INTERANNUAL-TO-PENTADAL CLIMATE PREDICTION BY USING A FOUR-DIMENSIONAL VARIATIONAL COUPLED DATA ASSIMILATION SYSTEM.

Shuhei Masuda, Takashi Mochizuki,

Japan Agency for Marine-Earth Science and Technology (JAMSTEC),

Yokosuka/Yokohama, Japan

Xueyuan Liu

Center fur Erdsystemforschung und Nachhaltigkeit, Universitat Hamburg, Hamburg, Germany

Interannual-to-pentadal climate prediction

- Major issues of inter-annual/decadal prediction with a coupled model are

e.g., Hawkins and Sutton (2009); Murphy et al. (2010)

☆Inconsistent initialization,

Dynamically self-consistency is preferable.

How is the impact of the in-consistency between the model and its initial conditions on the climate forecast?

e.g, Balmaseda and Anderson (2009); Smith et al. (2012)

☆lacking information about future external forcing

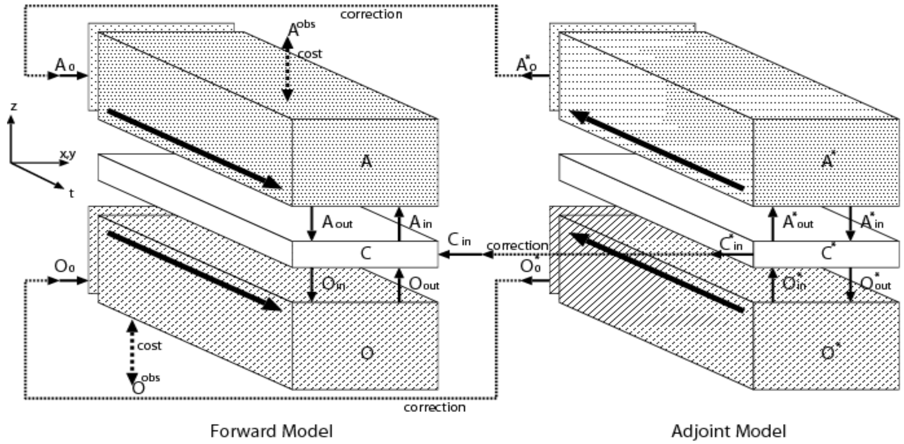
All the climate factors should be included in the model, but it seems impossible.

What strategy is possible for a specific prediction?

Here, I will demonstrate how is the advantage of our 4D-VAR CDA system to these issues.

4D-VAR coupled data assimilation system (K7-CDA)

Sugiura et al. (2008)



- Coupled Model (CFES):
  - T42L24 AFES for AGCM
  - 1x1deg L45 MOM3 for OGCM
  - IARC SeaIce model
  - MATSIRO Model for Land
- Observational Data
  - Atmosphere:
    - NCEP's BUFR data U,V,T,Q (10daily)
    - SSM/I sea wind scalar x ERA40 wind direction (10daily)
  - Ocean:
    - T/P altimeter data(10daily)
    - Reynolds SST (10daily)
    - WOD data T,S (monthly)
    - Ocean Data Assimilation Product T,S(monthly)
- Adjoint Code
  - Adjoint OGCM and adjoint AGCM are coupled [Line by line transformation by TAMC,TAF]
  - Temporal averaging of forward field for the adjoint integration is applied to smooth the basic field [coarse-grained formalism]
  - Adjoint AGCM contains damping terms to suppress the strong adjoint sensitivity from weather fluctuations.

$$-\frac{\partial \boldsymbol{\lambda}}{\partial t} = \left(\frac{\partial \mathrm{M}}{\partial \mathbf{x}}\right)^{T}_{\mathbf{x}=\bar{\mathbf{x}}} \boldsymbol{\lambda} - \boldsymbol{\Gamma}\boldsymbol{\lambda} + \mathbf{H}^{T}\mathbf{R}^{-1}\left(\mathbf{H}\bar{\mathbf{x}} - \mathbf{y}\right)$$

$\boldsymbol{\lambda}$: adjoint variables, $\bar{\mathbf{x}}$: temporal average, $-\boldsymbol{\Gamma}\boldsymbol{\lambda}$: damping.

Update from Sugi2008: historical radiative forcing with greenhouse gases (CH4, CO2, N2O :annual), aerosol (black and organic carbon, dust, sulfur: monthly) and volcanic effect (monthly) from Historical and RCP4.5 scenario-based data/simulations in CMIP5.

How we improve a coupled model which contains different time scales

- Forward model forecasts both weather + seasonal + interannual modes

- Adjoint code runs under the forcing of monthly mean gap to improve background state

Temporal averaging of forward field for the adjoint integration is applied to smooth the basic field

- Leave weather mode to the ability of CGCM with improved background states

$$\mathbf{x} = \mathbf{x}_{\text{weather}} + \mathbf{x}_{\text{clim}} + \mathbf{x}_{\text{ia}},$$

$$\bar{\mathbf{x}} = \frac{1}{30}\sum \mathbf{x} \cong \mathbf{x}_{\text{clim}} + \mathbf{x}_{\text{ia}} \quad \text{(monthly)},$$

What did we control?

1. Ocean initial condition
2. Bulk parameters controlling Air-sea fluxes of

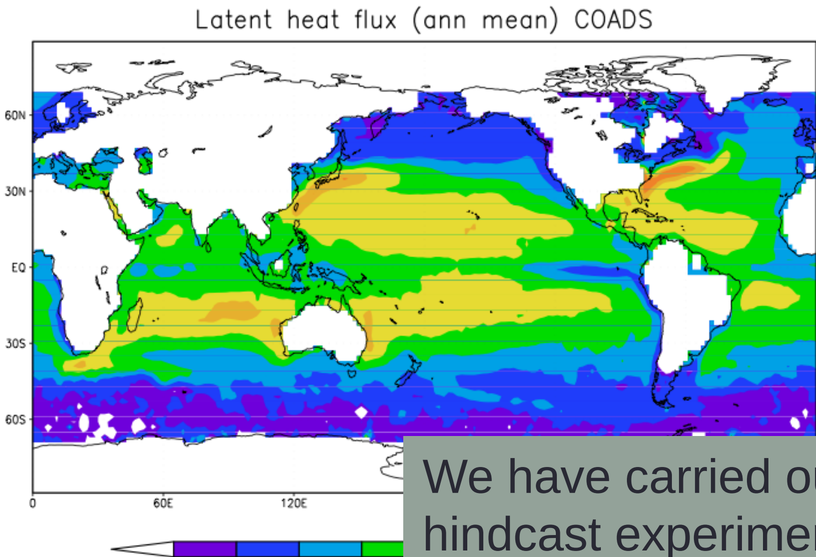
Momentum $$F_{\mathbf{v}} = -\rho \alpha_M C_M |\mathbf{v}| \mathbf{v}$$

Sensible heat $$F_\theta = \rho c_p \alpha_H C_H |\mathbf{v}| \left(\theta_g - \theta \right)$$

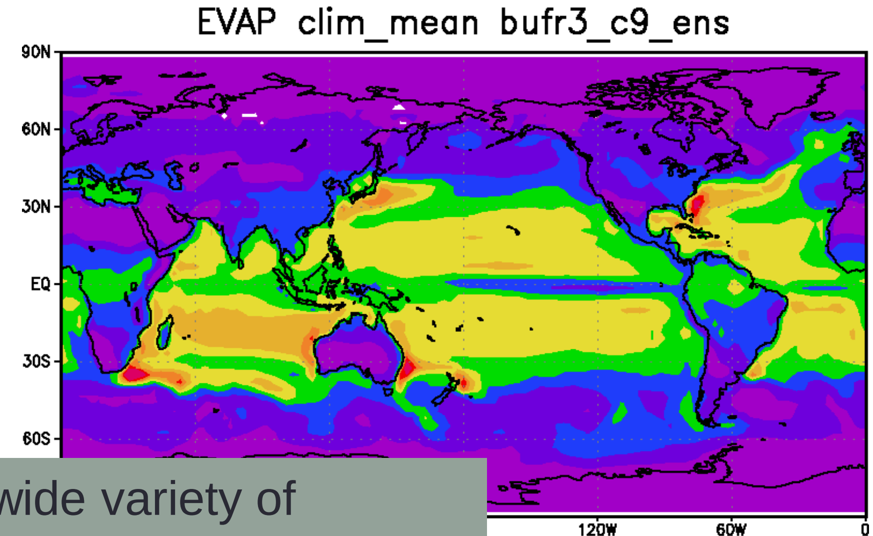
Latent heat $$F_q = \rho \alpha_E C_E |\mathbf{v}| \left(q_g - q \right)$$

adjustment factors (x,y,10-daily)

