Issues about initial conditions

True state + Perfect model

True state + Imperfect model

→ Is true state a best initial condition of imperfect forecast model?

Imperfect IC + Imperfect model

→ How to reduce uncertainties ?

- **Obtain optimal initial condition**
  -Data assimilation
- **Reducing inherent uncertainties**
  -Ensemble prediction

Is True state a best initial condition of imperfect forecast model?

Experiments with Lorenz model

$$\frac{dx_1}{dt} = -px_1 + px_2$$

$$\frac{dx_2}{dt} = rx_1 - x_1x_3 - x_2$$

$$\frac{dx_3}{dt} = x_1x_2 - bx_3$$

r=28 : true world (perfect forecast model)

r=26 : Imperfect forecast model

Is True state a best initial condition of imperfect forecast model?

$$\Psi_{Initial\_Condition} = (1-k)\cdot\Psi_{Model} + k\cdot\Psi_{TRUE}$$

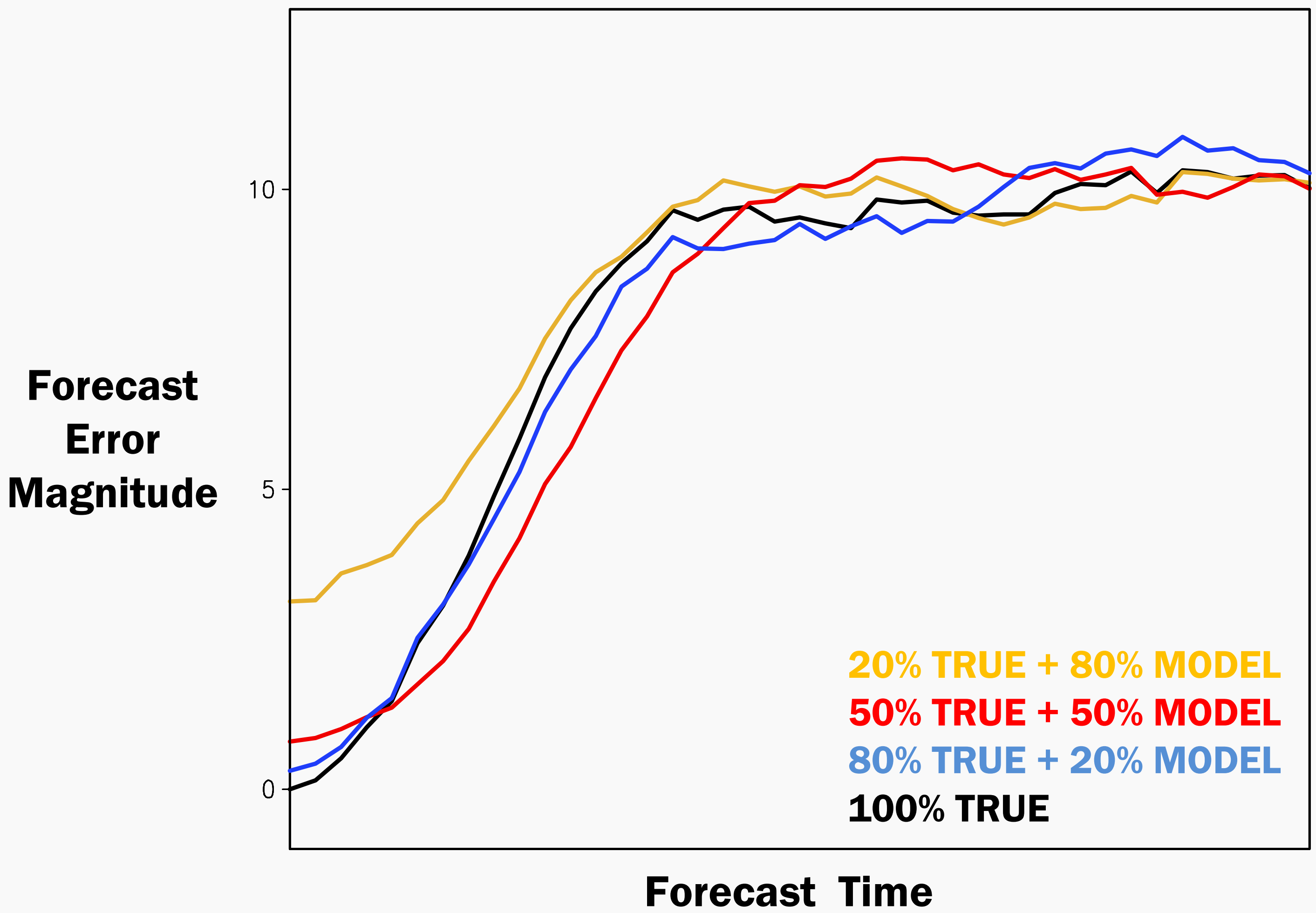
K = nudging coefficient

Experimental Design

k=1 : TRUE state
k= 0.8 : 80% TRUE + 20% MODEL free run
k= 0.5 : 50% TRUE + 50% MODEL free run
k= 0.2 : 20% TRUE + 80% MODEL free run

Is True state best initial condition of imperfect forecast model?

