Coupled Ocean-Atmosphere Assimilation

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Content

- **Background**
  - Why coupled DA is different from single-component DA? What are the difficulties for the coupled DA?
- **Obtain slow coupled modes in a dynamically coupled system**
  - In a simple coupled model (triple-coupled Lorenz 3-variable model)
  - In the NASA fully coupled model (CGCM)
- **Coupled data assimilation**
  - Applications of the slow coupled modes
  - Perform DA with a coupled model
  - Operational framework

Background

- Single numerical model: one dominant source of instability
  - ex: DA for the NWP model: errors are dominated by baroclinic instability
- Coupled numerical model:
  - Instabilities span different time-scales: convection, weather, MJO, El Nino-Southern Oscillation... From minutes to years…
  - Fast atmosphere coupled with slow ocean: fast weather synoptic instability + slow ENSO instability. Errors are influenced by the air-sea interaction: Need to correct the slowly-varying coupled instability.

Goal

Coupled DA should provide the “coupled” initial conditions for initializing the coupled forecasts.

Challenges:

- Instabilities have different temporal and spatial time scales: the coupled instability is not the fastest growing instability.
- For coupled data assimilation/ensemble forecasting, we need to be able to represent the structures of the coupled errors.
  - Linearized methods (like Singular vectors) without decomposing scales automatically pick up the fastest growing errors.
  - Nonlinear methods (EnKF, Breeding) allow the errors of fast instabilities to saturate quickly.

Coupled slow and a fast Lorenz (1963) 3-variable models (Peña and Kalnay, 2004)

Fast equations

$$\frac{dx_1}{dt} = \sigma(y_1 - x_1) - C_1(Sx_2 + O)$$

$$\frac{dy_1}{dt} = rx_1 - y_1 - x_1 z_1 + C_1(Sy_2 + O)$$

$$\frac{dz_1}{dt} = x_1 y_1 - bz_1 + C_1(Sz_2)$$

Slow equations

$$\frac{1}{\tau}\frac{dx_2}{dt} = \sigma(y_2 - x_2) - C_2(x_1 + O)$$

$$\frac{1}{\tau}\frac{dy_2}{dt} = rx_2 - y_2 - Sx_2 z_2 + C_2(y_1 + O)$$

$$\frac{1}{\tau}\frac{dz_2}{dt} = Sx_2 y_2 - bz_2 + C_2(z_1)$$

τ=10, makes the ocean slow

Coupled slow and a fast Lorenz (1963) 3-variable models (Peña and Kalnay, 2004)

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Interactions between components!

$C_{1,2}$ is the coupling strength

Triple-Coupled Lorenz 3-variable models (Peña and Kalnay, 2004)

Tropical atmosphere (X_t, Y_t, Z_t)

$$\dot{x}_t = \sigma(y_t - x_t) - c(SX + k_2) - c_e(Sx_e + k_1)$$
$$\dot{y}_t = rx_t - y_t - x_t z_t - c(SY + k_2) + c_e(Sy_e + k_1)$$
$$\dot{z}_t = x_t y_t - bz_t + c_z Z$$

strongly coupled

weakly coupled

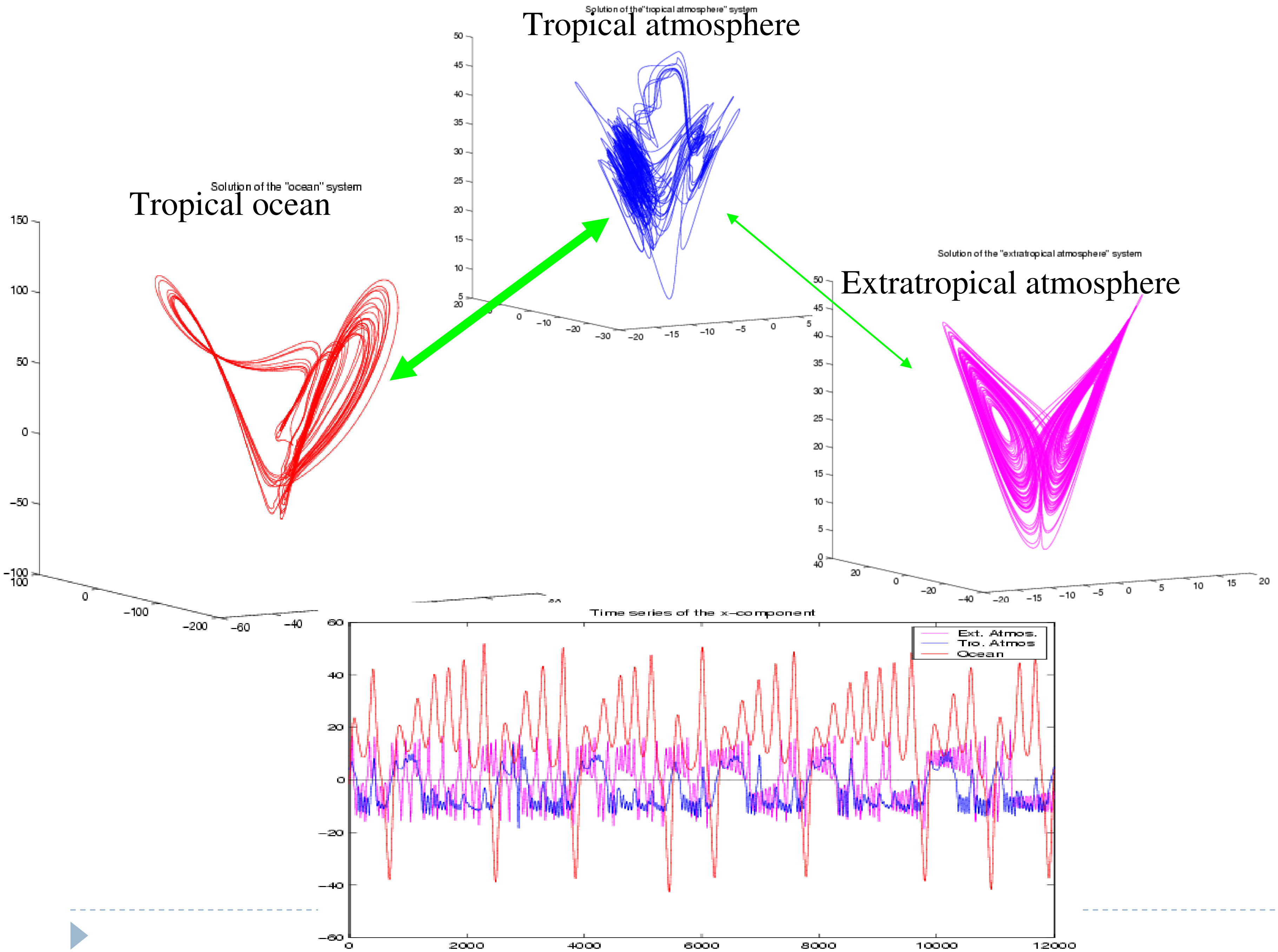
Ocean (X, Y, Z)

$$\dot{X} = \tau\sigma(Y - X) - c(x_t + k_2)$$
$$\dot{Y} = \tau rX - \tau Y - \tau SXZ + c(y_t + k_2)$$
$$\dot{Z} = \tau SXY - \tau bZ + c_z z_t$$

Extratropical atmosphere (X_e, Y_e, Z_e)

$$\dot{x}_e = \sigma(y_e - x_e) - c_e(Sx_t + k_1)$$
$$\dot{y}_e = rx_e - y_e - x_e z_e - c_e(Sy_t + k_1)$$
$$\dot{z}_e = x_e y_e - bz_e$$

"Tropical-extratropical" (triply-coupled) system:
the ENSO tropical atmosphere is weakly coupled to a fast "extratropical atmosphere" with weather noise



Solution of the "tropical atmosphere" system
Tropical atmosphere
Solution of the "ocean" system
Tropical ocean
Solution of the "extratropical atmosphere" system
Extratropical atmosphere
Time series of the x-component
Ext. Atmos.
Tro. Atmos
Ocean

Background error covariance estimated directly from the Lorenz triple-coupled model (1000 time-steps)

$\varepsilon_e = [\varepsilon_{exp\text{-}atm}, \ \varepsilon_{trp\text{-}atm}, \ \varepsilon_{trp\text{-}ocn}]$, $\overline{\mathbf{B}_{9\times 9} = < \varepsilon_e,} \ \varepsilon_e^T >$

We will see that the fast extratropical atmosphere dominates the errors in B.

With this B, the analysis corrections will ignore the coupled errors originated from the tropics!

Background error covariance estimated directly from the Lorenz triple-coupled model (1000 time-steps)

$\varepsilon_e = [\,\varepsilon_{exp\text{-}atm},\ \varepsilon_{trp\text{-}atm},\ \varepsilon_{trp\text{-}ocn}],\ \overline{\mathbf{B}_{9\times 9} = \langle \varepsilon_e,\ \varepsilon_e^T \rangle}$

$$\mathbf{B}_{9\times 9} = \begin{bmatrix} 14.365 & 16.645 & 0.276 & 0.028 & 0.151 & -0.055 & 0.002 & 0.020 & -0.003 \\ 16.645 & 32.499 & 0.120 & 0.023 & 0.192 & 0.020 & -0.015 & -0.010 & -0.011 \\ 0.276 & 0.120 & 40.104 & 0.025 & 0.023 & 0.055 & -0.012 & 0.035 & 0.014 \\ 0.028 & 0.023 & 0.025 & 0.165 & 0.171 & -0.065 & -0.003 & 0.035 & 0.061 \\ 0.151 & 0.192 & 0.023 & 0.171 & 0.332 & -0.004 & 0.012 & 0.039 & 0.038 \\ -0.055 & 0.020 & 0.055 & -0.065 & -0.004 & 0.476 & -0.022 & -0.074 & 0.004 \\ 0.002 & -0.015 & -0.012 & -0.003 & 0.012 & -0.022 & 0.134 & 0.175 & 0.000 \\ 0.020 & -0.010 & 0.035 & 0.035 & 0.039 & -0.074 & 0.175 & 0.914 & -0.072 \\ -0.003 & -0.011 & 0.014 & 0.061 & 0.038 & 0.004 & 0.000 & -0.072 & 1.012 \end{bmatrix}$$

Eigen vectors (V_i) are dominated by the extra-tropical component

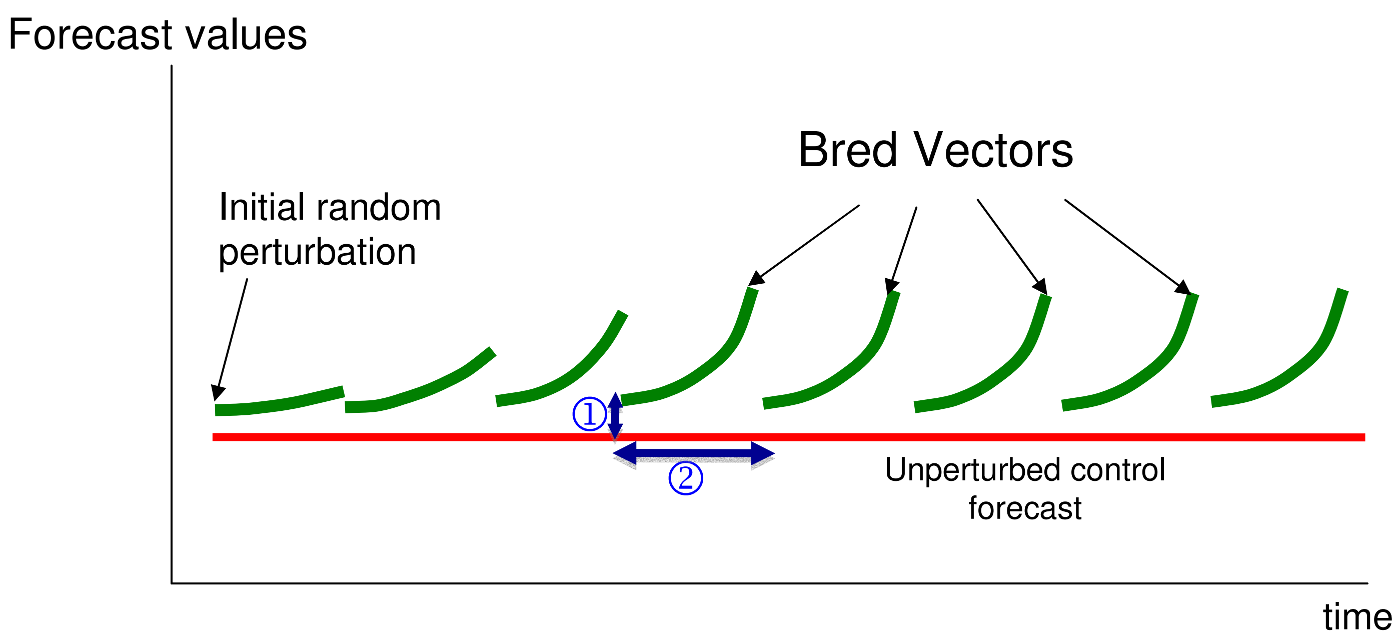
eigen values λ_i= [42.4, 40.1, 4.5, 1.1, 0.9, 0.5, 0.4, 0.1, 0.04]

V_1=[**-0.51** **-0.86** 0.09 0.0002 -0.0054 0.0015 -0.0002 0.0046 0.0003]
V_2=[-0.04 -0.08 **-1.00** 0.0007 0.0009 0.0021 -0.0019 0.0009 0.0001]
V_3=[**0.86** **-0.51** 0.0021 0.0060 0.0171 -0.0085 -0.0016 -0.0053 0.0049]

Errors associated with coupled instability

- Coupled breeding aims to isolate the slowly growing, coupled instability from the fast noise
  - Coupled BVs can be used to construct the structures of coupled errors, “errors of the month”
- Data assimilation in a coupled framework
  - Perform data assimilation with individual component, but evolve the states with the fully coupled model
  - Perform coupled assimilation with the fully coupled model (Are we able to assimilation fast/slow observations together!?)