Latent Heat flux [W/m^2]

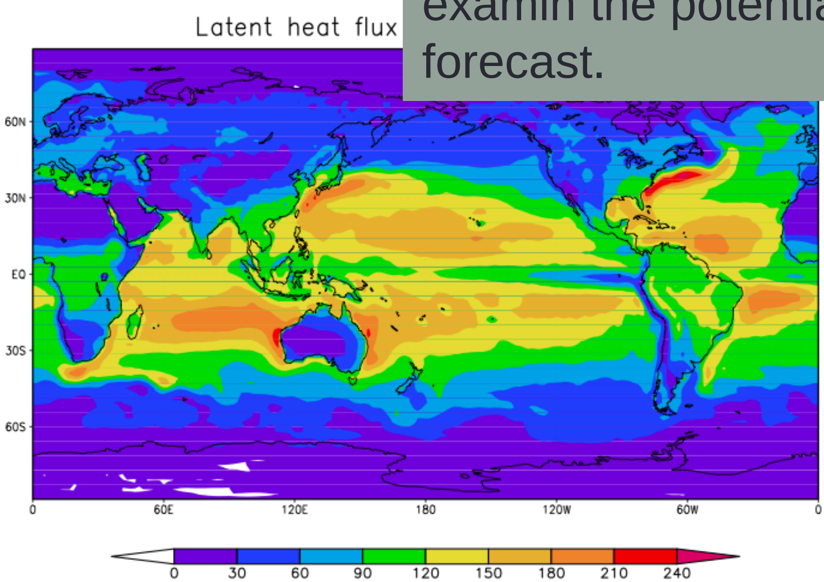


Observatio

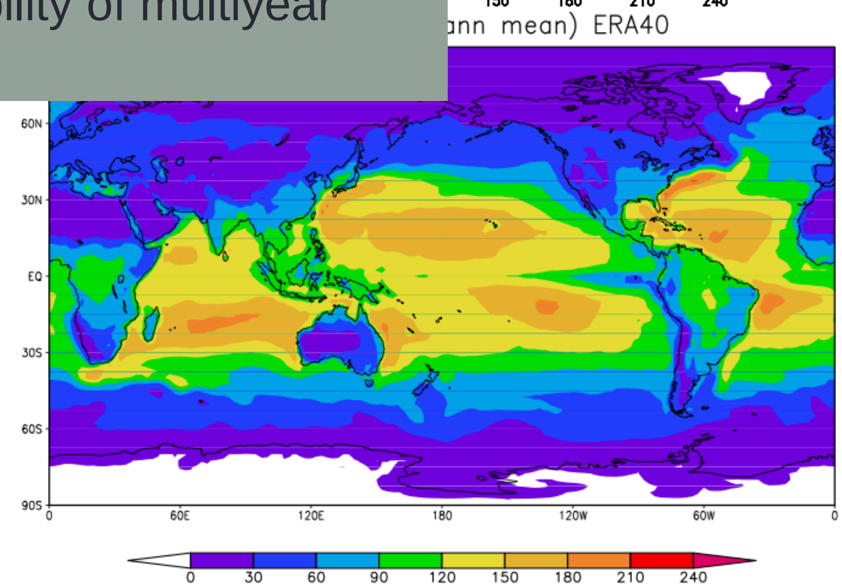


A

We have carried out wide variety of hindcast experiments by using this 4D-Var coupled data assimilation system, to examin the potential ability of multiyear forecast.



NCEP2



ERA40

1) Impact of in-consistency between the climate model and its initial conditions on climate prediction is examined

Initialization

Liu et al., (2016)

Table 1 Summary of the experiments

Experiments	Initialization	Forecast period	Initial condition	Forcing	Realization
20C[*]	Jan of 1946	1946–2007	1980-CDA	GHG, Aerosol, volcano	1
CIH[a]	Jan of each year	1980–2007	CDA, full state	GHG, Aerosol, volcano	1
GIH[b]	Jan of each year	1980–2007	GECCO2, full state	GHG, Aerosol, volcano	1
AGIH[c]	Jan of each year	1980–2007	$Ano_{GECCO2} + Clim_{20C}$, anomaly	GHG, Aerosol, volcano	1

[*] 20C: Un-initialized 20th century simulation

[a] CIH: CDA initialized hindcasts

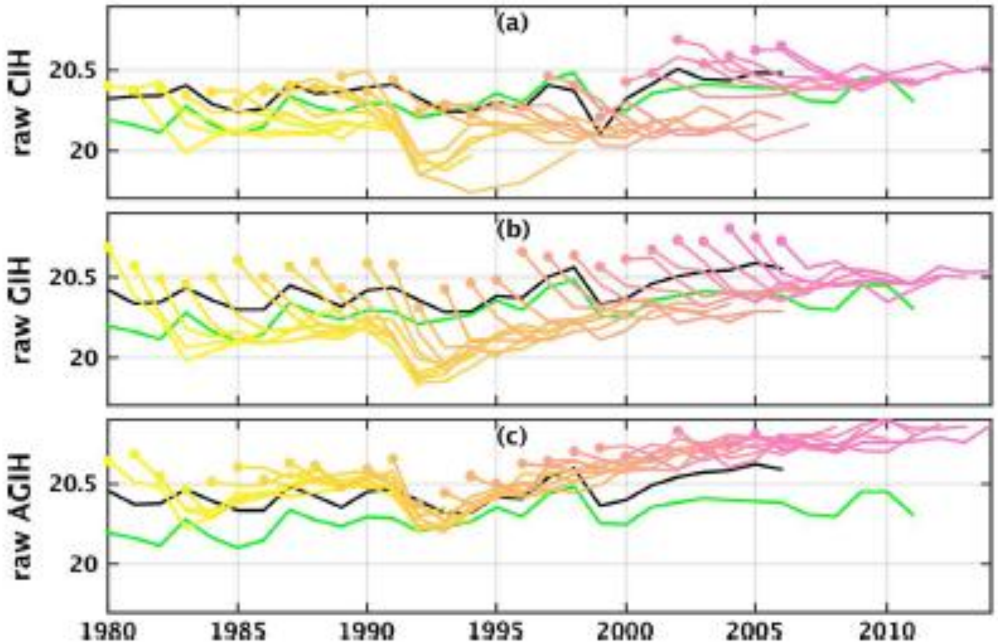
[b] GIH: GECCO2 initialized hindcasts

[c] AGIH: GECCO2 initialized hindcasts, with anomaly initialization strategy

9-year hindcasts
(start from 1980-2006)

Global-averaged
Annual mean SST

HadISST
ODAs' estimations
Coupled hindcasts



Self-consistent

In-consistent

In-consistent
only for Anomaly

Is GECCO2 wrong? =>No

CDA

GECCO2

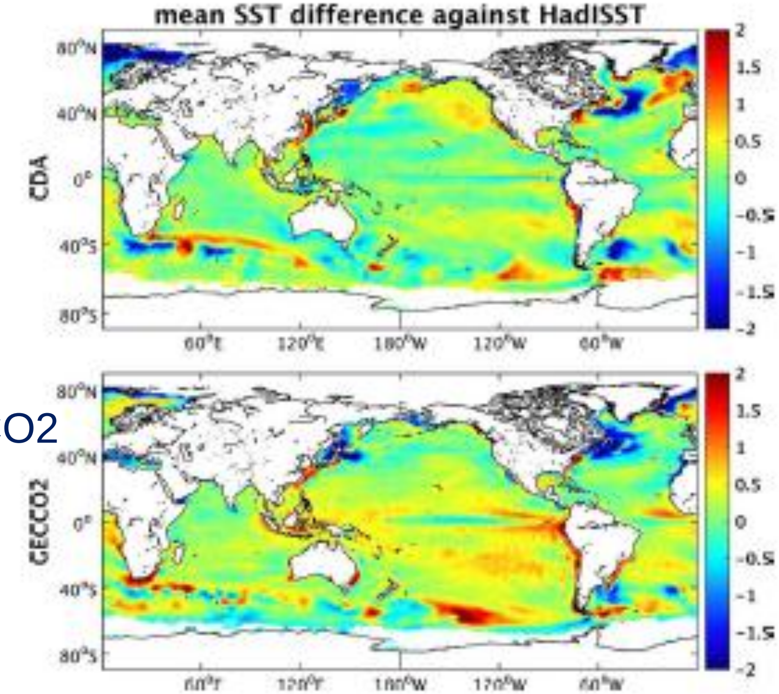


Fig. 4 SST difference to HadISST averaged over 1980–2006 for CDA (*top panel*) and GECCO2 (*bottom panel*)