True world ≠ Forecast model (Imperfect forecast model)



100 cases average

True state is not always best initial condition of imperfect model
→ Physical balance of forecast model should be considered for optimal initial condition

What determines quality of Initial conditions?

- **Optimal (accurate & well-balanced) initial conditions**

  - **Accurate : Errors in initial condition is minimized**
  - **Well-balanced : Physical laws in forecast model is satisfied**

  (e.g. geostrophic balance, T-S relationship, thermal wind relationship, etc.)

- **Reducing inherent uncertainties**

  → Ensemble Prediction

  - **Reduction of noise by averaging many ensemble members**
  - **If number of ensemble members is infinite, unpredictable component will be zero in the ensemble mean**

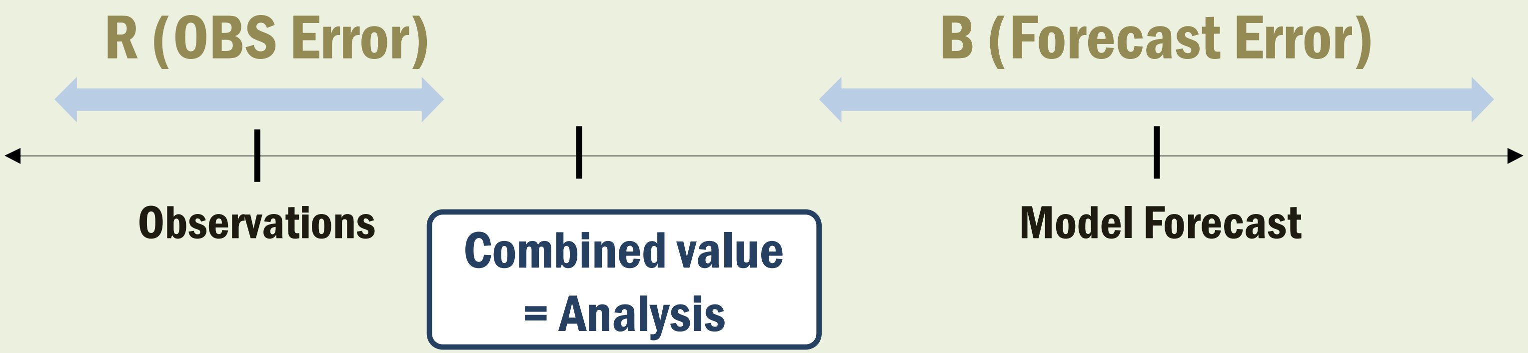
Data assimilation

" Produce well-balanced initial condition through a
statistical combination of
observations and short-range forecasts "

$$\Psi_{Analysis} = (1-k)\cdot\Psi_{Model} + k\cdot\Psi_{OBS}$$

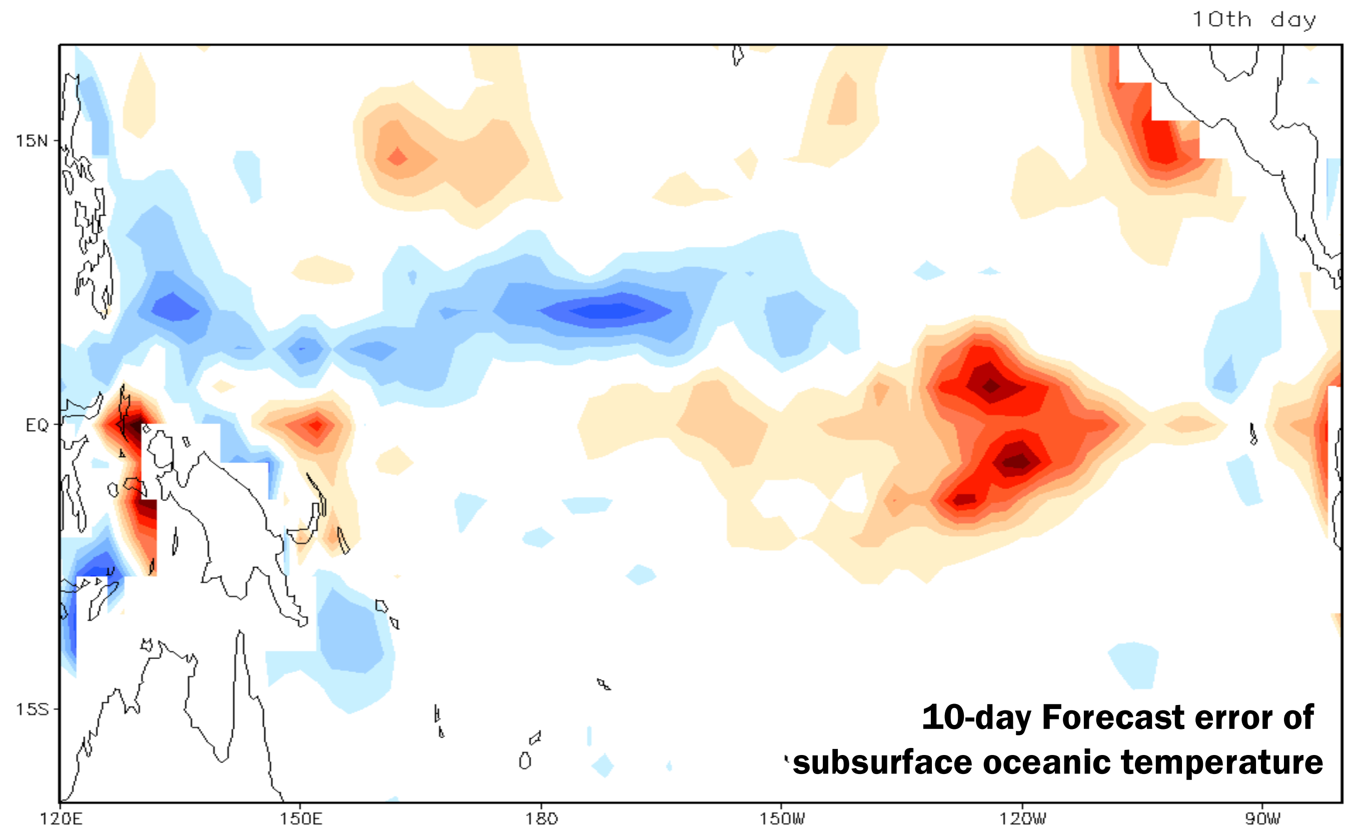
$$\text{Weighting coefficient } (k) = \frac{B}{R+B}$$