Breeding: simply running the nonlinear model a second time, from perturbed initial conditions.

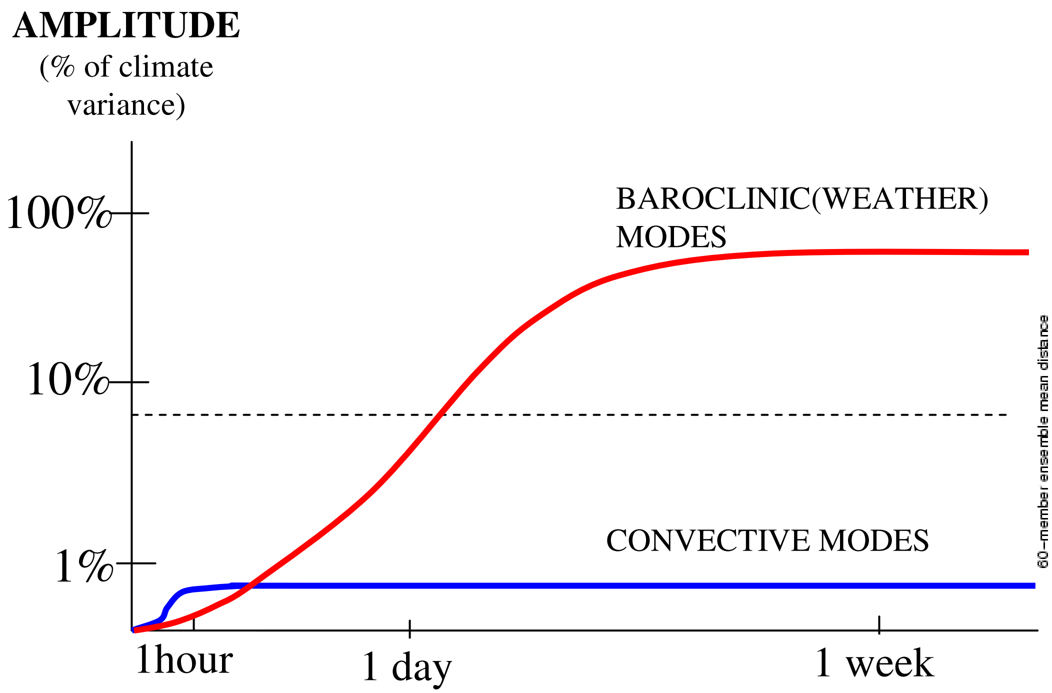


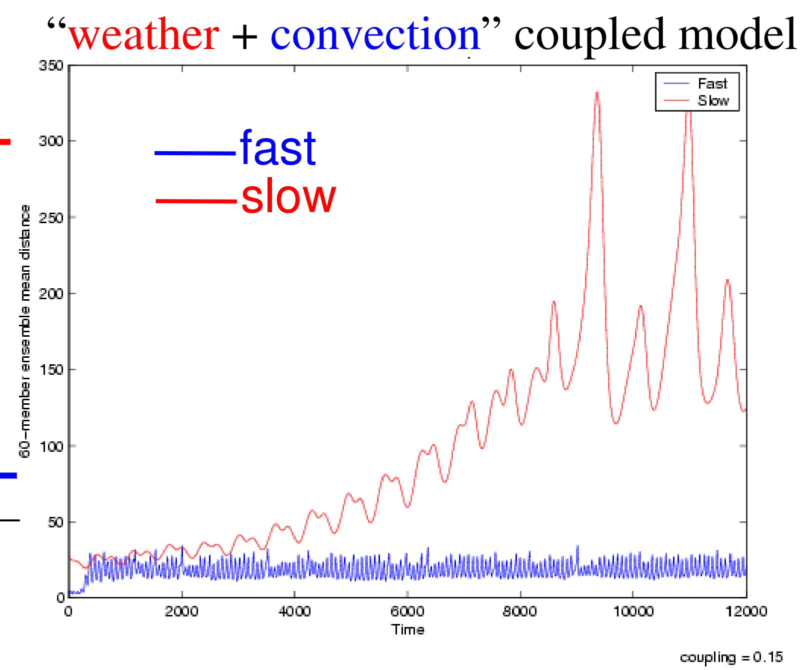
Breeding: finite-amplitude, finite-time instabilities of the system (~Lyapunov vectors)

Only two tuning parameters: (1) rescaling amplitude and (2) time interval

Local breeding growth rate: $g(t) = \frac{1}{n\Delta t} \ln\left(|\delta \mathbf{x}| / |\delta \mathbf{x}_0|\right)$

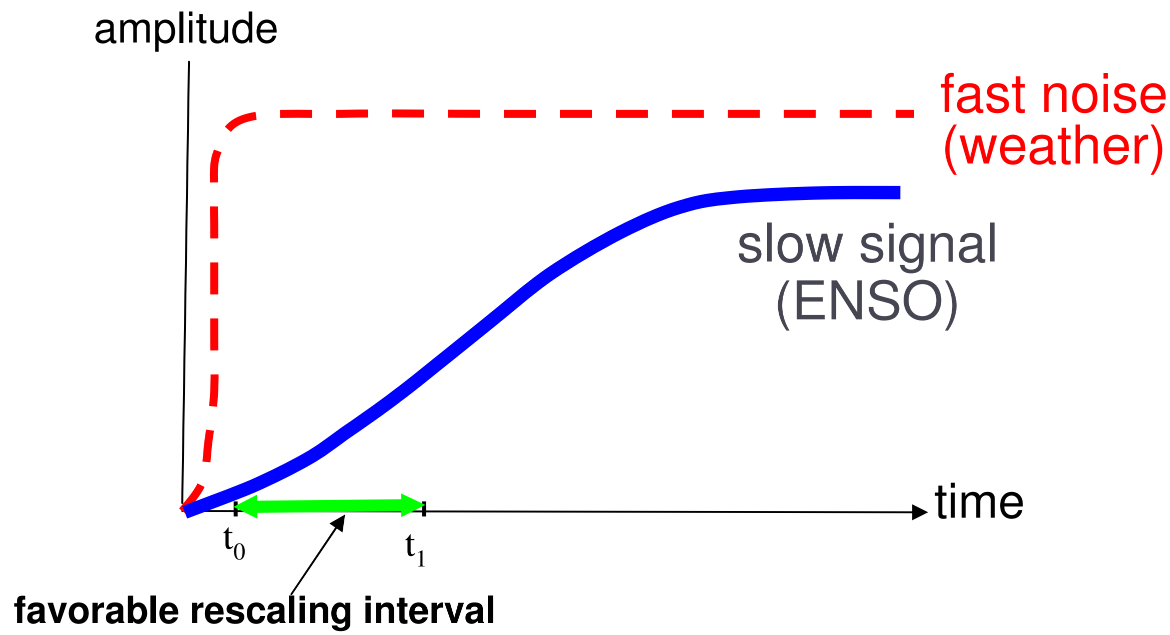
Nonlinear saturation allows filtering unwanted fast, small amplitude, growing instabilities like convection (Toth & Kalnay, 1993, Peña & Kalnay, 2003, NPG)





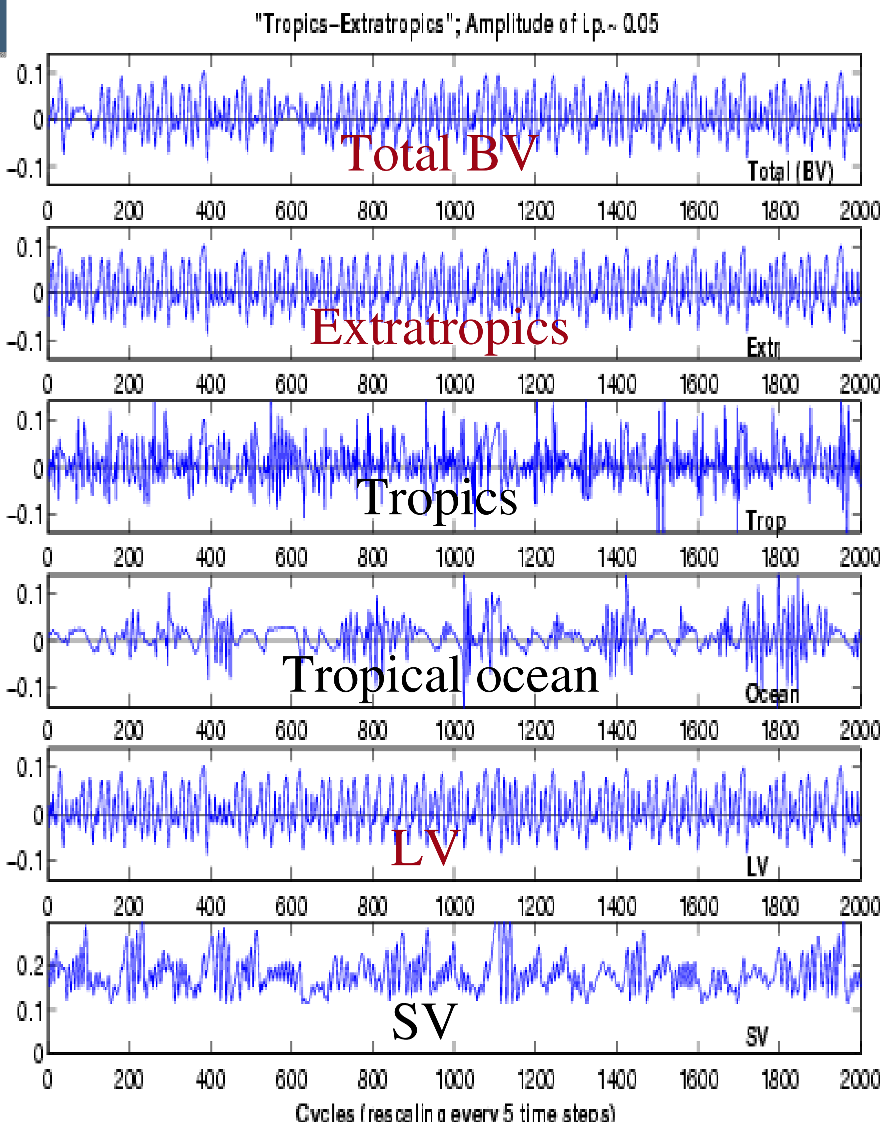
Breeding in the coupled Ocean-Atmosphere system

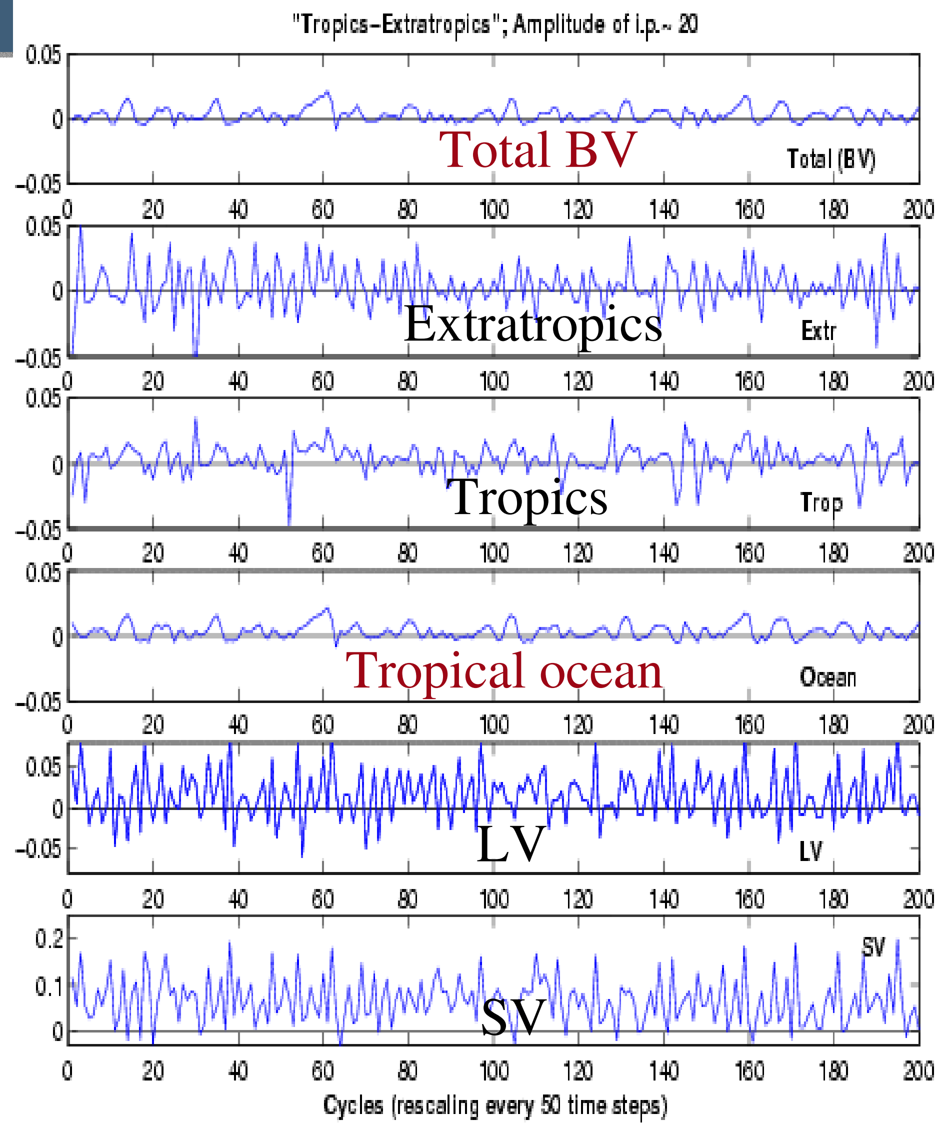
Error related to coupled instability, like ENSO, has **small** amplitude and evolve **slowly**.