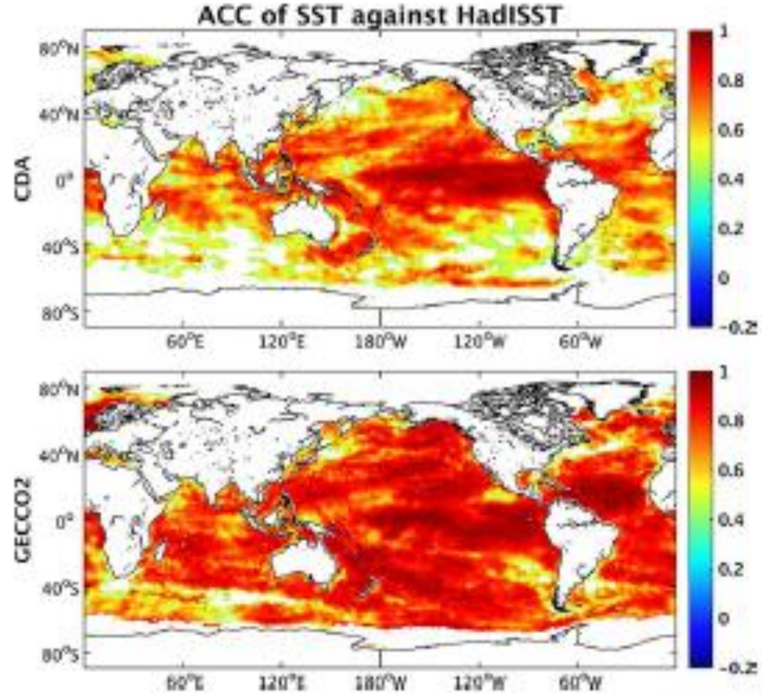


Fig. 5 Spatial distribution of the anomaly correlation coefficient for annual-mean SST between CDA and HadISST (*top*), and GECCO2 and HadISST (*bottom*). Only the significant correlation coefficients (at 95 % level) are shown here

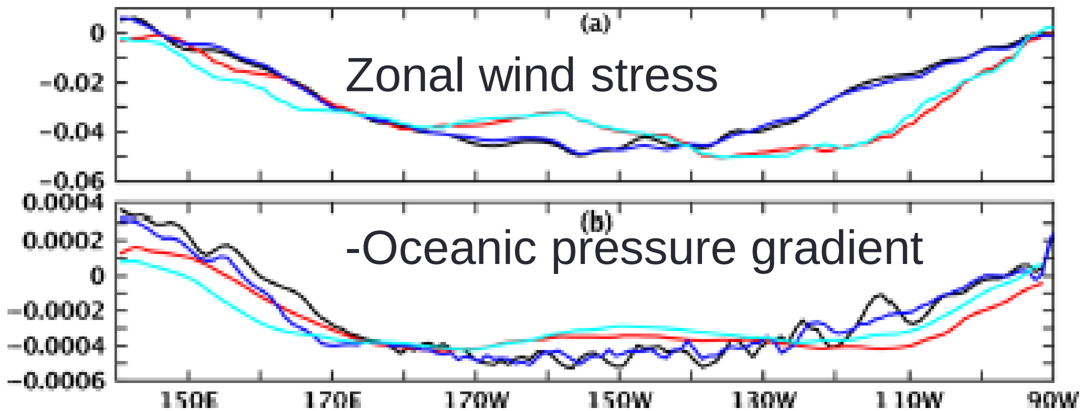
SST difference

Anomaly correlation coefficient

Huge initial shocks in tropical ocean

Red, Cyan: CDA
Black, Blue: GECCO2

El Niño non-EN



Wind stress /SST Differences (GECCO2-CDA) after initial shock

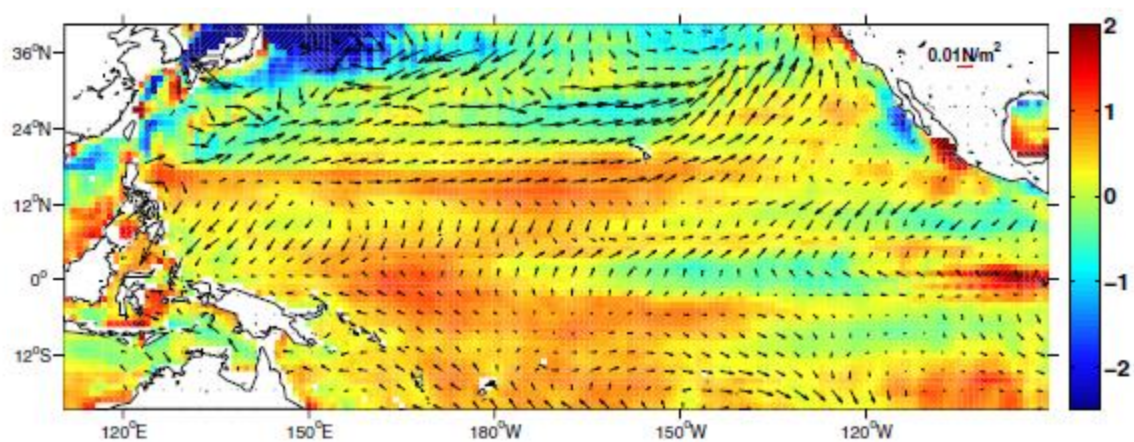
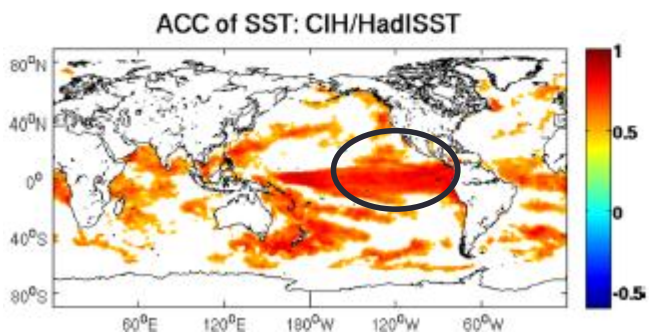


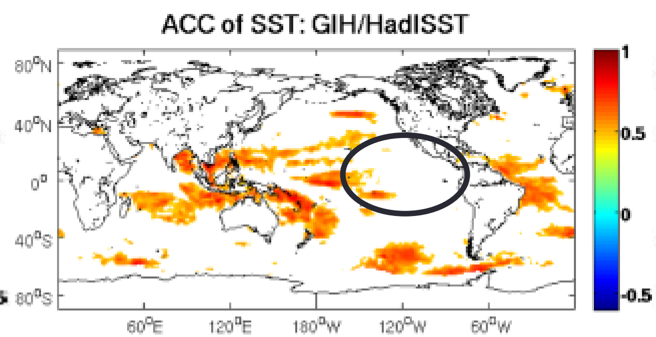
Fig. 10 The January SST/wind stress difference between GECCO2 and CDA as an average over pseudo El Niño years. *Color shading* indicates SST anomaly (°C) and the *vectors* indicate wind stress anomaly (N/m^2)

Skill of SST forecast

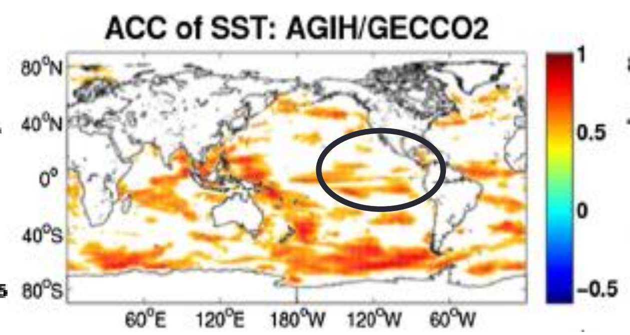
Anomaly Correlation Coefficient with 1-year lead time.



Self-consistent



In-consistent



In-consistent only for Anomaly

One example illustrating the importance of dynamical consistency. Note: Not only representing values but structures based on fundamental nature is vital for accurate forecasts.