B :Forecast error
R : OBS error



Characteristics of forecast error

1. Non-local (spatially correlated)
2. Time variant



Forecast error is assumed as…

1. Nudging

- Local & Time invariant

$$\frac{\partial T}{\partial t} = -\bar{v}\cdot\nabla T + \frac{Q}{\rho C_P H} + \boxed{\frac{T_{obs} - T}{\tau_T}}$$

Nudging term in temperature equation

τ_T **is constant**

2. 3DVAR, Optimal Interpolation (OI)

- Non-local & Time invariant

$$\Psi_{Analysis} = (1-k)\cdot\Psi_{Model} + \boxed{k}\cdot\Psi_{OBS}$$

K = constant, but having a spatial structure

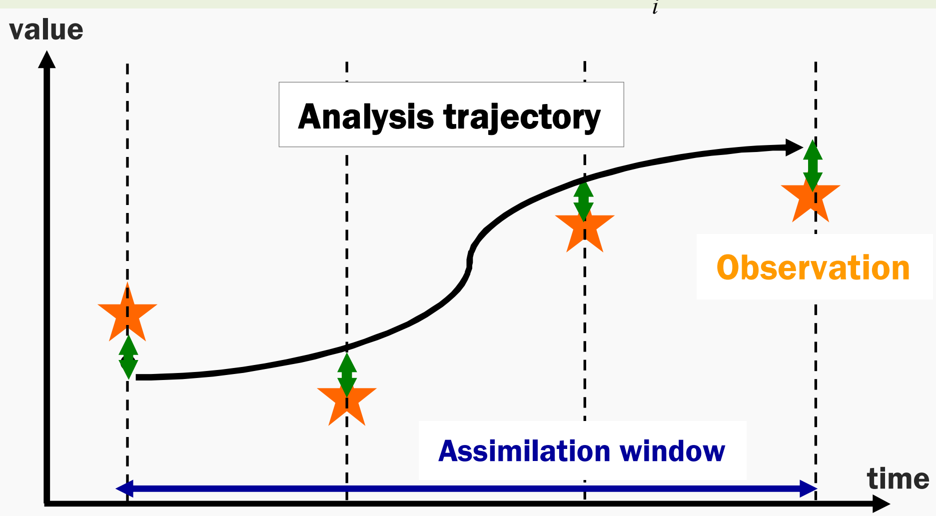
3. 4DVAR, Ensemble Kalman Filter

- Non-local & Time variant

4DVAR

Find the initial condition its forecast best fits the observations within the assimilation window by minimizing cost function

Cost function $= [x(t_0) - x^b(t_0)]^T B_0^{-1} [x(t_0) - x^b(t_0)] + \sum_i [y^o{}_i - H(x_i)]^T R_i^{-1} [y^o{}_i - H(x_i)]$



Assumptions

1. **Causality :**
   The forecast model can be expressed as the product of intermediate forecast steps.

$$\mathrm{x}_i = M_i M_{i-1} \ldots M_1 x$$

2. **Tangent linear hypothesis :**
   The cost function can be made quadratic by assuming that the M operator can be linearized.

$$\mathrm{y}_i - H_i M_{0\to i}(x) \approx y_i - H_i M_{0\to i}(x_b) - H_i M_{0\to i}(x - x_b)$$

Procedures

1. Integrate forecast model to get forecast values $x_{T+\alpha}$
2. Calculate difference between obs and model $y_{T+\alpha} - x_{T+\alpha}$
3. Integrate backward in time using adjoint model

$$\frac{\partial J(x)}{\partial x} = \sum_{i=1}^{\alpha} L_{T+\alpha\to T}{}^T R^{-1} (y_{T+\alpha} - x_{T+\alpha})$$