- To filter out the unwanted weather noise, we need to use the fact that the coupled (ENSO) mode is "slower".
- To isolate the slow ENSO mode, we need to choose slow variables and a long interval for rescaling
  - a **rescaling interval longer than 15 days** is required.
  - The rescaling norm is relevant to the ENSO variability and its amplitude is chosen to be 10% of the climate variability.

WEATHER - ENSO - breeding with different time intervals
(growth rate plotted)

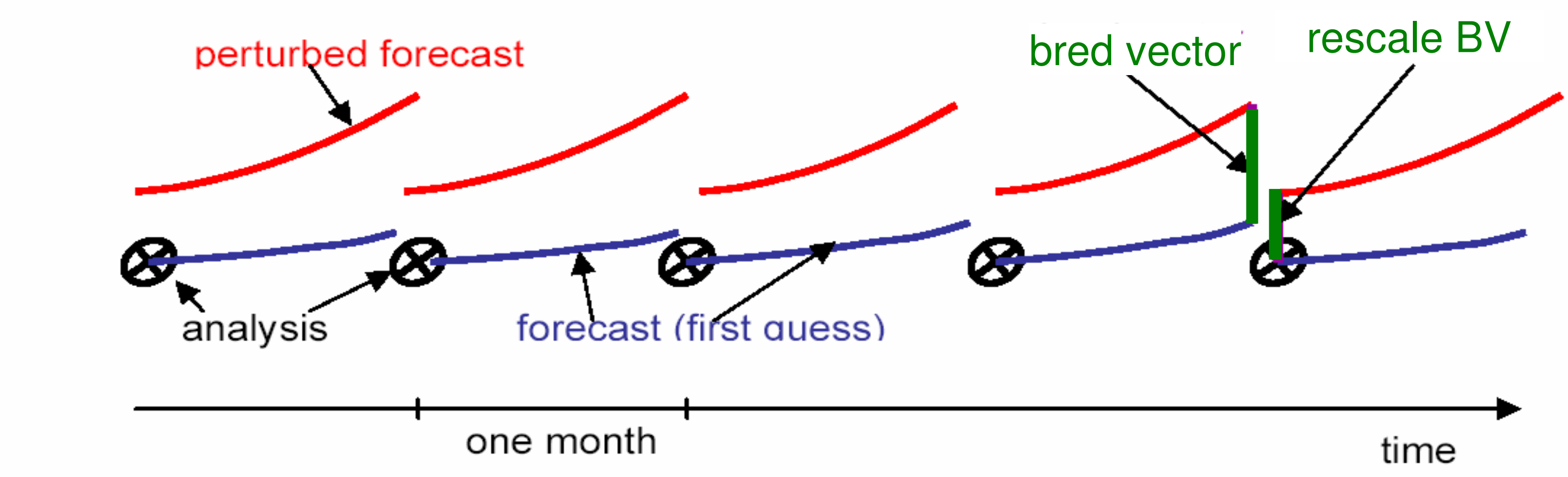




$\delta = 0.05, \Delta = 5$ steps

$\delta = 20, \Delta = 50$ steps

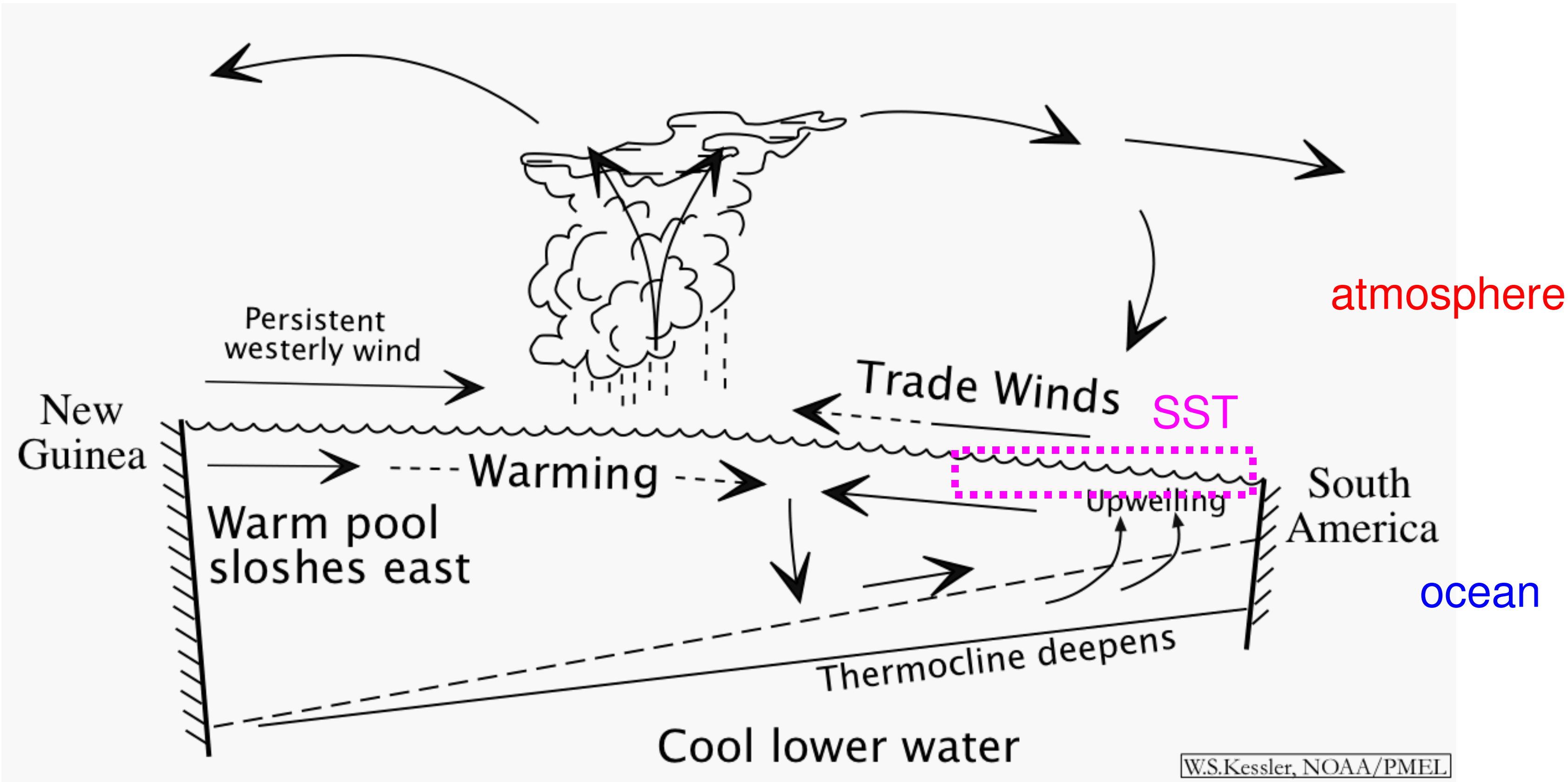
A shortcut for coupled data assimilation:
applications of coupled bred vector to the ocean data assimilation



- ❖ Breeding parameters:
  - RMS[BV_SST$_{\text{Niño3}}$] =0.1°C with one-month rescaling interval
- ❖ **Bred vectors** : Differences between **two nonlinear coupled runs**: the control forecast and perturbed run.
  - The bred perturbations are added on both atmosphere and ocean.
- ❖ Coupled bred vectors (BV) generated from coupled GCM provide the uncertainties related to coupled instability and the structures of "errors of the month"
- ❖ This is related to nonlinear filtering and to EnKF

BV1: $|SST_{BV}|$=0.1°C

(150°W~90°W, 5°S~5°N, Niño3 region)



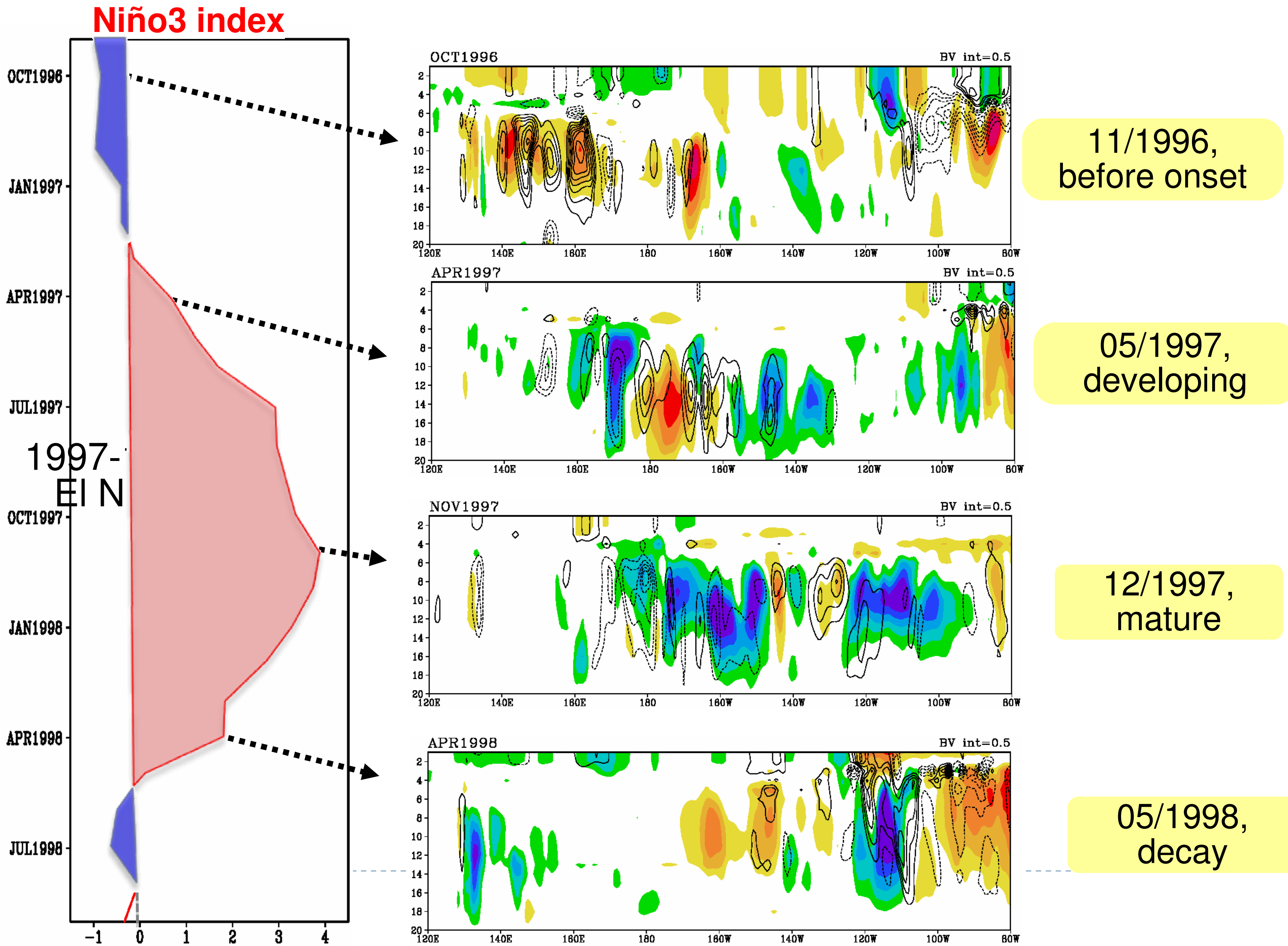
Coupled breeding with real observations (realistic setting with CGCM)

❖ **Coupled BVs :** designed to capture the uncertainties related to ENSO variability.

- Rescaling interval: 1month
- Rescaling amplitude: BV SST in Niño3 region

- If BVs are similar to the one-month forecast errors (without knowing about the new observations) then they have potential for use in ensemble forecasting and data assimilation.
- BVs provide information about the coupled "errors of the month"

One-month forecast error vs. BV during 1997-1998 El Niño

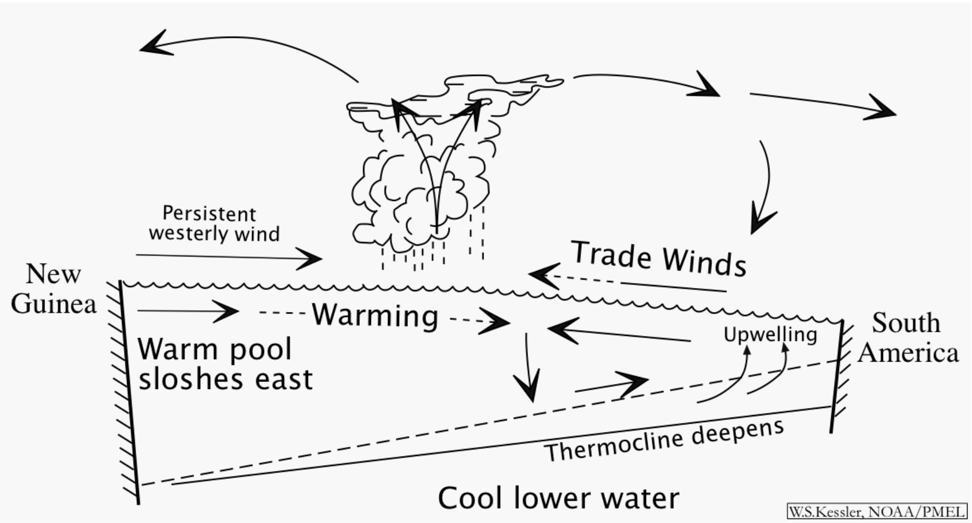


Implications of BVs from real observations

- The one-month forecast errors and coupled BVs have many similarities.
  - BVs can represent the structures of coupled uncertainties associated with ENSO variability
- Applications of coupled BVs
  - Ensemble forecasting: use coupled BVs to represent the structures of ENSO-related errors for the initial ensemble perturbations
  - Data assimilation: incorporate the errors associated with seasonal-to-interannual scale for the background error covariance