2) Results of multiyear climate prediction to illustrate how the 4D-Var approach can improve the skill in hindcasting pentadal climate changes

Multiyear climate prediction with initialization based on 4D-Var data assimilation

Mochizuki et al. JGR2016 (poster)

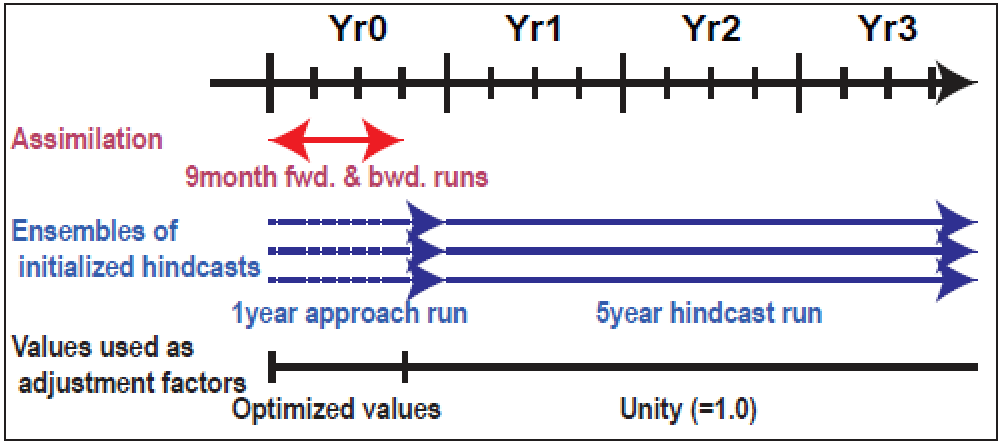


Fig. 1. Schematics of the experimental designs of the data assimilation and the subsequent ensembles of multiyear hindcasts.

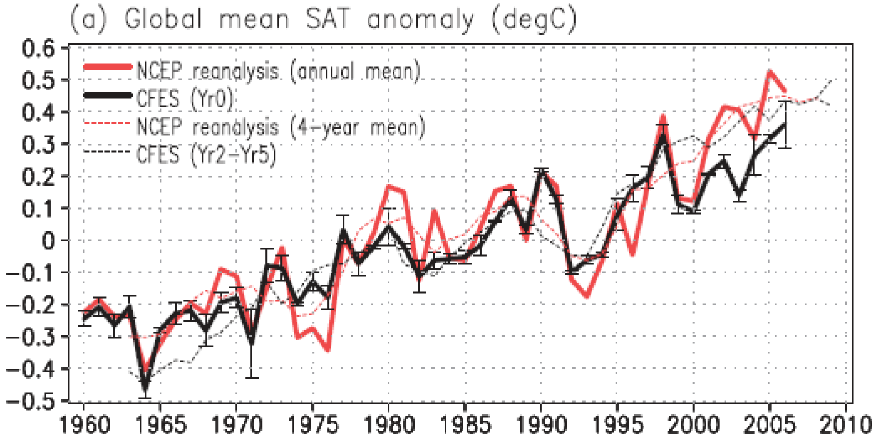


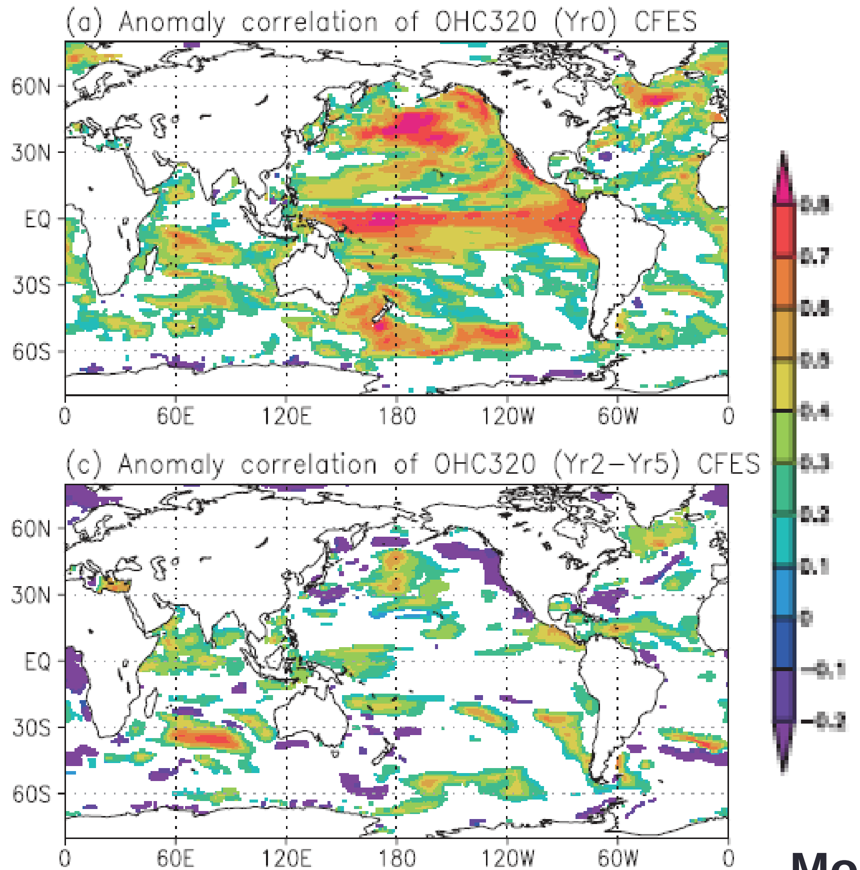
Fig. 2. (a) Global mean SAT anomalies (relative to the average during 1971-2000) derived from the CFES ensemble mean and the NCEP reanalysis. (b) Anomaly correlation coefficients of the CFES approach run (i.e., yr0) with the NCEP reanalysis at each grid point (>95% confidence levels). (c) The same as in panel b, except data are 4 year means of the CFES hindcasts in yr2-yr5.

Multiyear climate prediction with initialization based on 4D-Var data assimilation

Annomaly correlation coefficient of ocean heat content (upper 320m)

Optimized State Estimation

Pentadal Hindcast (2-5yr mean)



The hindcasts in yr2-yr5 fairly reproduce the global mean states and exhibit high skills over the North Atlantic and Indian Oceans, consistent with the CMIP5 results.

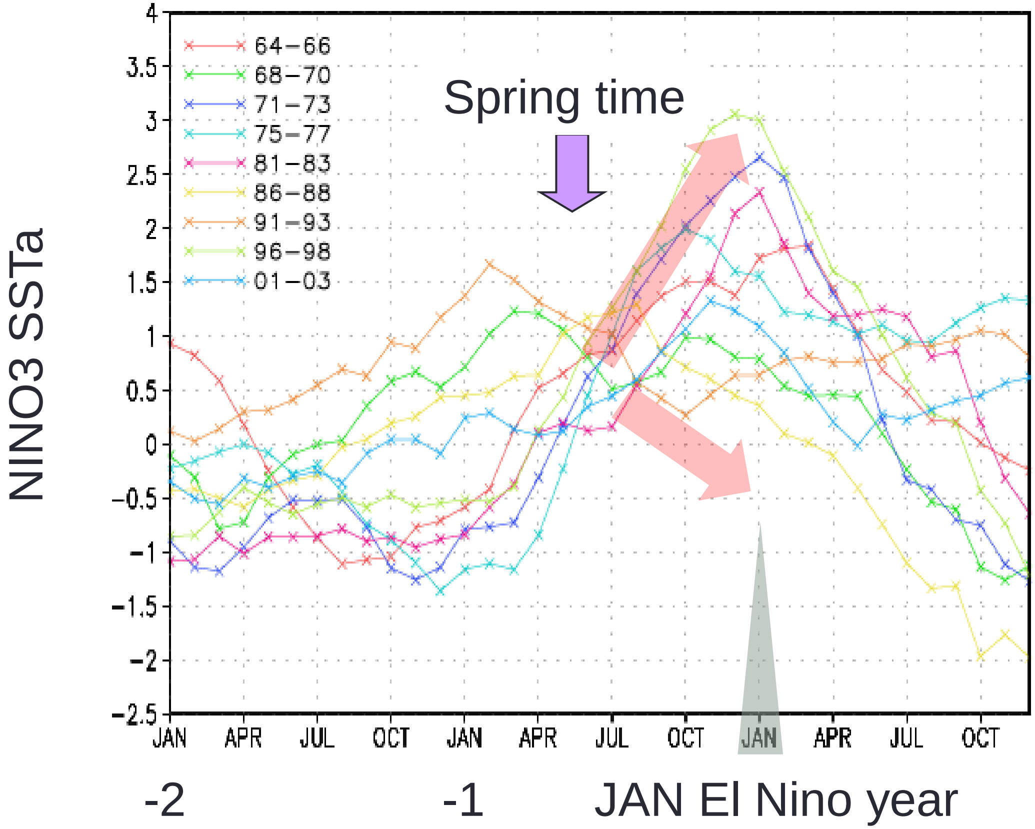
In addition, Pacific gets better…

Mochizuki et al. JGR2016 (poster)

Fig. 3. Anomaly correlation coefficients of the simulated OHC upper 320m with the ocean objective analysis (Ishii and Kimoto 2009 JO) (>90% confidence levels). Climate drifts and linear trends are removed at each grid point. Plotted values in the left and right panels are calculated using the CFES and ~~MIROC5~~ simulations, respectively.