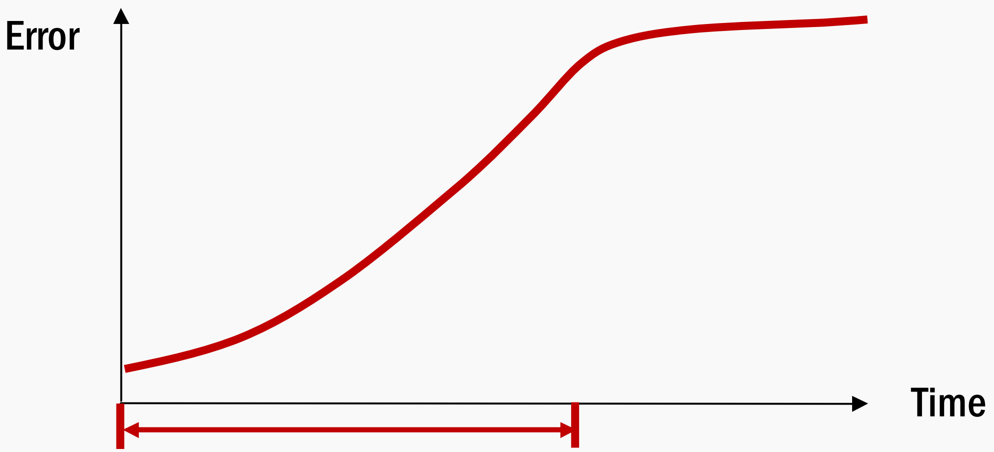
4. Gradient of cost function is used to determine the direction to search the minimum cost function

$$X_{new} = X_{old} - \frac{\partial J(x_{old})}{\partial x}$$

5. 1-4 procedure is repeated until find stable solution

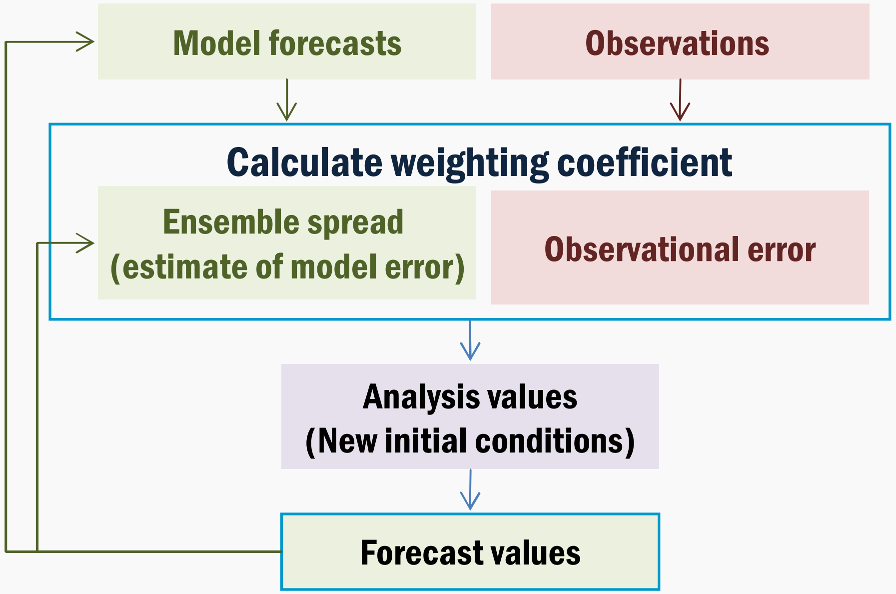
Is 4DVAR applicable for seasonal prediction?
: Linear assumption in CGCM

1. Is linearized CGCM dynamically meaningful?
   - Ocean physics is highly nonlinear
2. Is linear assumption valid in seasonal time scale?
   - Assimilation window is about several months for seasonal prediction
3. Problem in 4DVAR procedure
   - Forward integration with nonlinear model,
     Backward integration with linearized model } Inconsistency problem



Linear assumption should be valid during several month

Ensemble Kalman Filter (EnKF)