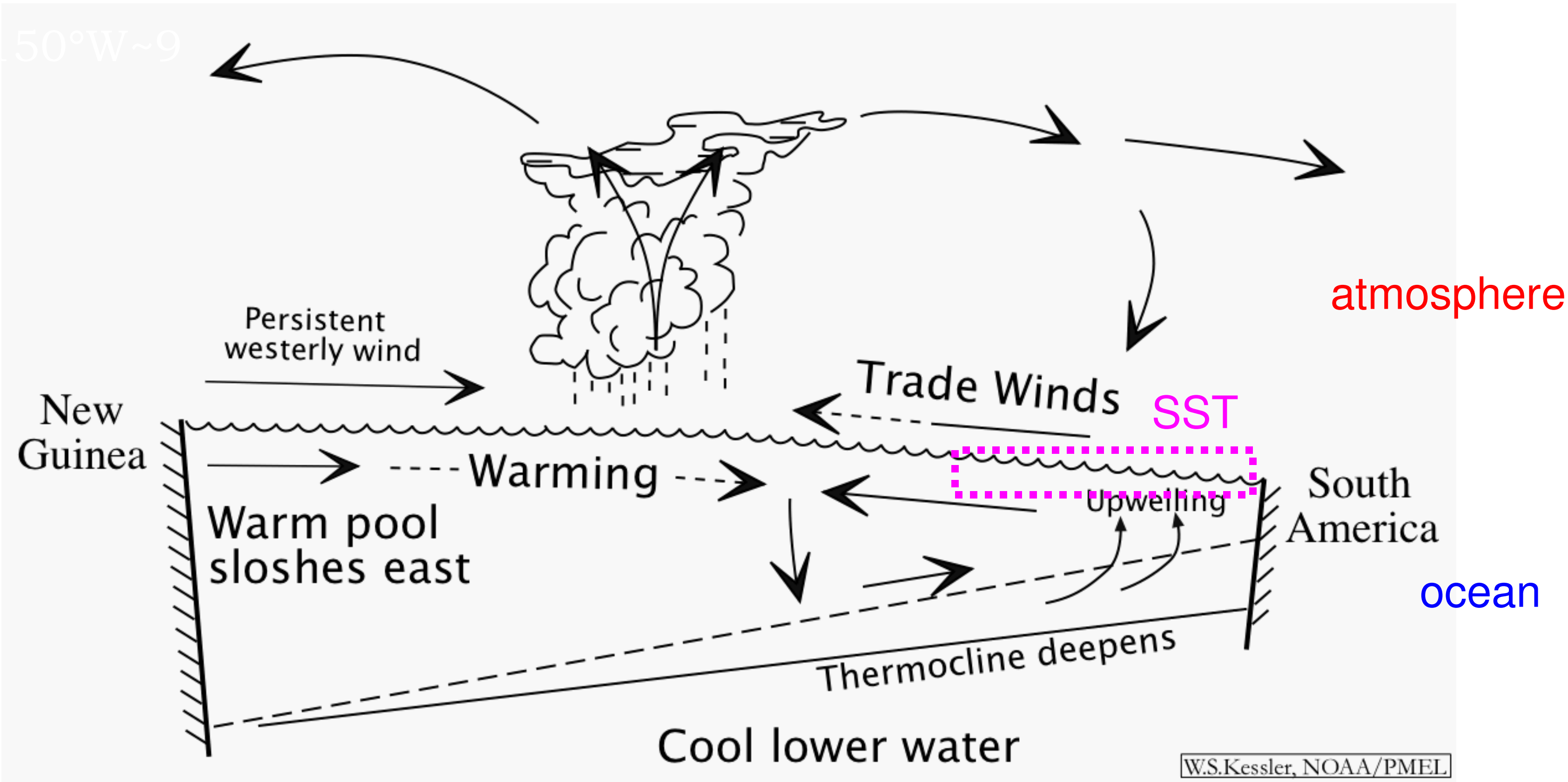
Generate Coupled BVs with different rescaling norms

- Generate 4 pairs of ±BVs from 1993-2005 with one-month rescaling interval. Four rescaling norms are chosen to measure the coupled atmosphere-ocean instability (10% of Climate variability)



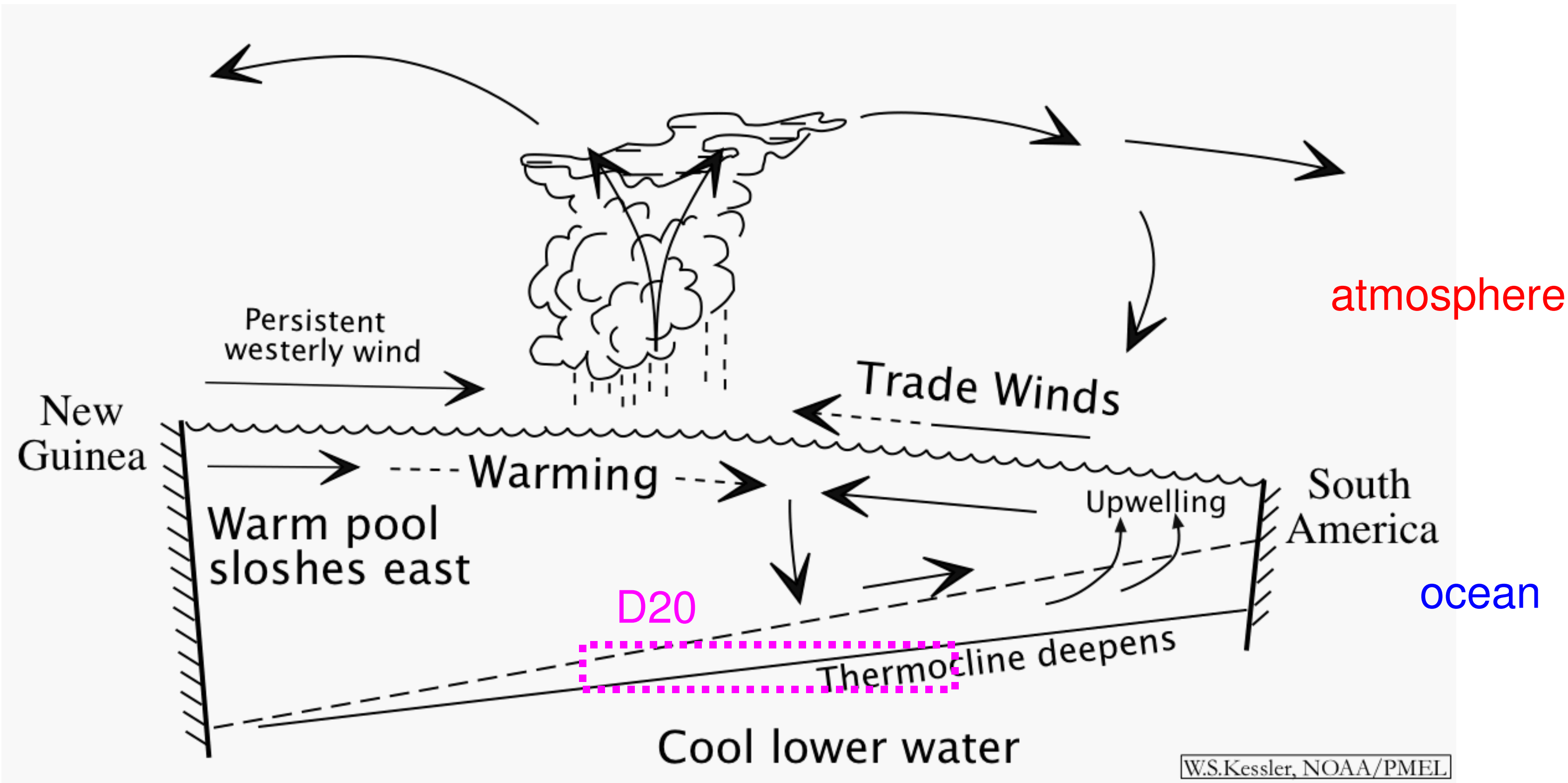
- Initialize ensemble forecasts with 4 pairs of ±BVs from February, May, August and November conditions

BV1: $|SST_{BV}|=0.1°C$
(150°W~90°W, 5°S~5°N, Niño3 region)



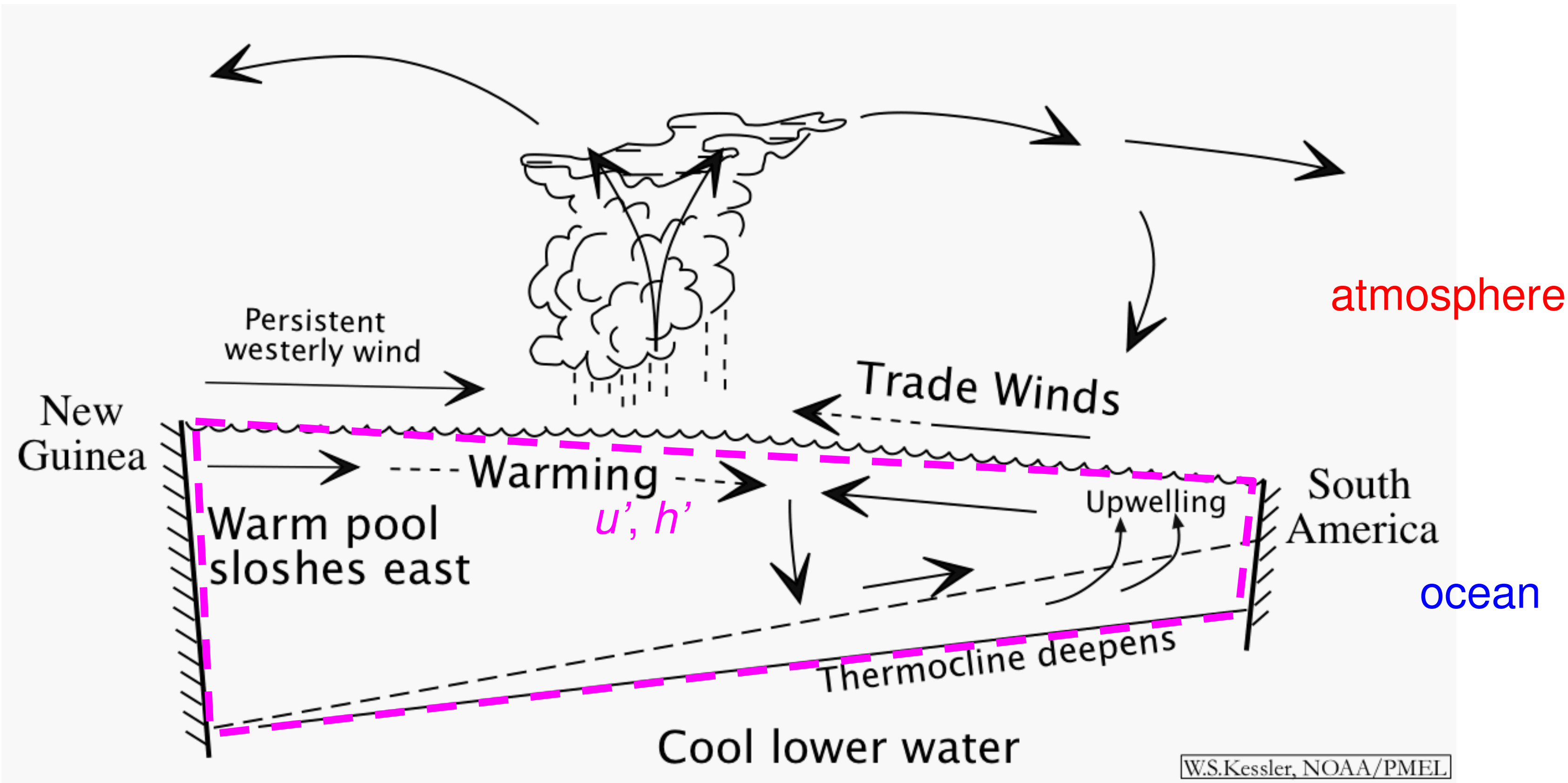
BV2: $|D20_{BV}|$=1.5 m

(160°E~140°W, 2.5°S~2.5°N, Central Equatorial Pacific)