3) Applicability of our system to El Niño predictions

Spring Persistent Barrier



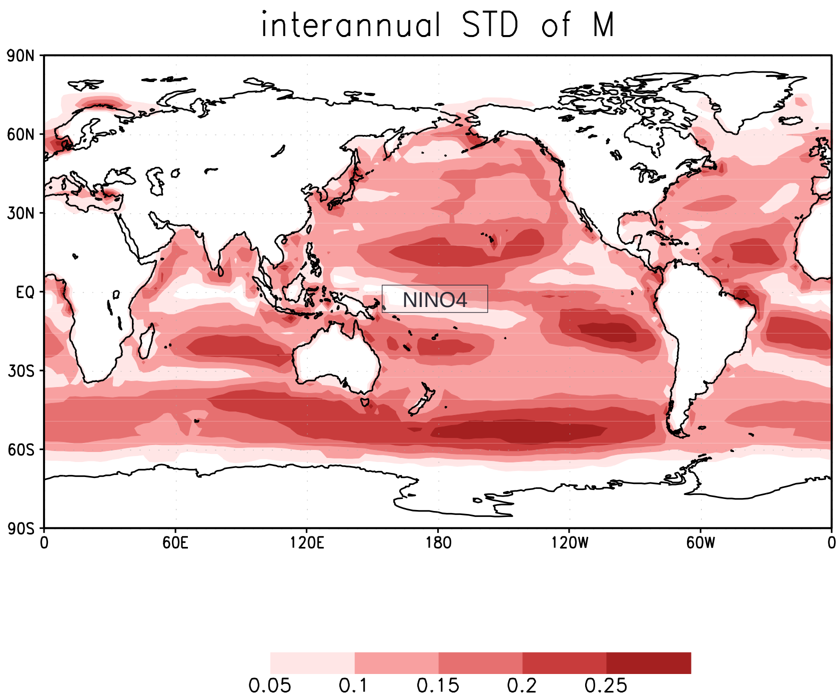
Our predictive capabilities were once more shown to be inadequate in 2014 when an El Niño event was widely predicted by international climate centers but failed to materialize.

opaque spring persistence barrier severely restricts longerterm, accurate forecasting beyond boreal spring.

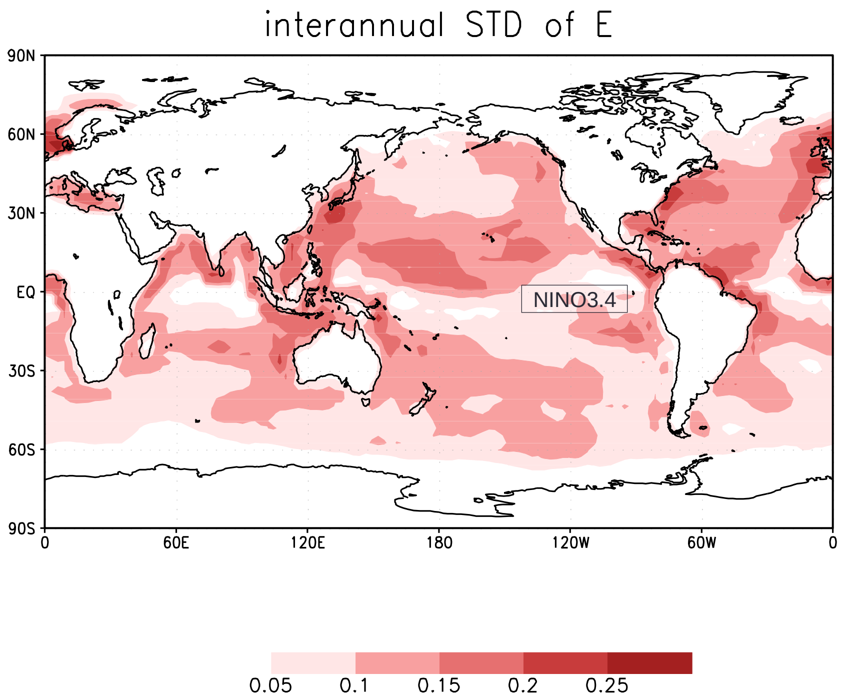
We have focused on a coupled data assimilation approach to analyze the temporal changes of climate state and reduce the abrupt drop in forecast skill that develops as a result of the SPB

Interannual variation of the bulk adjustment factors

For Momentum



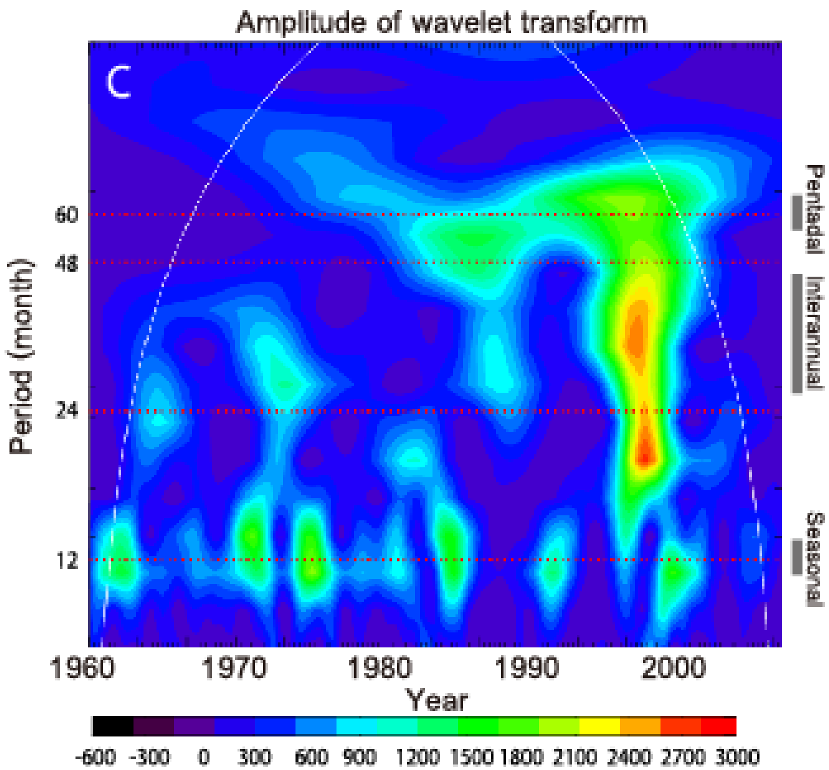
For Latent heat

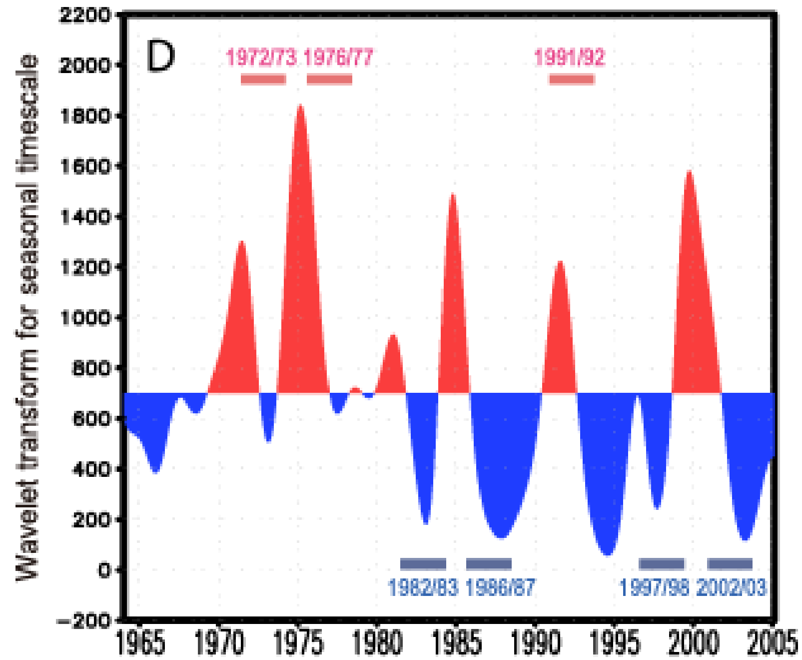


α is changeable year by year……

(due to some missing factors of model/bulk formulation, etc.)