Procedures

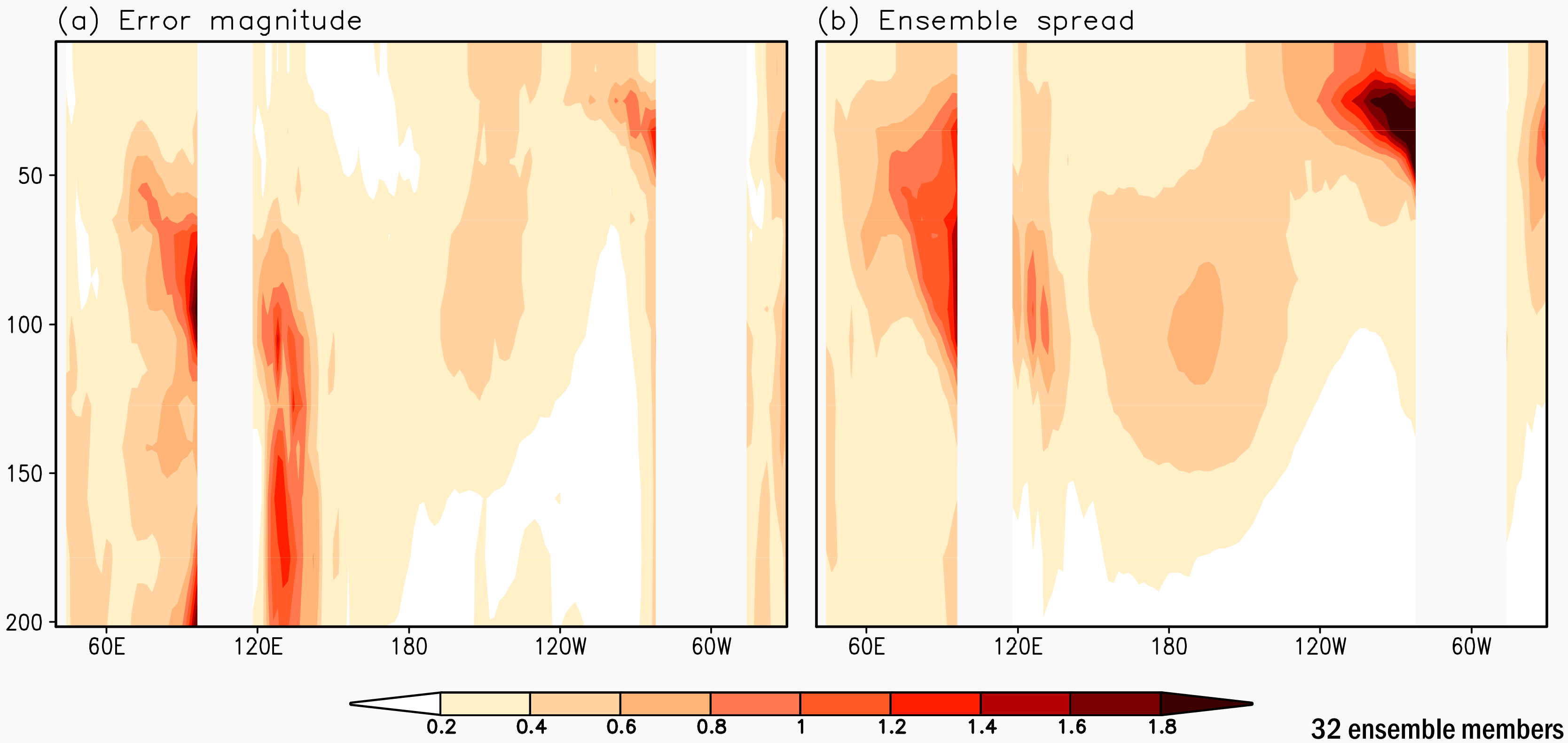
1. Integrate one cycle from random perturbation plus control initial condition
2. Calculate the forecast error covariance based on ensemble spread
3. Update the each ensemble states with analysis equation
4. Repeat 1-3 processes

Assumptions

1. Ensemble spread is assumed as model forecast error
2. Model & observational error distribution is gaussian

Forecast error & ensemble spread

Equatorial Oceanic Temperature
Error Magnitude & Ensemble Spread at 10 day forecast



32 ensemble members are used.

Pattern Correlation coefficient = 0.47

Forecast error magnitude is represented by ensemble spread to a certain extent

Is ensemble spread always appropriate tool to measure model forecast error?

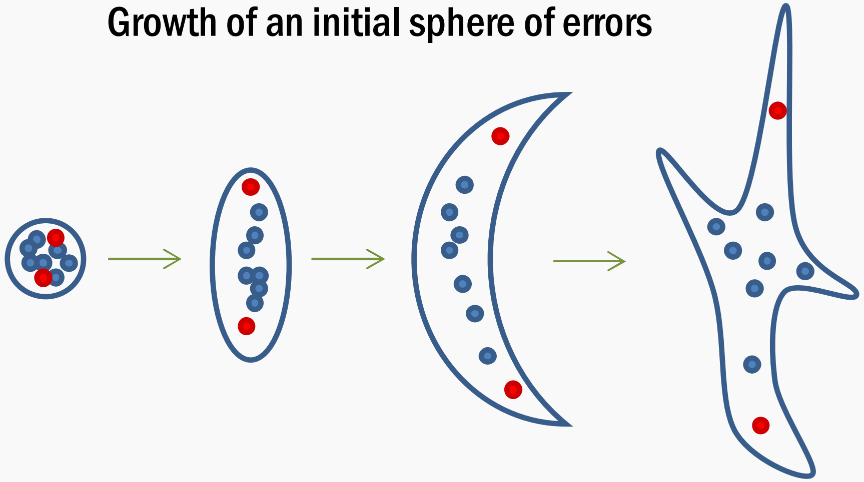
Optimal Perturbation Method for Ensemble Prediction