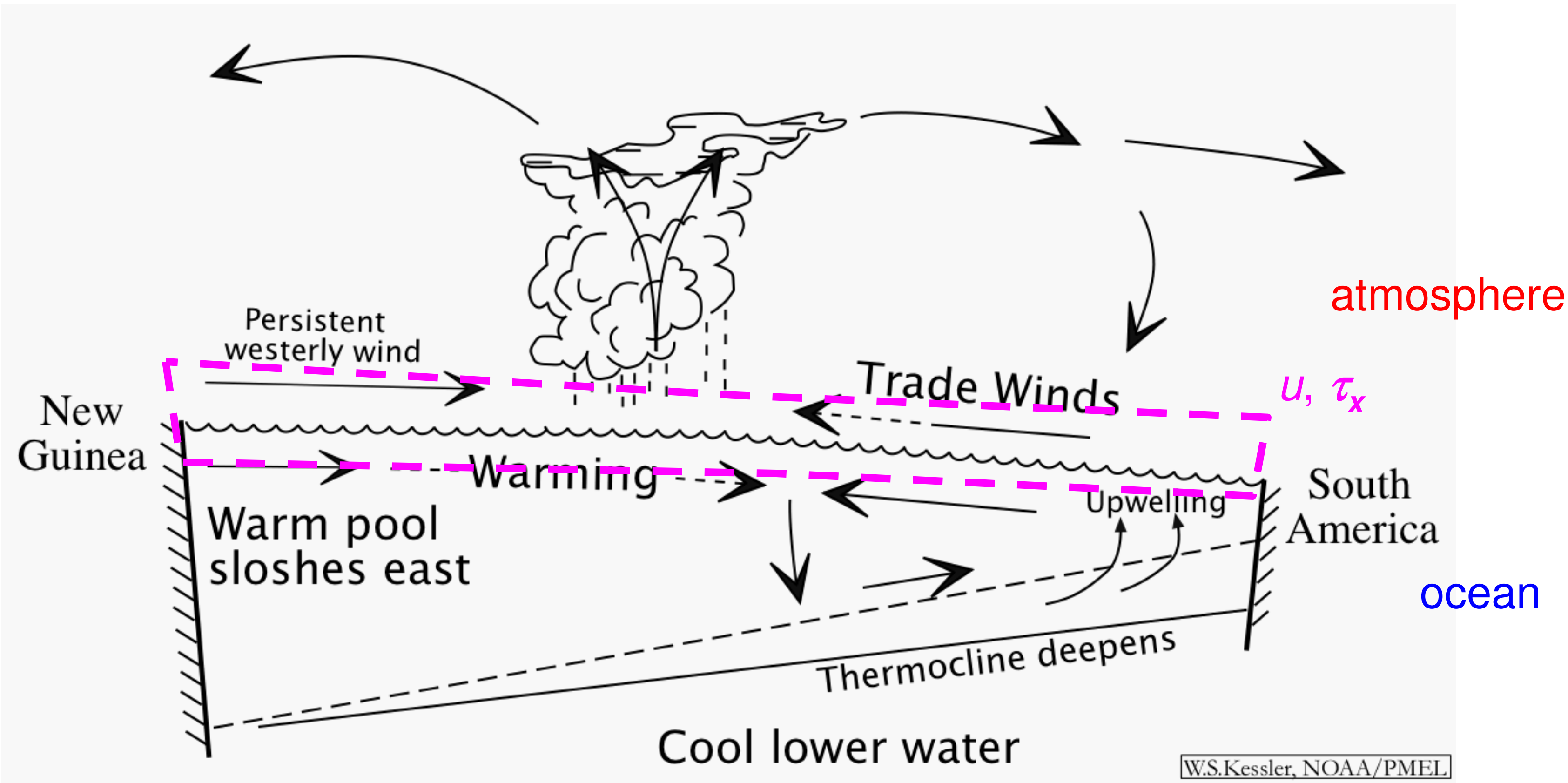
BV3 :The first 4 long wave modes (Kelvin+3 Rossby waves)

$||[u'_{BV}, h'_{BV}]|| = 6.5\times10^{-3}$ (130°E-80°W, 5°S~5°N, tropical equatorial Pacific)



BV4: work done on the ocean by the atmospheric pert.

$|[u_{BV}\tau_{xc}+u_c\tau_{xBV}]|=0.1$ (130°E-80°W, 5°S~5°N, tropical equatorial Pacific)



How to incorporate the coupled error structures to ocean data assimilation

Ensemble-based covariance in hybrid-OI scheme

- **Hybrid** data assimilation (Hamill and Snyder, 2000,Corazza et al 2002) :
  Augment the state-independent background error covariance with a covariance sampled from ensemble vectors

$$\mathbf{P}_f = (1-\alpha)\,\mathbf{P}_{\mathrm{CNT}} + \alpha\,\mathbf{P}_f^0$$

$\mathbf{P}_f$ **:** the background error covariance
$\mathbf{P}_f^0$ **:** Ensemble-based background error covariance
$\mathbf{P}_{\mathrm{CNT}}$: Gaussian-type covariance (x_s=20º, y_s=5º, z_s=100m)
α : the hybrid coefficient (30%)

$$\mathbf{X} = \begin{bmatrix} T'_{i,1} & T'_{i,2} & T'_{i,3} & T'_{i,4} \\ S'_{i,1} & S'_{i,2} & S'_{i,3} & S'_{i,4} \\ U'_{i,1} & U'_{i,2} & U'_{i,3} & U'_{i,4} \\ V'_{i,1} & V'_{i,2} & V'_{i,3} & V'_{i,4} \end{bmatrix} \quad \mathbf{P}_f^0 = \frac{1}{K-1}\mathbf{X}\mathbf{X}^T$$

Multi-variate background error covariance

Assimilation experiment setup

Experiments:

(1) only the Gaussian function (control)

- used as the benchmark

(2) P_f is based on 4 EOF modes (constant in time)

- EOFs are constructed from long and large ensemble runs for MvOI experiments (Borovikov et al. 2005)

(3) P_f is based on 4 BVs (updated every 4 days)

Observations	Temp: TAO, XBT, ARGO, Salinity: ARGO
Assimilation interval	4-day (Jan2006 ~ Dec2006)
Covariance localization	x_s=8º, y_s=4º, z_s=100m
Horizontal Filter	x_f=4º, y_f=2º
Covariance amplitude	σ_{TEMP}=0.7°C, σ_{Salin}= 0.1psu

Background error covariance

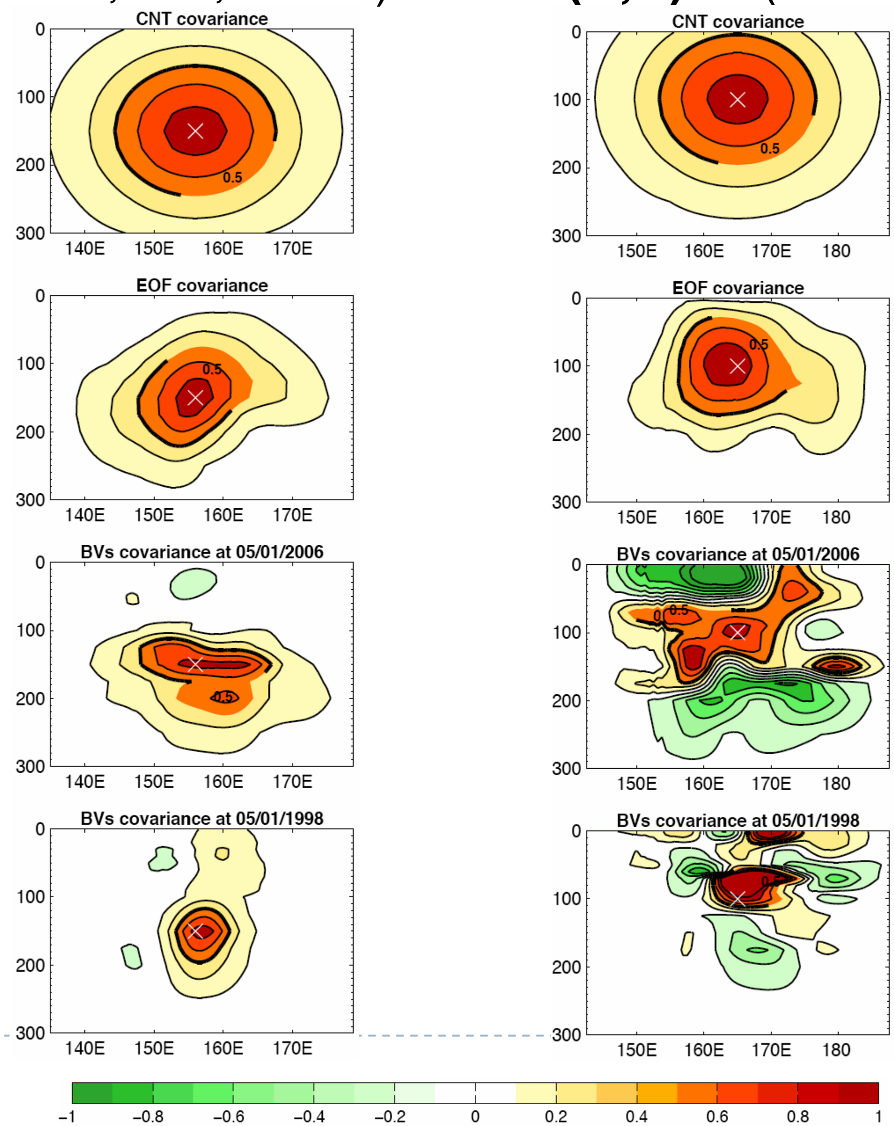
Cov(T,T) at (155°E, EQ, 150m) **Cov(S,S)** at (165°E, 4°S, 100m)