ENSO energetics





$$u'\overline{T} + \overline{u}T'$$

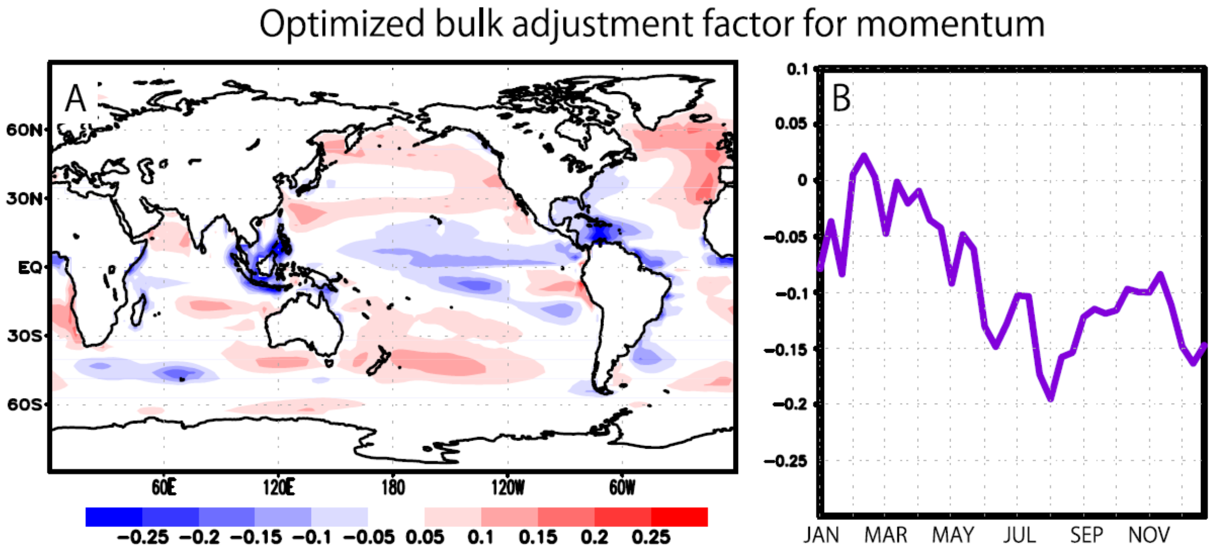
Magnitude of wavelet transform of Mean perturbation wind power (Wmp) averaged in 150ºE-100ºW, 5ºS-5ºN.

Decomposed Wmp spectrum on seasonal timescale.

The annual exchange of kinetic energy between the atmosphere and ocean responsible for ENSO genesis is modulated on pentadal to decadal timescales largely independent of the inherent ENSO variability

Masuda et al.(2015)

A new approach to ENSO prediction



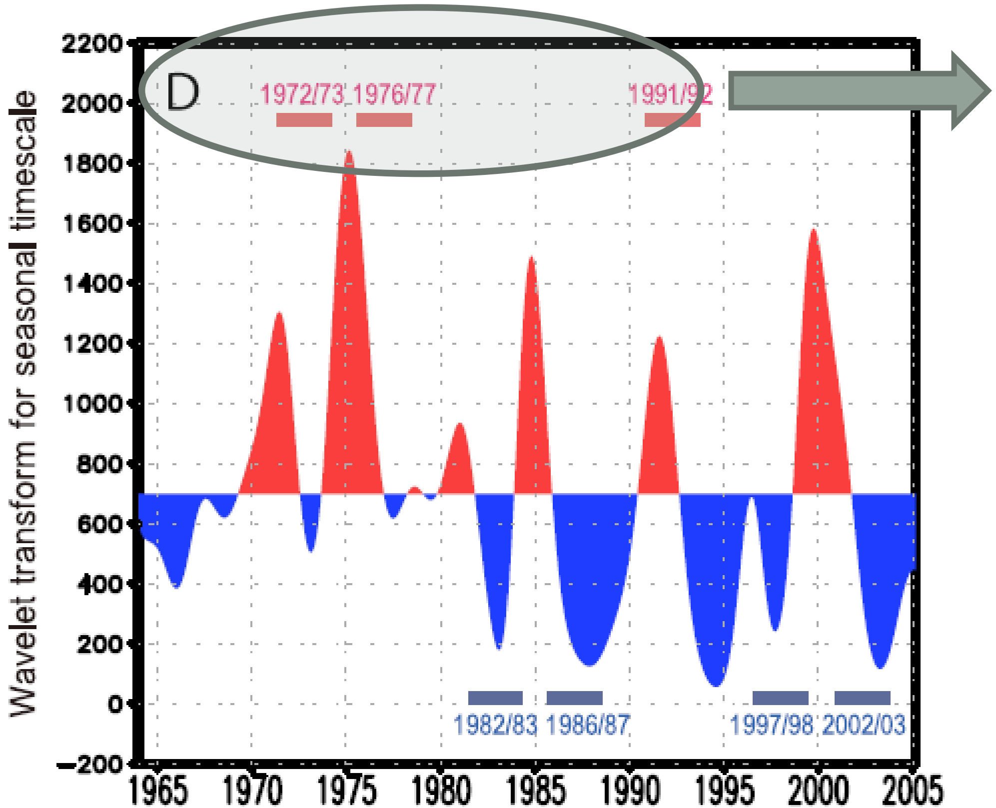
Clim(x,y,36)

We start by constructing a set of seasonal adjustment factors “Clim” from the climatology by simply averaging the historical values of the optimal adjustment factor which are calculated over the 27-year period from 1980 to 2006. (10-daily value)

This will be applied in ENSO forecast.

Masuda et al.(2015)

A new approach to ENSO prediction

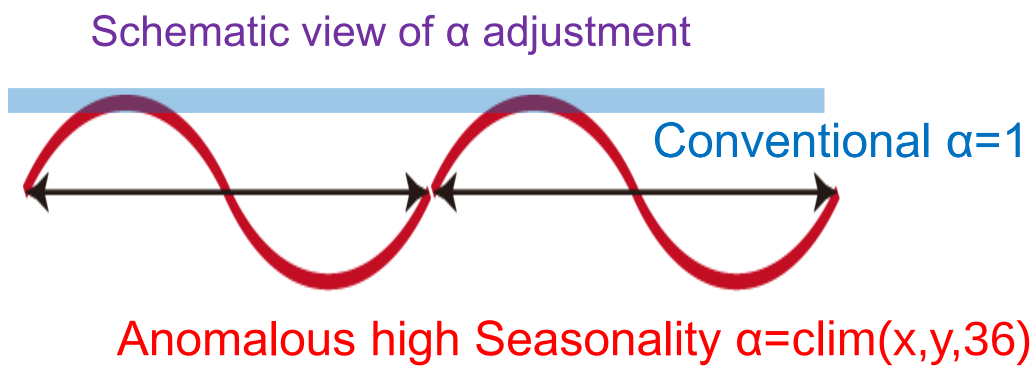


we identify which phase of the pentadal to decadal cycle in the tropical seasonal state is appropriate on the basis of the estimated time series of Wmp.

Under the assumption that long-term modulations continue along their recent trend within a few years of prediction, we determine the values of the appropriate adjustment factor for the future projection.