Conditions for optimal Ensemble prediction

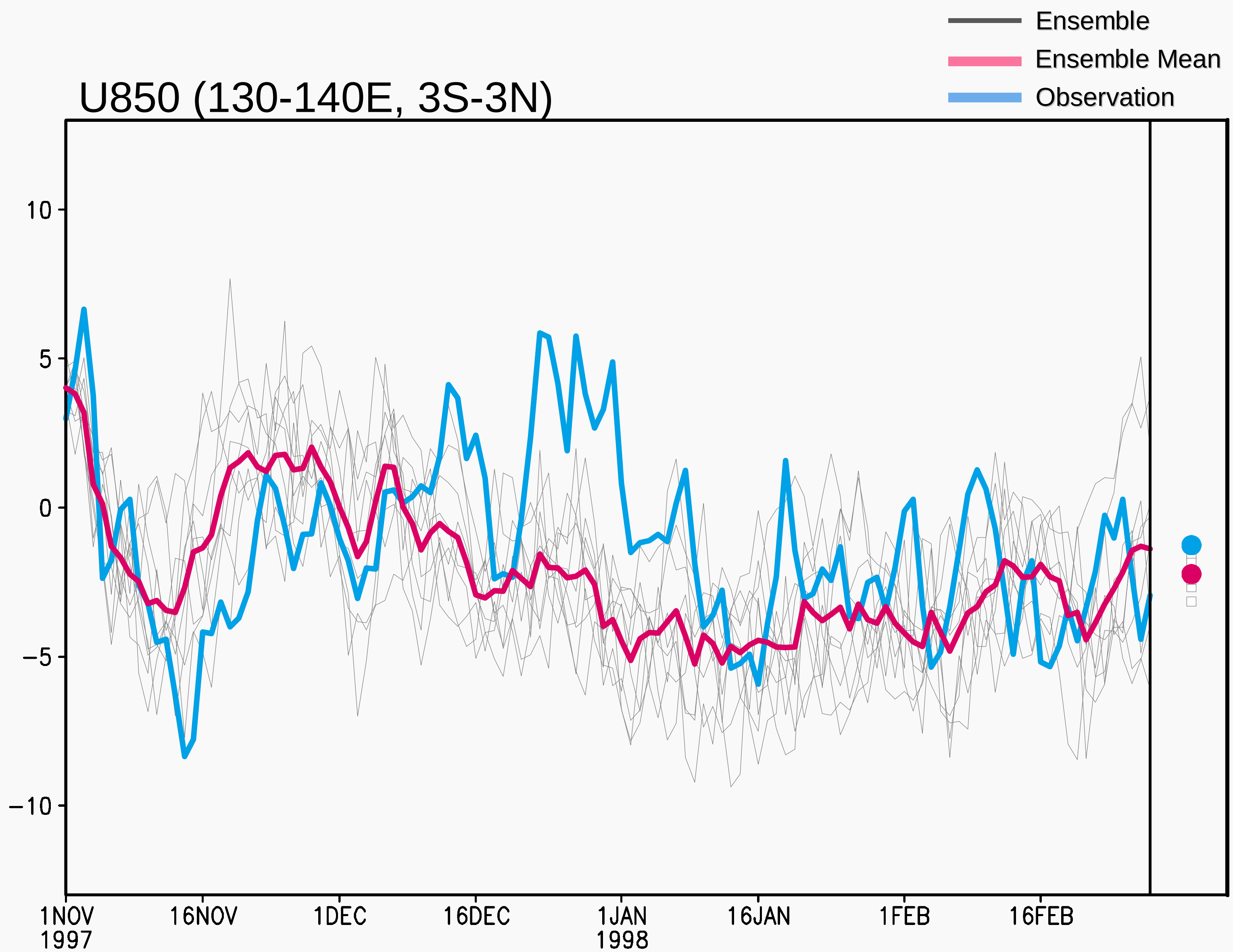
1. **Knowledge about initial error distribution**
   → **Information about initial error distribution is never given**
2. **Infinite ensemble members**
   → **Only finite ensemble member is possible**

Generate few ensemble members to efficiently describe forecast uncertainty → Fast-growing perturbations