CNT

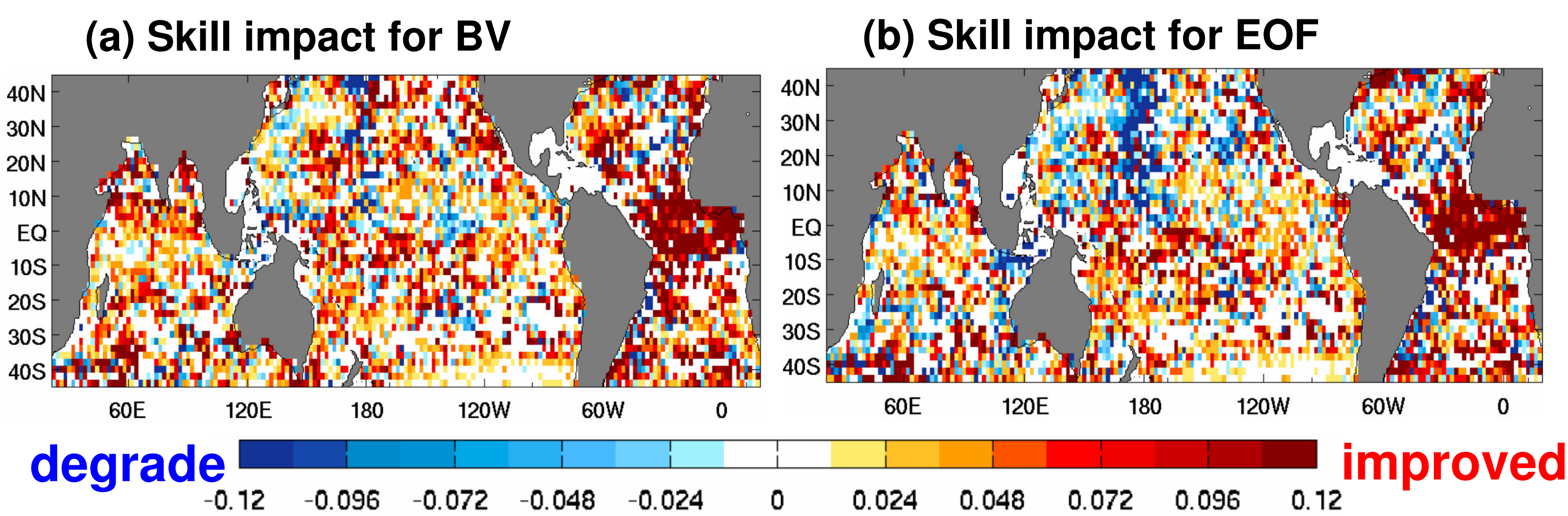
4EOF

4BV
at 05/2006

4BV
at 05/1998

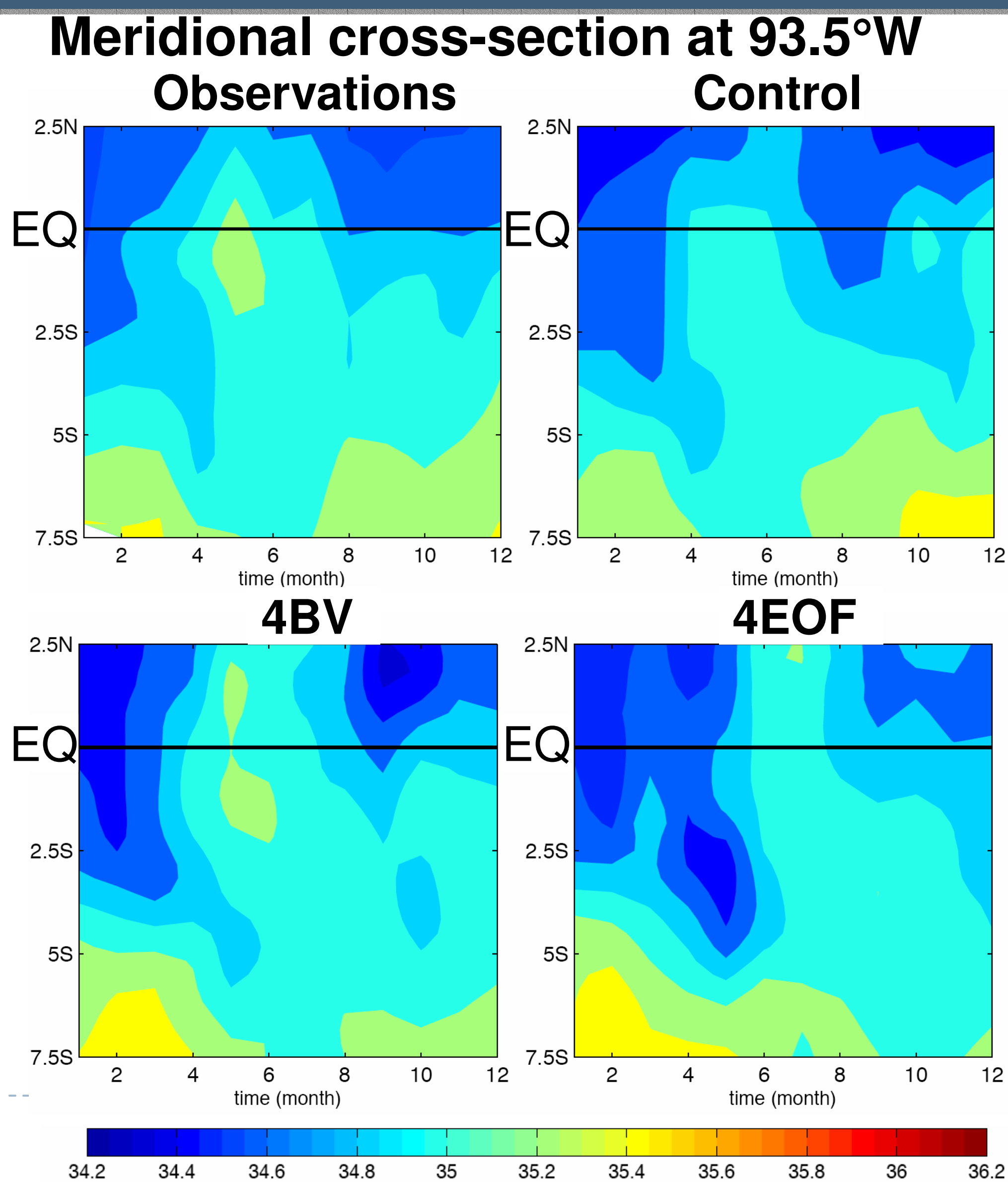


Impact on Salinity analysis from the augmented background error covariance



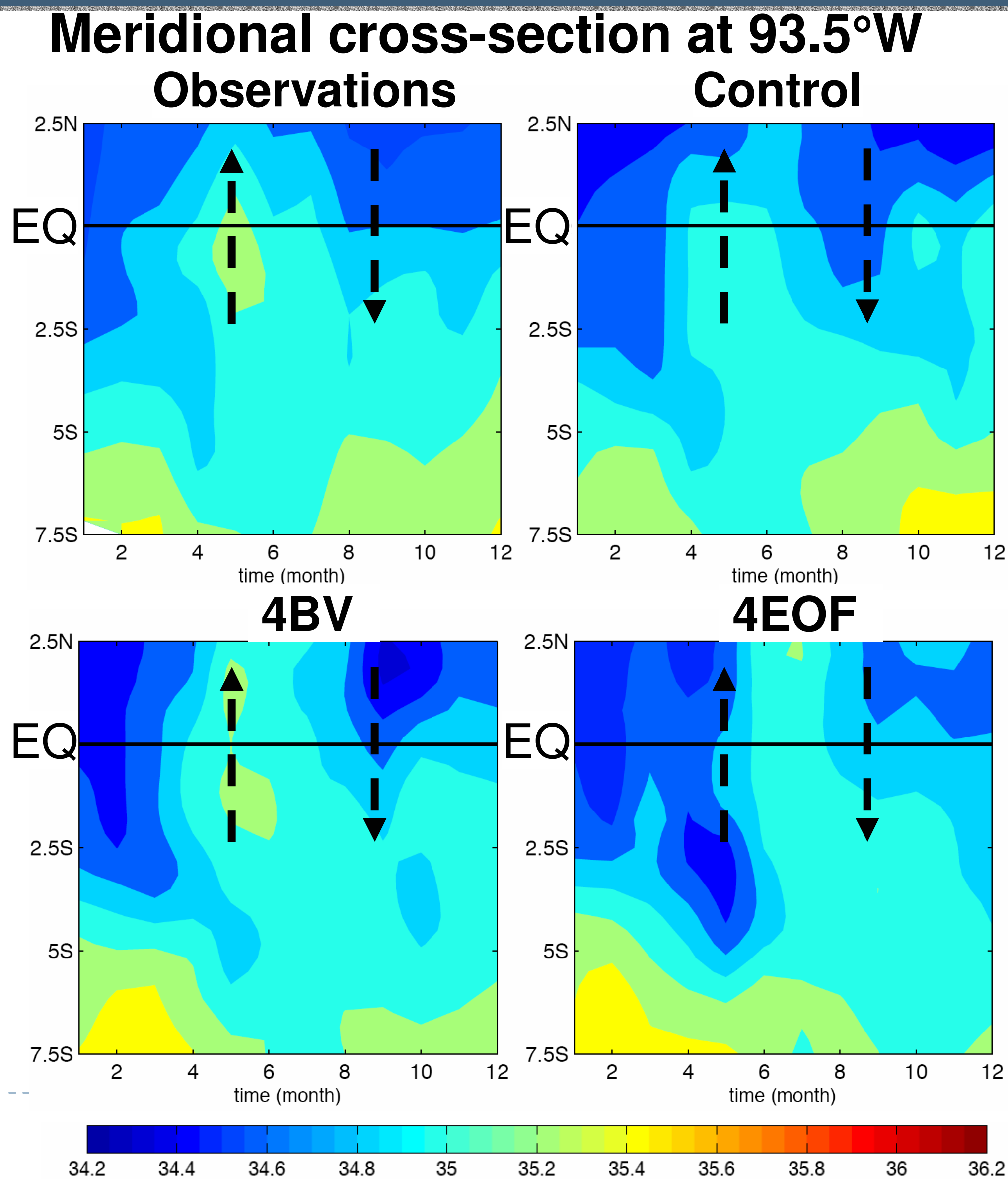
- Positive impacts are shown in three ocean basins
- BV analysis shows more “red” and less “blue”
- The BV-based covariance indicates better corrections in N. Pacific and Indonesian Throughflow.

Temporal evolution of salinity state (24.5 kg/m³ density surface)



Water movement cross the equator is better represented in the 4BV analysis.

Temporal evolution of salinity state (24.5 kg/m³ density surface)

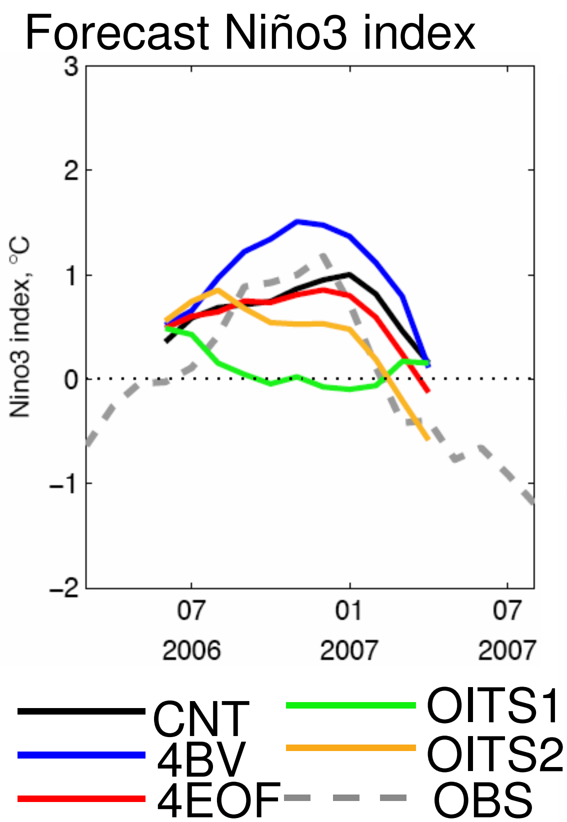


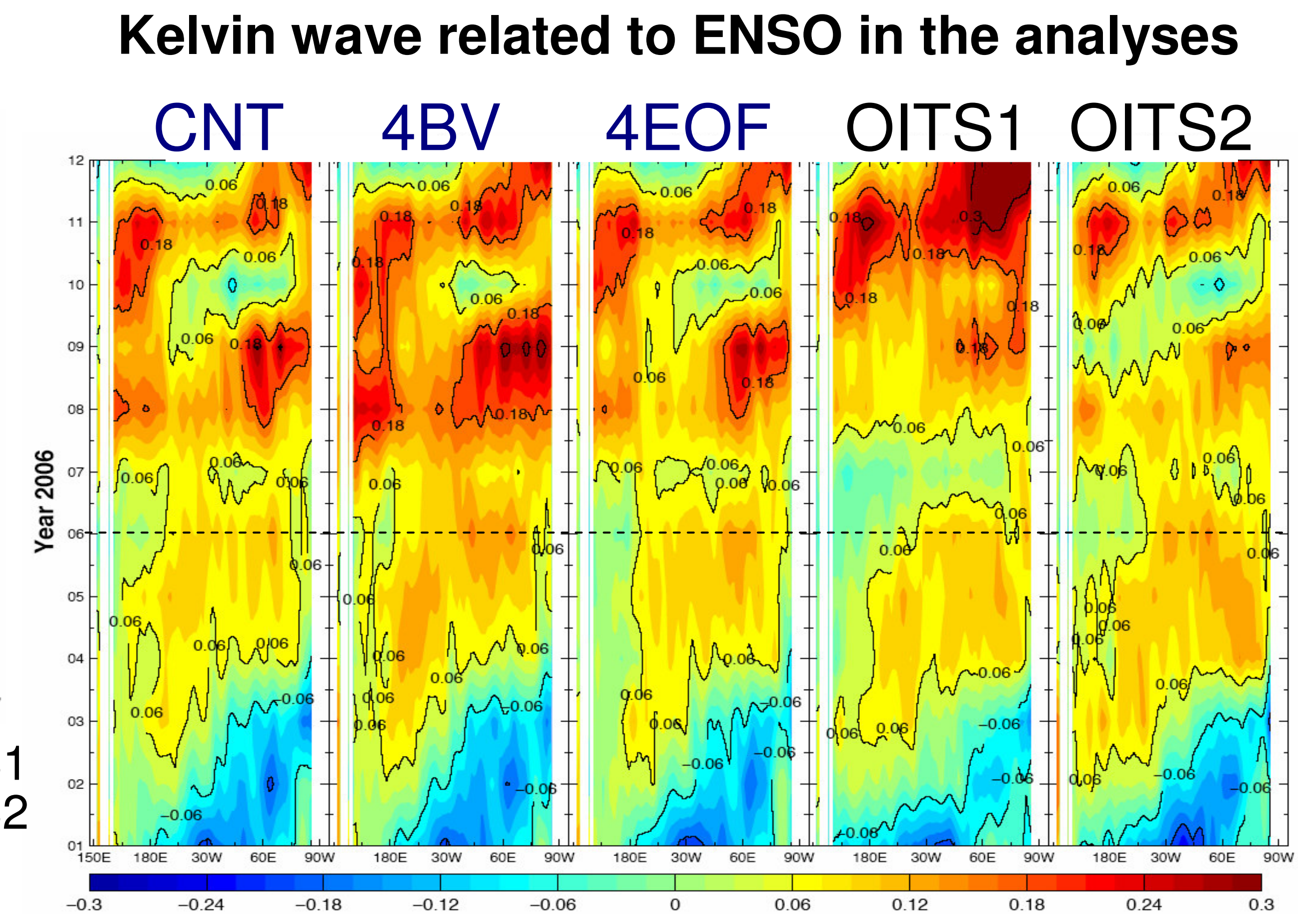
Water movement across the equator is better represented in the 4BV analysis.

Will these corrections improve ENSO prediction?

- Incorporating the state-dependent errors (seasonal-to-interannual scale) helps to improve the oceanic state in time and in space.
  - With the improved salinity, the density, current, dynamic height… can also be improved.
- What is the impact for ENSO prediction?
  - Can these analysis corrections modify the large-scale features for ENSO variability?

Impact on ENSO prediction (2006) with different ocean analyses





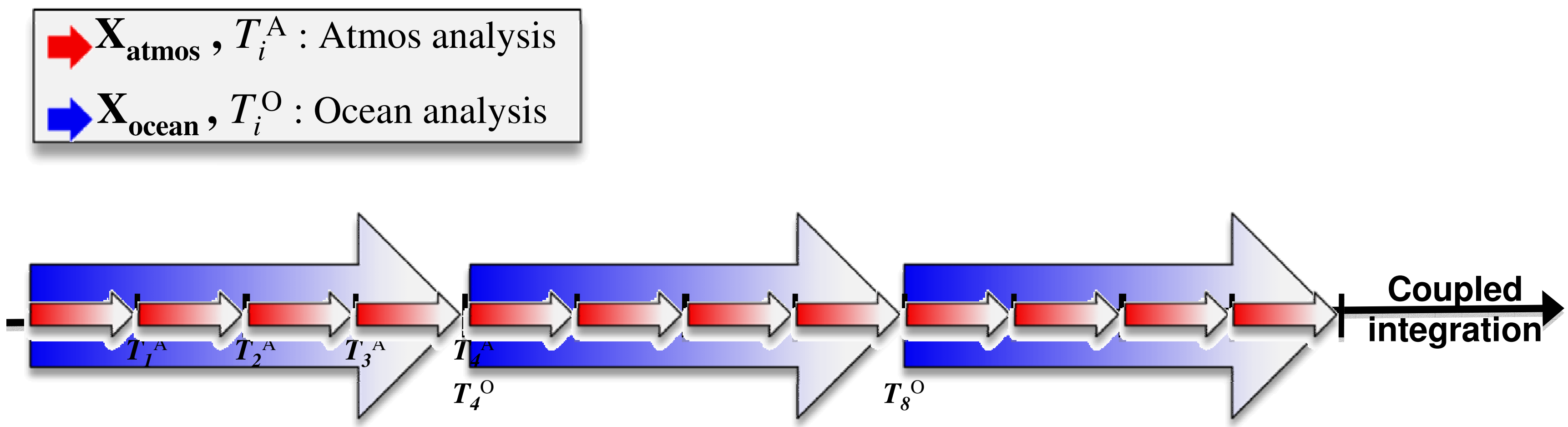
Forecast initialized from the BV-incorporated analysis has the earliest warm anomaly.