Masuda et al.(2015)

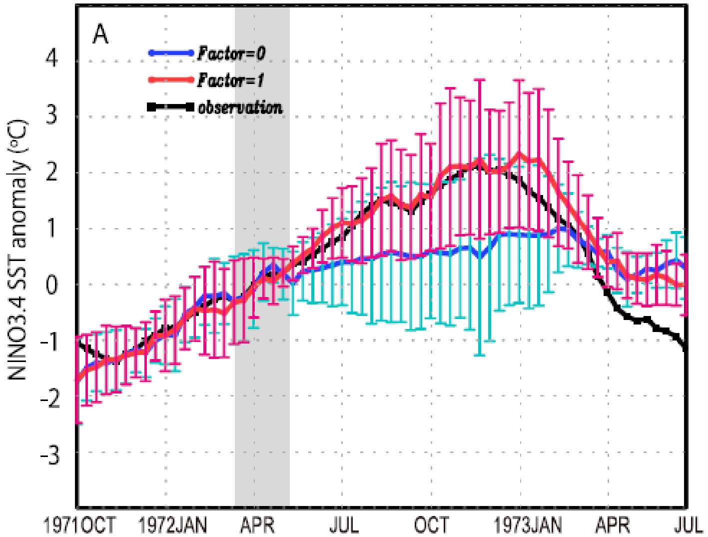
Adjusting coupling parameters in ENSO forecast

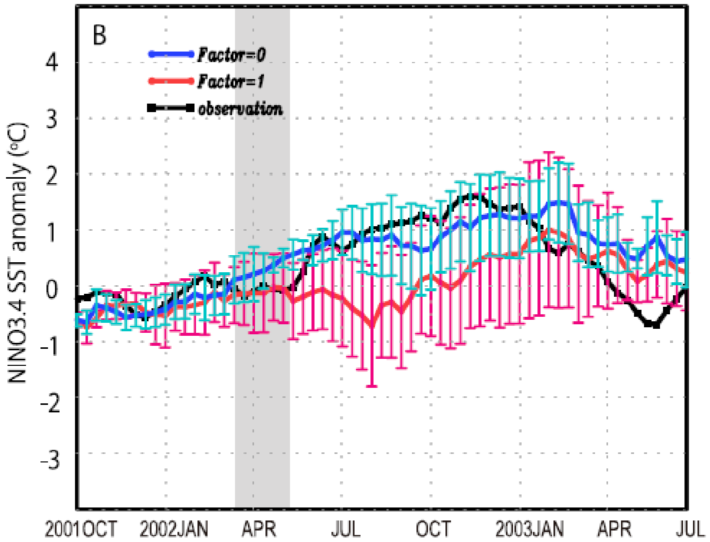


For practical use, we simply apply the adjustment factor as either a "1" or a "Clim".

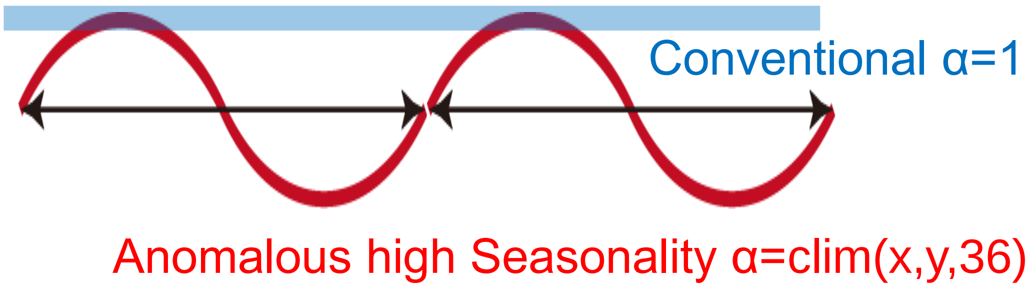
☆"1" are relevant to periods with relatively weak seasonal variations in energy exchange
☆"Clim" should be applied to (pentadal/decadal) periods with strong seasonality such as in the 1970 s, so that the modeled coupling intensities are boosted by their respective seasonal adjustment factor.

Results of hindcast for the past major El Niños



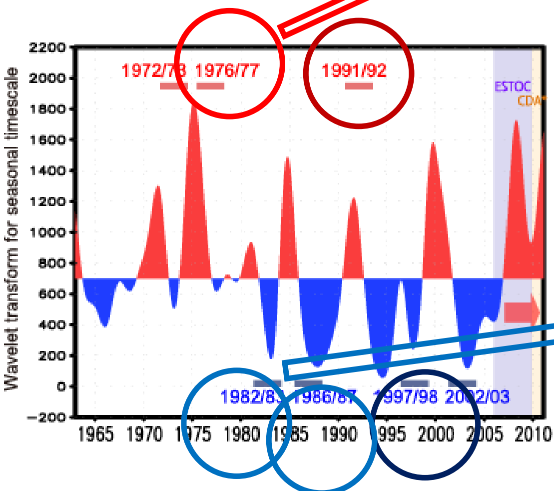


Schematic view of α adjustment

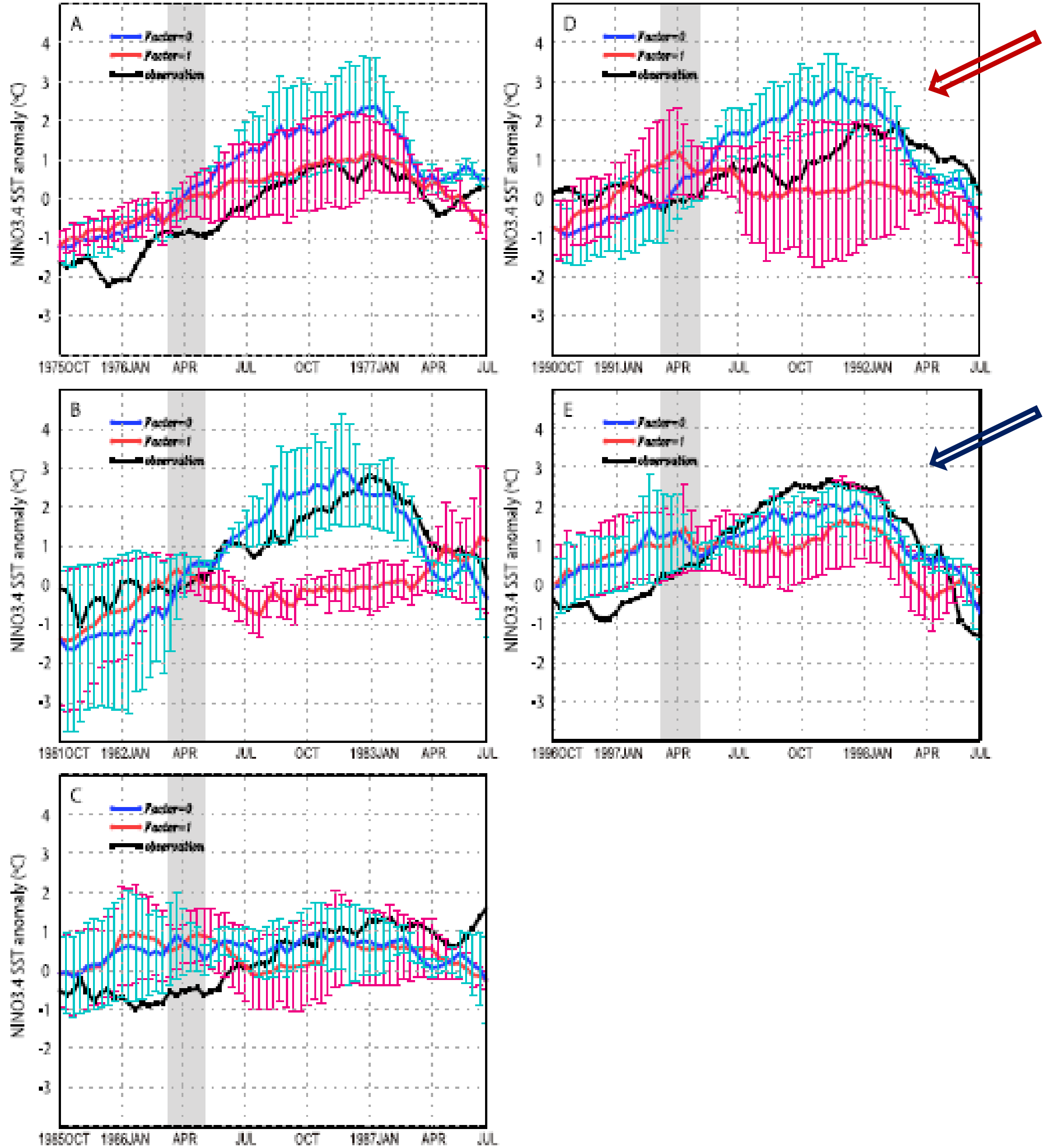


This adjustment can clearly control the bifurcation behavior of El Niño development after spring time.