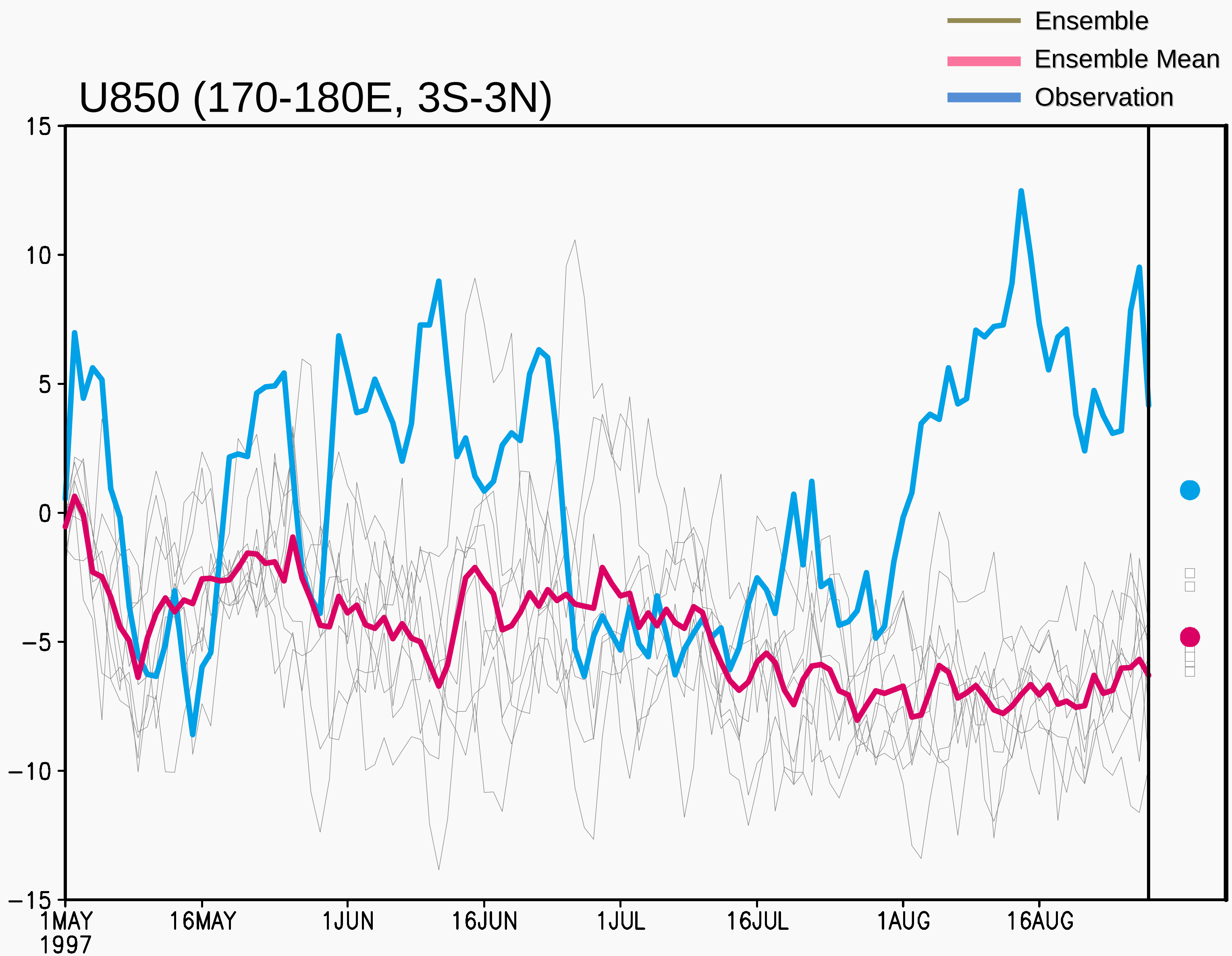
Growth of an initial sphere of errors



Ensembles Forecasts with Small Initial Perturbations



Ensembles Forecasts from Small Initial Perturbation



Optimal Perturbation Method for Ensemble Prediction

To extract fast growing initial perturbation

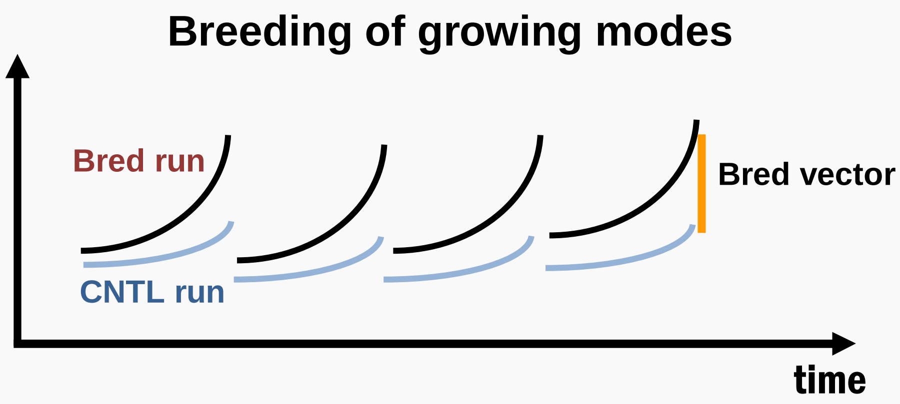
- **Breeding Method**
  - Repeat breeding and rescaling in the (nonlinear) model integration
  - Bred vector as a fast growing mode
  - NCEP for medium-range prediction

- **Singular Value Decomposition (SVD) Method**
  - Linear Stability of linearized model
  - Singular vector as a fast Growing mode
  - ECMWF for medium-range prediction

Breeding method

Procedure of Breeding Cycle

1. Integrate one cycle from random perturbation plus control initial condition
2. Calculate error by control run
3. Rescaling the error
4. Integrate one cycle from rescaled error perturbation plus control initial condition
5. Repeat 2-4 processes to initial forecast time