Errors associated with coupled instability

- Coupled breeding aims to isolate the slowly growing, coupled instability from the fast noise
  - Coupled BVs can be used to construct the structures of coupled errors (error of the month)
- Data assimilation in a coupled framework
  - Perform data assimilation with the individual component, but integrate with the fully coupled model
  - Perform coupled assimilation with the fully coupled model (assimilation fast, slow observations together)

Data assimilation in a coupled framework (I)

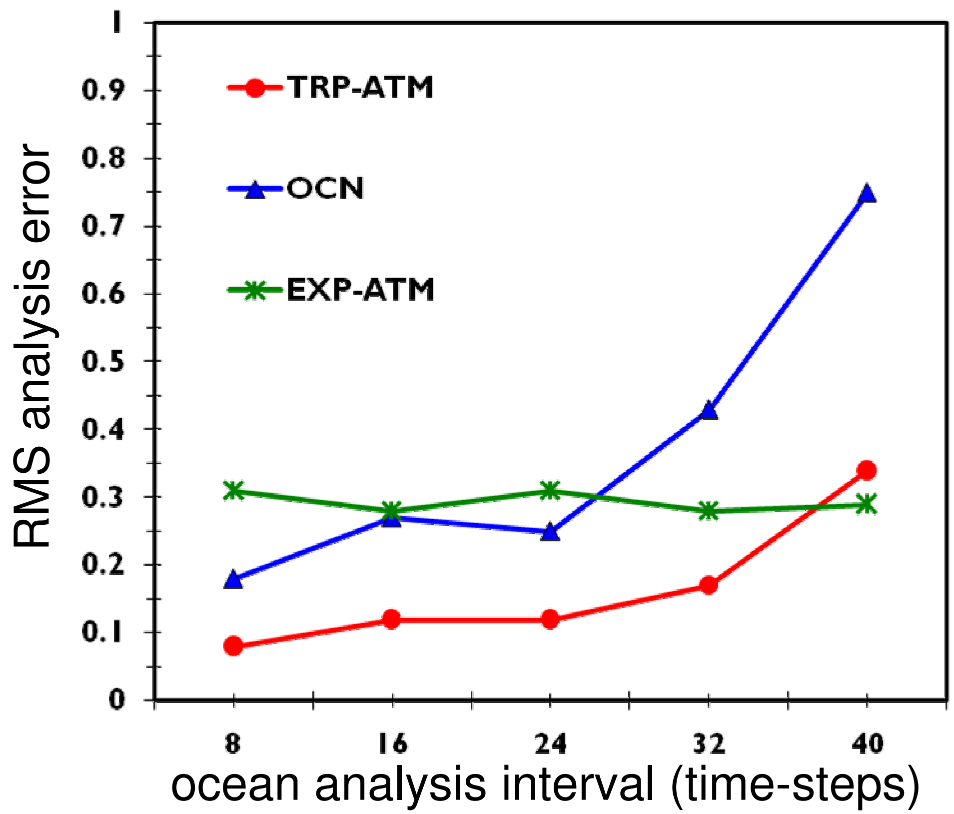
- Forward integration with the fully coupled model
- Update the atmospheric and oceanic component individually
- Operationally, atmospheric analysis is done every 6 hour; ocean analysis is done every 1-4 day.



Coupled DA in the triple-coupled model

- Local Ensemble Transform Kalman Filter (Hunt et al. 2007) is used to update each component (ocean and atmosphere).
- Assimilation experiments
  - Atmosphere: perform DA every 8 time-steps
  - Ocean: Vary the length of the DA analysis cycle

Individual atmospheric and ocean DA in a coupled framework



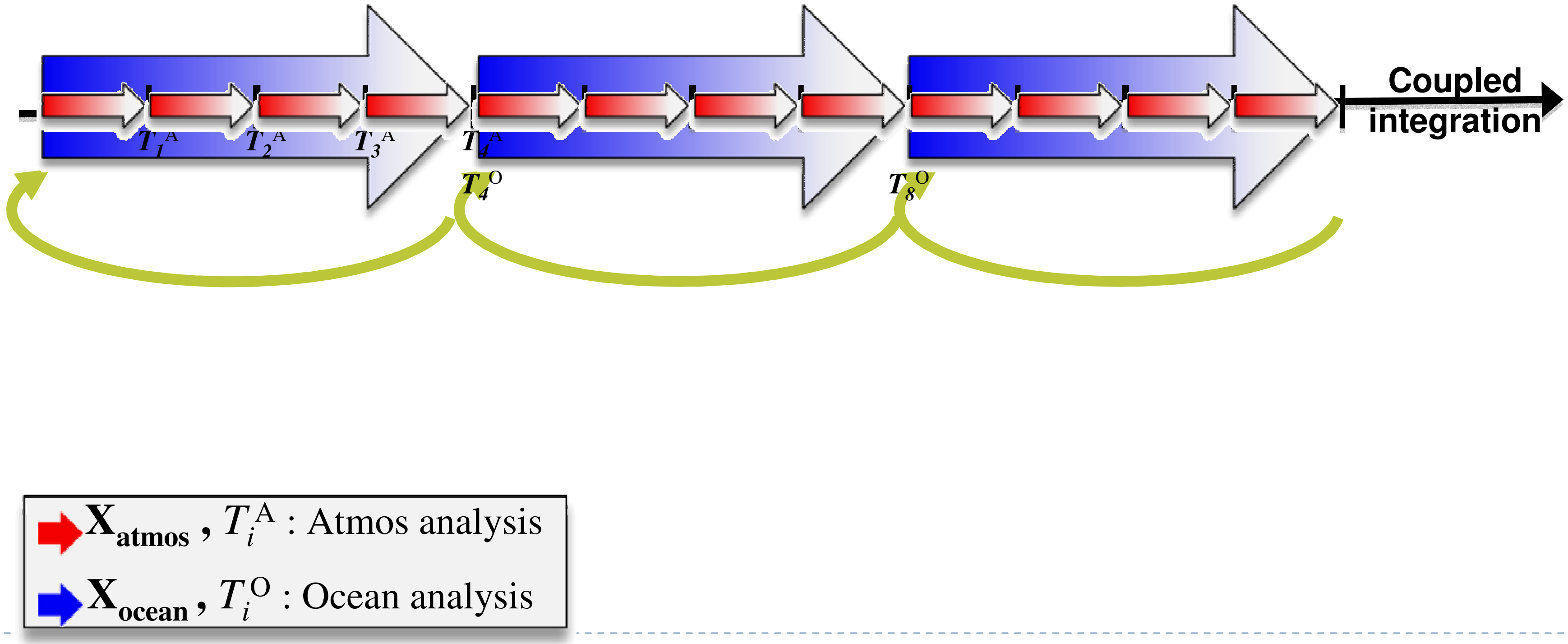
- Observation error is 2.0
- Fast atmospheric DA (every 8 time-steps)
- Ocean analysis's accuracy strongly influences the tropical atmosphere due to the strong coupling.

Long or short assimilation windows?

- Problem for ocean to use long assimilation windows
  - Error growth in the ocean affects the tropical atmosphere, e.g. the strong coupled area
  - The coupling is from the coupled model.
- Problems for ocean to use short assimilation windows
  - Not enough observations in the ocean
  - The ocean corrects the small scales (OGCM: dynamically complicated)
  - The atmosphere is always shocking the ocean

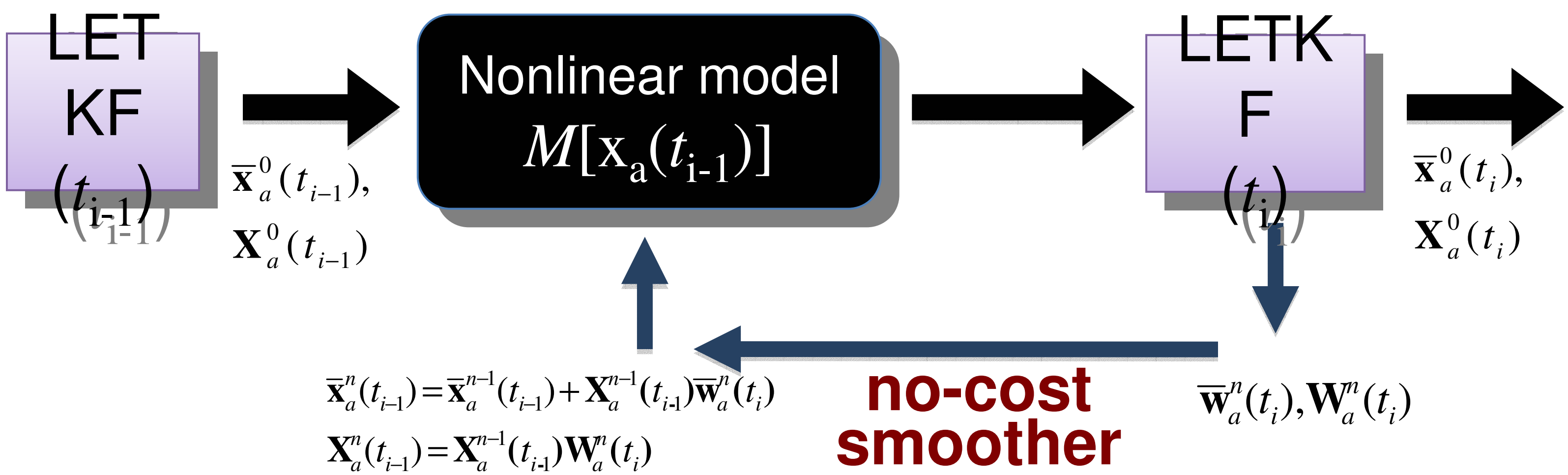
Improve the coupling condition for the long ocean analysis cycle

Rewind: improve the previous ocean analysis. Let the evolution of the atmosphere and ocean closer to the nature.

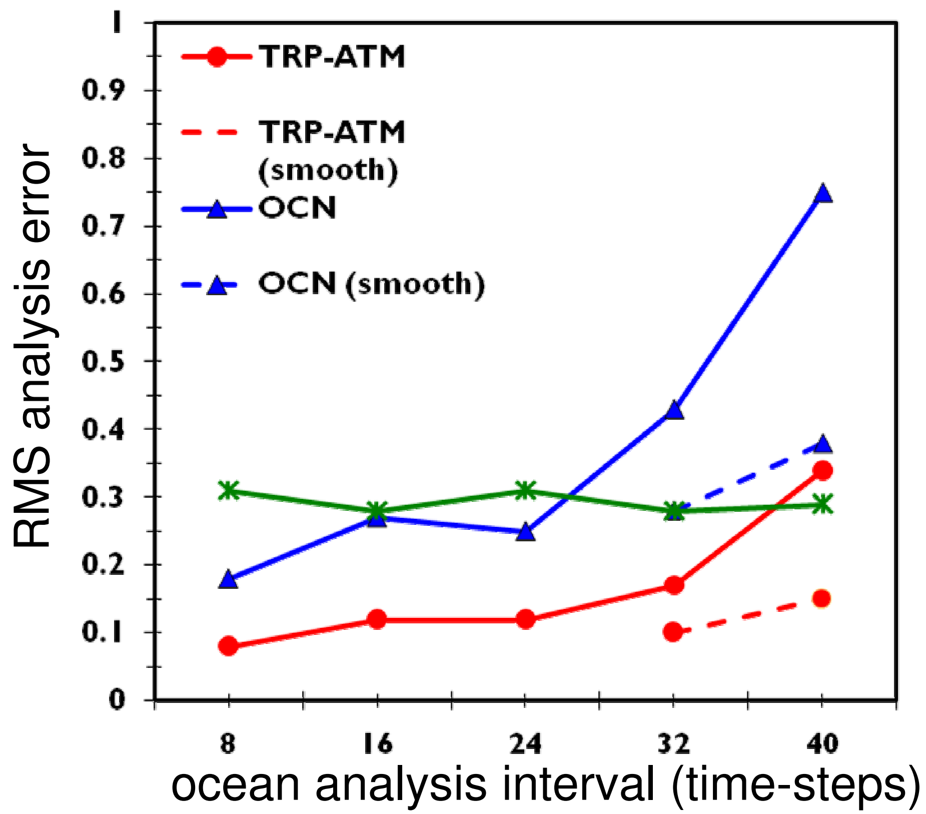


Iteration and no-cost smoother for the "Running in place"

- Accelerate the ensemble to catch up the nature, informed by the observations. "Running in place" until we extract the maximum information form the observations.
  - The no-cost smoother + iteration scheme



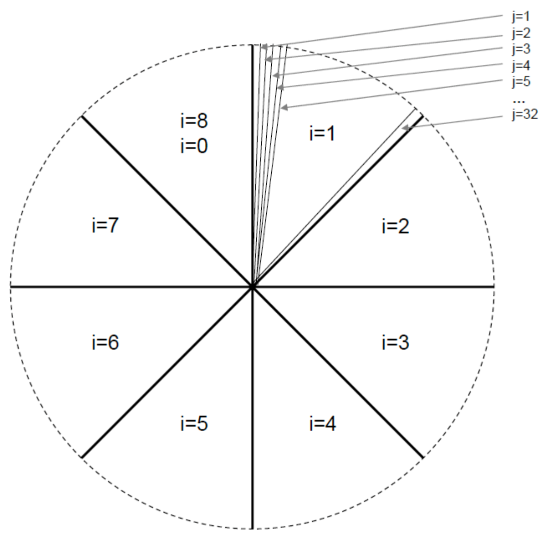
Individual atmospheric and ocean DA in a coupled framework



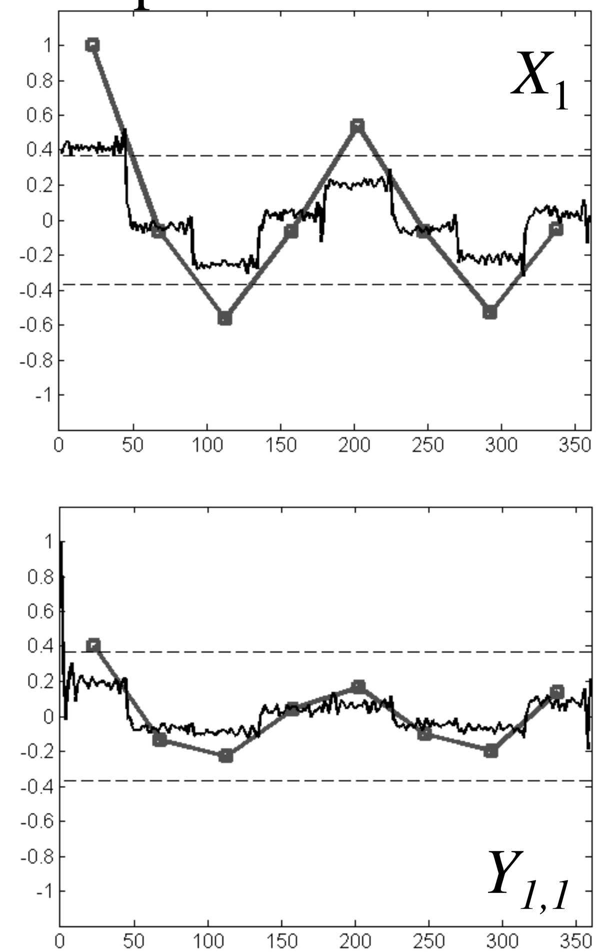
- Fast atmospheric DA (every 8 time-steps)
- Ocean analysis's accuracy strongly influences the tropical atmosphere due to the strong coupling.
- Rewind the atmospheric and oceanic states with improved oceanic state.