Validation

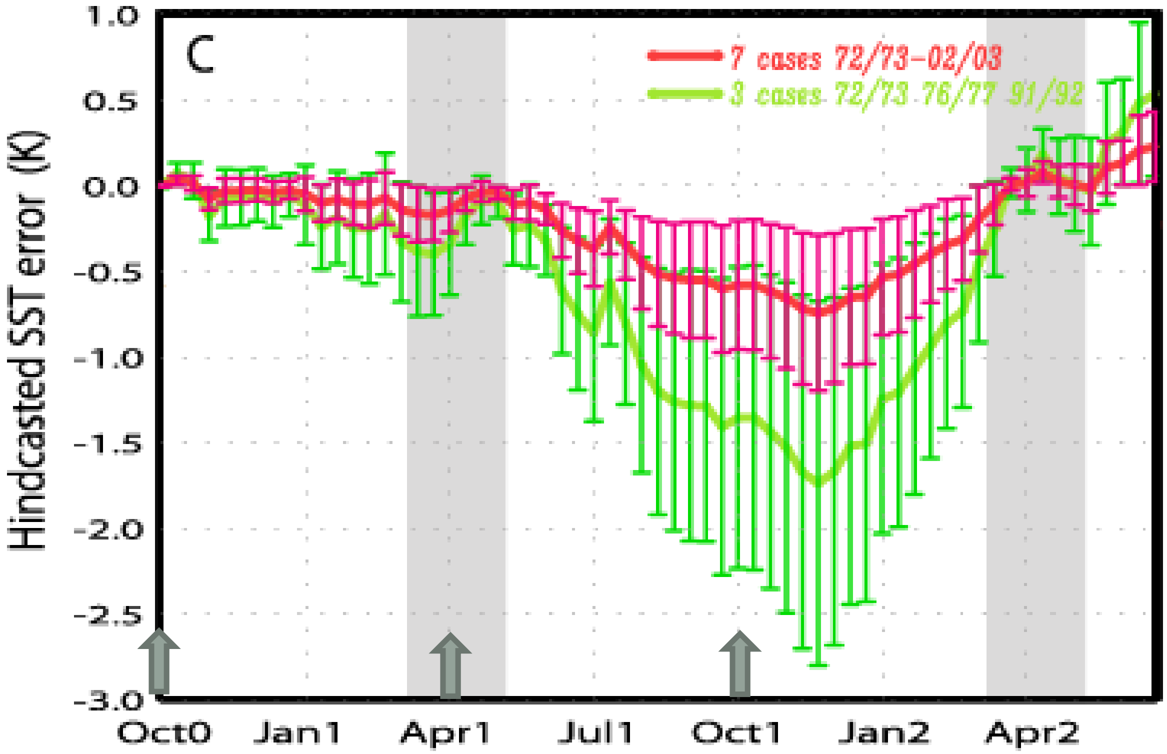


Wavelet transform for seasonal timescale
1972/73
1976/77
1991/92
ESTOC
CDA
1982/83
1986/87
1997/98
2002/03
1965
1970
1975
1980
1985
1990
1995
2000
2005
2010



A
B
C
D
E
Factor=0
Factor=1
observation
NINO3.4 SST anomaly (°C)
1975OCT
1976JAN
1977JAN
1981OCT
1982JAN
1983JAN
1985OCT
1986JAN
1987JAN
1990OCT
1991JAN
1992JAN
1996OCT
1997JAN
1998JAN
APR
JUL
OCT

Error reduction



Prediction error estimated by difference in root mean square differences for hindcasted NINO3.4 SSTs between conventional and advanced predictions for 7 El Nino events (red) and 3 events in a period of strong seasonality (green).

Note: Being a priori info given.

Masuda et al.(2015)

Summary

The benefit of initializing a decadal prediction system with dynamically consistent initial conditions is explored by comparing multi-year-hindcast results with different ocean initial conditions. We can clearly identify that not only representing values but structures based on fundamental nature is vital for accurate forecasts.

---In our case, the most significant improvement is identified over the tropical Pacific. Inconsistency between wind stress (atm.) and pressure field (ocn) caused critical shock at the initial stage of hindcasts.

By using dynamically self-consistent initial conditions, the hindcasts in yr2-yr5 fairly reproduce the global mean states and, in particular, exhibit high skills over the North Atlantic and Indian Oceans, consistent with the CMIP5 results.
[Pacific => see the poster by Dr. Mochizuki]

Our new coupled climate simulation which incorporates long-term influences directly, generates more accurate hindcasts for the major historical El Niños. The error value between predicted and observed sea surface temperature (SST) in a specific tropical region can consequently be reduced by 0.6 Kelvin for one-year predictions.

Future work: one theoretical approach

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Coarse-grained sensitivity for multiscale data assimilation

Nozomi Sugiura*
Japan Agency for Marine-Earth Science and Technology, Yokosuka 237-0061, Japan

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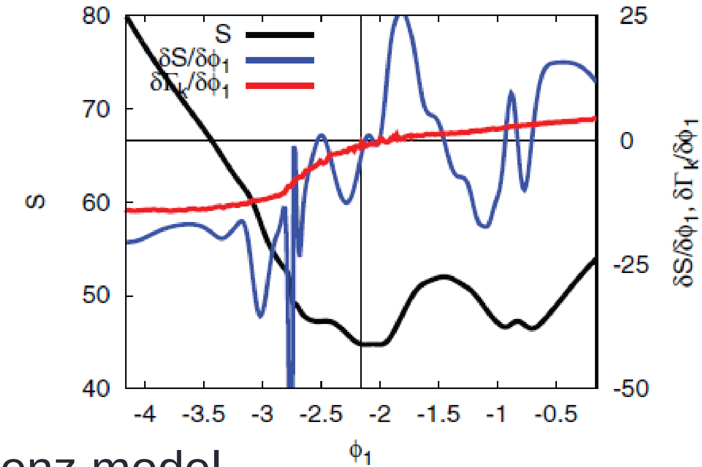
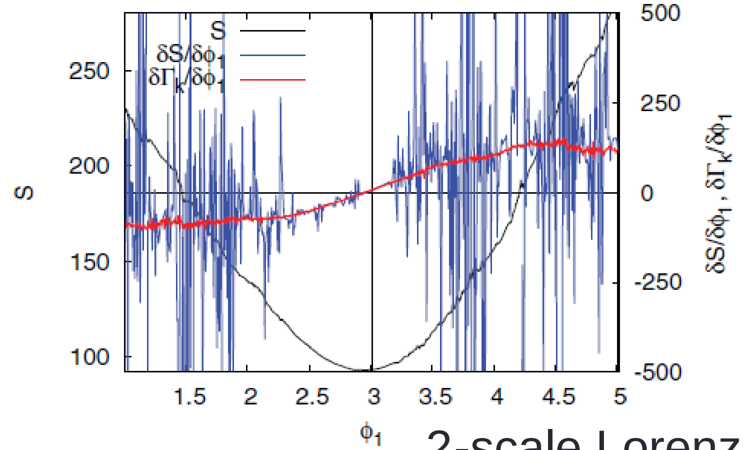
We show that the effective average action and its gradient are useful for solving multiscale data assimilation problems. We also present a procedure for numerically evaluating the gradient of the effective average action and demonstrate that the variational problem for slow degrees of freedom can be solved properly using the effective gradient.

Availability of effective average action is been examining.



Lorenz model

FIG. 6. Action $S[\phi]$ (black curve), gradient of action $\delta S[\phi]/\delta\phi_1$ (blue curve), and effective gradient of action $\delta\Gamma_k[\phi]/\delta\phi_1$ (red curve) for the Lorenz model. The true value for the data assimilation problem is $\phi_1 = -2.156$ and the first guess is -0.156.



2-scale Lorenz model

FIG. 7. Action $S[\phi]$ (black curve), gradient of action $\delta S[\phi]/\delta\phi_1$ (blue curve), and effective gradient of action $\delta\Gamma_k[\phi]/\delta\phi_1$ (red curve) for the two-scale Lorenz model. The true value for the data assimilation problem is $\phi_1 = 3.011$ and the first guess is 5.011.

This hopefully leads to a new adjoint-based system.