Potential Benefit

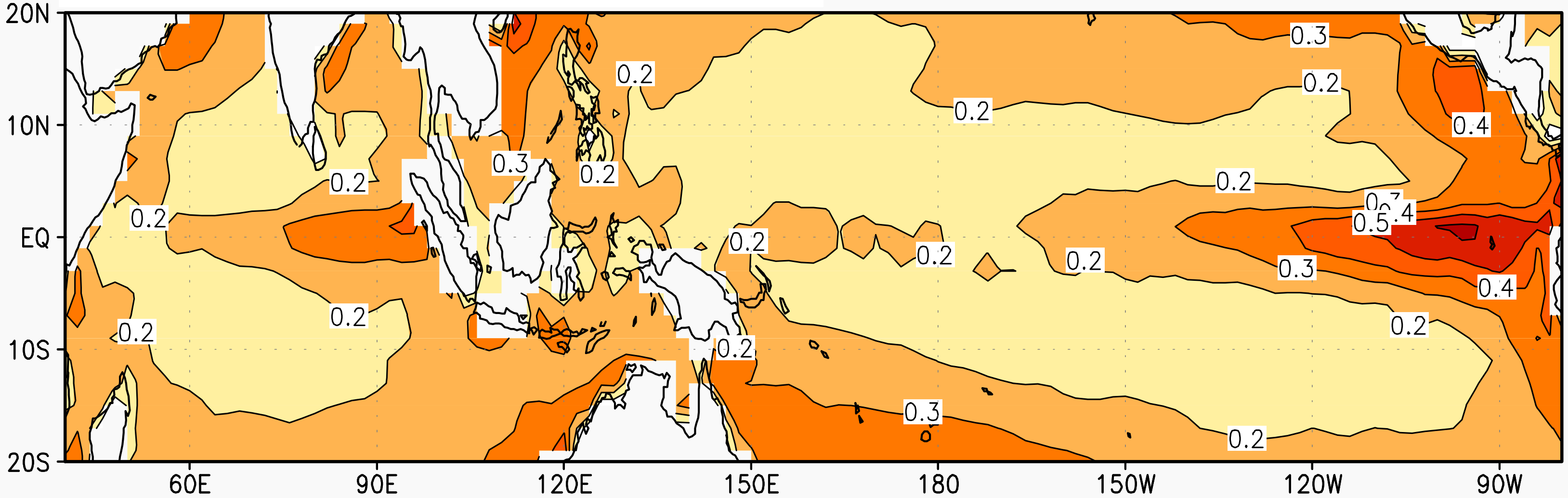
- Ensemble prediction using Bred vector
- The bred vector represents fast growing mode of the model and nature

Is Bred Vectors applicable for seasonal prediction?

❑ Rescaling time interval : 1 month
- To catch up longer time-scale variability

❑ Selection of Norm : RMS of Monthly mean SST over Indo-Pacific Region
- To reduce effects of fast atmospheric fluctuation because SST is slowly varying.

STD of Bred Vector SST in SNU CGCM



Singular Vector method

$$Let\ \mathrm{X} = \Psi(\mathrm{t}),\ \mathrm{Y} = \Psi(\mathrm{t}+\tau)$$

$$\mathrm{Y} = \mathrm{L} \cdot X$$

By solving singular value of L operator

$$\mathrm{L} = \mathrm{U}SV^T$$

$$\mathrm{UY} = SV\mathrm{X}$$

$$u_i \cdot \mathrm{Y} = \mathrm{s}_i v_i X$$

If S_i > 1, then V_i is an initial perturbation of growing mode

U_i is a final perturbation of growing mode

For maximum S_i : fast growing perturbation

Singular Vector method

SVD Method : linear stability of linearized model

- Usually linearized model is not available, especially for fully coupled system

Empirical linear operator is formulated using time-lag relationship

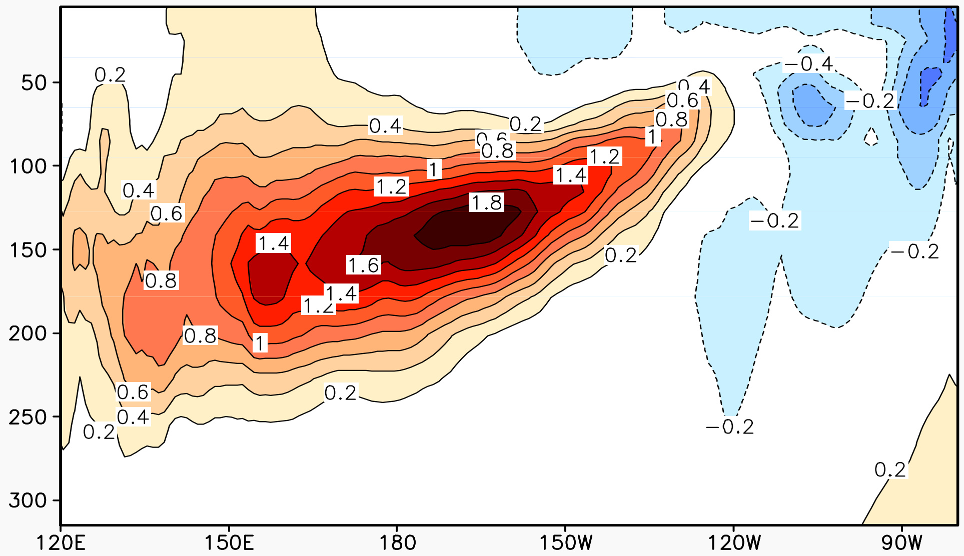
Tangent linear operator

$$\mathrm{Y} = \mathrm{L} \cdot X$$

$$\mathrm{L} = \underbrace{\boxed{\mathrm{Y}X^{\mathrm{T}}}}_{\text{Covariance between X and Y}} \underbrace{\boxed{(XX^{T}}}_{\text{Variance of X}})^{-1}$$

X: 5 EOF modes of thermocline depth
Y: 5 EOF modes of SST after 6-month

Equatorial Temperature perturbations at May 1st



Thank you