Data assimilation in a coupled framework (II)
(Ballabrera et al. 2008)

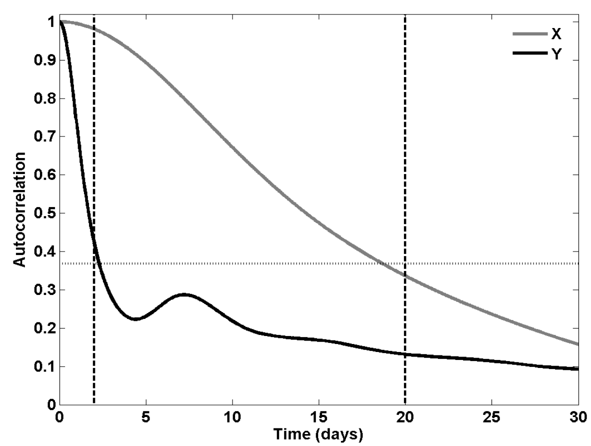
Coupled Lorenz 96 model
Model variables: 8 slow + 256 fast
Analysis cycle: 6 hour



Spatial correlation



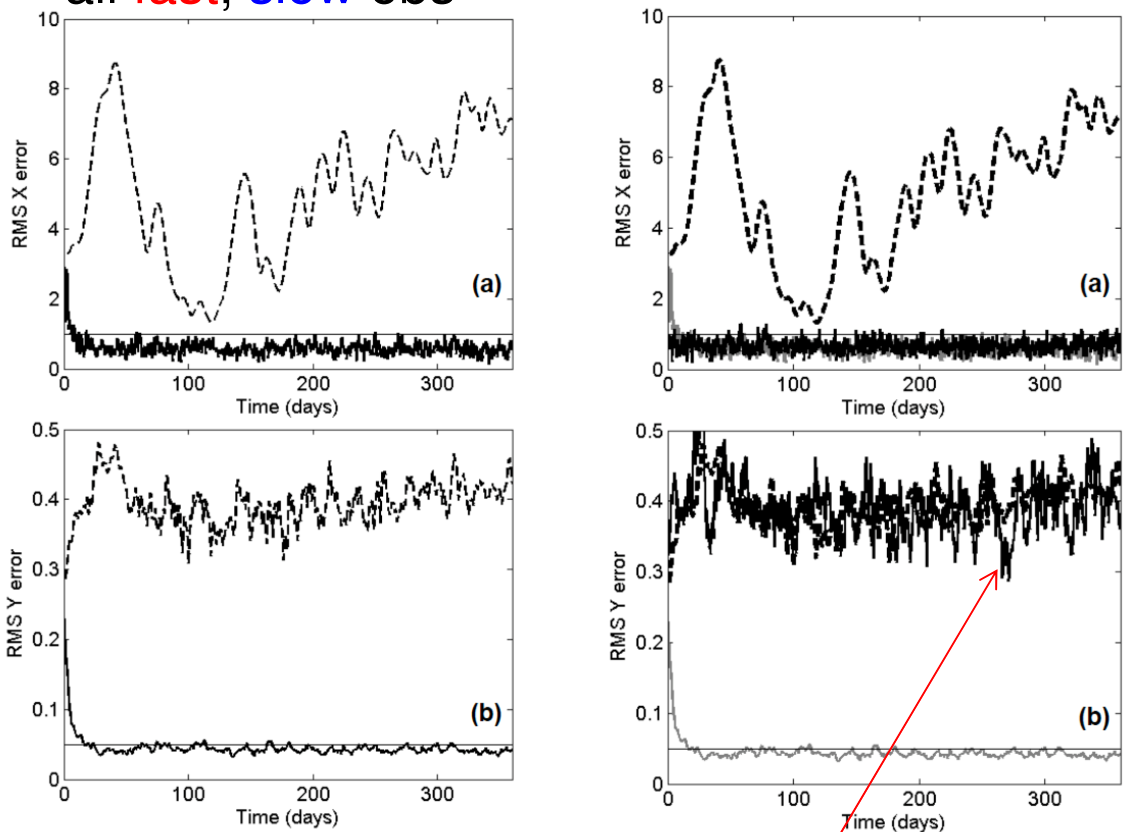
autocorrelation of the variables



Data assimilation in a coupled framework (II)

all fast, slow obs

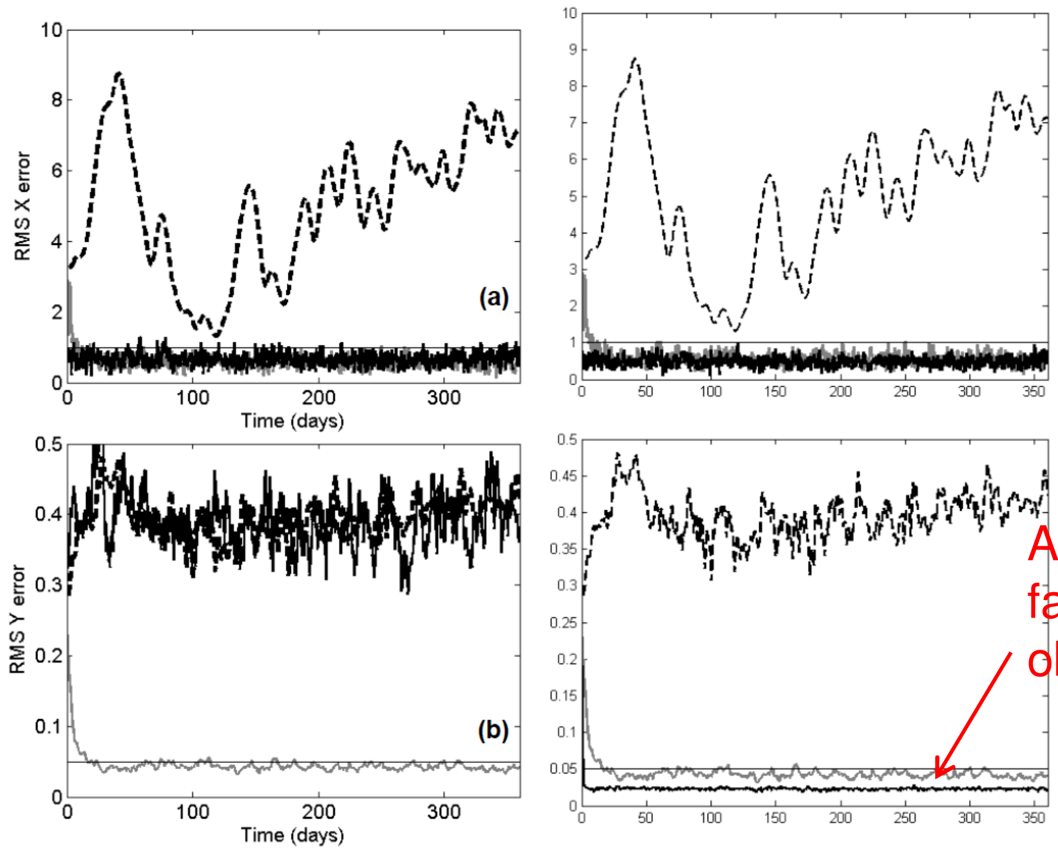
all slow obs + some fast obs



When the fast observations are only partially available: assimilate fast + slow observations may not be useful

Data assimilation in a system with two scales (Ballabrera et al. 2008)

all slow + some fast obs



LETKF

LETKF +
Nudge for the fast

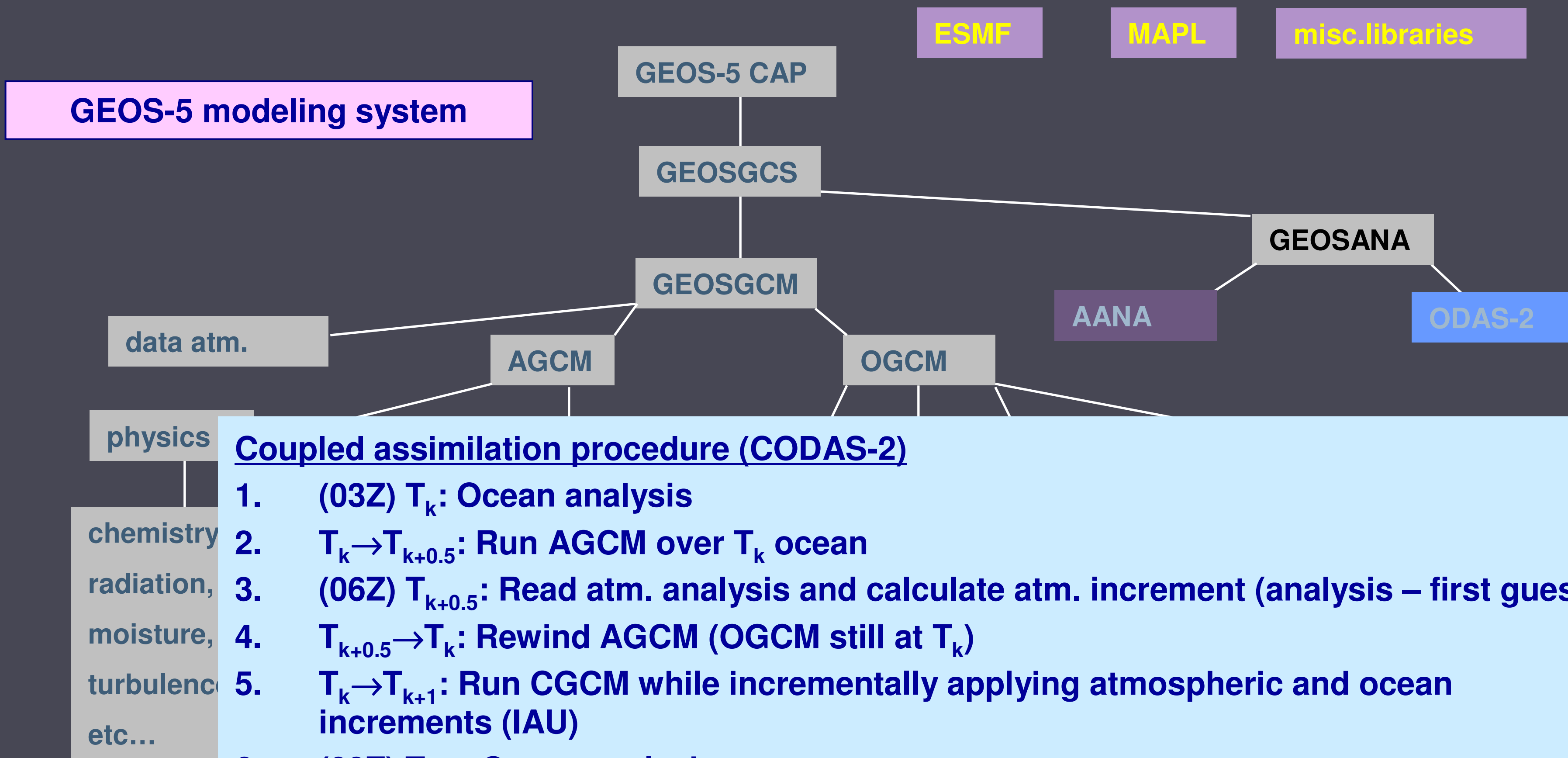
Assimilate slow obs + nudge fast variables toward fast observations

Coupled data assimilation with a coupled general circulation model (CGCM)

- Obtain the "coupled" initial conditions for coupled forecasting (vs. use the analysis products from the independently prepared data assimilation)
- Difficulties:
  - Obtain/Identify the error statistic spatially and temporally related to the coupled instability.
  - Computational cost (assimilation window, rewind the modeling time)
  - Dealing with the model drift

Coupled data assimilation with GEOS-5 AGCM, MOM4 OGCM & ODAS-2

- Impact of SSH assimilation on seasonal hindcast skill is less than hoped for
  - -> probably at least in part due to forecast initialization schock at coupling time
  - -> one more argument for coupled data assimilation



<u>Coupled assimilation procedure (CODAS-2)</u>

1. (03Z) T_k: Ocean analysis
2. $T_k \rightarrow T_{k+0.5}$: Run AGCM over T_k ocean
3. (06Z) $T_{k+0.5}$: Read atm. analysis and calculate atm. increment (analysis – first guess)
4. $T_{k+0.5} \rightarrow T_k$: Rewind AGCM (OGCM still at T_k)
5. $T_k \rightarrow T_{k+1}$: Run CGCM while incrementally applying atmospheric and ocean increments (IAU)
6. (09Z) T_{k+1}: Ocean analysis

In practice ocean analysis takes place at T_k, T_{k+n}, T_{k+2n},…

Hence ocean IAU is applied over $T_k \rightarrow T_{k+n}$ $T_{k+n} \rightarrow T_{k+2n}$,…

Summary (I)

- Slowly-varying coupled instabilities can be isolated by coupled breeding. Coupled BVs represent the structures of "errors of the month".
- A shortcut for coupled data assimilation:
  - BV can be used to augment the background error covariance to incorporate the errors associated with the seasonal-to-interannual scale.
  - The improved ocean initial condition can improve the prediction skill for El Niño.

Summary (II)

- Generate the coupled initial conditions from data assimilation
  - Ensure the quality of the analysis accuracy of the slow components (the strongly coupled region):
    - The “running in place” method allows to perform the single-component data assimilation individually but improves the coupling to make it closer to the nature.
    - To avoid the influence from the fast error covariance uncorrelated to the slow variables, nudging can be applied to constrain the fast dynamical evolution.