GFDL's Coupled Ensemble Data Assimialtion System, 1980-2006 Coupled Reanalysis and Its Impact on ENSO Forecasts

S. Zhang*, A. Rosati, M. J. Harrison, R. Gudgel and W. Stern

Geophysical Fluid Dynamics Laboratory, Princeton, New Jersey

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ABSTRACT

A coupled data assimilation (CDA) system, consisting of an ensemble filter applied to GFDL's global fully-coupled climate model (CM2), has been developed to facilitate the detection and prediction of seasonal-to-multidecadal climate variability and climate trends. The assimilation provides a self-consistent, temporally-continuous estimate of the coupled model state and its uncertainty, in the form of discrete ensemble members which can be used directly to initialize probabilistic climate forecasts without initial shocks.

Then 1976-2006 real oceanic observations (XBTs,ARGOs,CTDs,MRBs,OSDs,MBTs and SSTs) and atmospheric (NCAR/NCEP) reanalyses were assimilated into the coupled ensemble system to form 24 member atmosphere/ocean/land/sea-ice state estimates. This talk focuses on the obtained oceanic reanalysis and its impact on ENSO forecasts. Hindcast statistics show this ensemble climate state estimate and prediction system improved ENSO forecast skills dramatically. This happens mainly because the self-consistent ensemble initial conditions from this coupled assimilation system make all components of the coupled model stay in a physically-balanced state, which help model dynamics project the initial signals onto a seasonal-interannual time scale.

1 Description of GFDL's CDA system

Viewing the evolution of climate states as a continuous stochastic dynamical process, the GFDL's coupled ensemble data assimilation system (Zhang et al. 2007) directly solves for a temporally-varying joint probability density function (joint-PDF) of oceanic states. The filtering assimilation combines the observational PDF and the prior PDF derived from the CGCM to produce an analysed PDF (Fig. 1). In a super-parallelization configuration, the coupled assimilation is a continuous data-incorporation process (Fig. 2), which includes currently the atmospheric and oceanic data assimilation components (Fig. 3). Due to capturing the probabilistic nature of climate evolution, this system has been used to facilitate the detection (Zhang et al. 2008) and prediction of seasonal-to-multidecadal climate variability and climate trends. This study addresses the estimates and forecasts of the seasonal and interannual variability in the tropical Pacific Ocean.

2 Data

Oceanic observations include the real-time oceanic states' samples from available oceanic observing net-

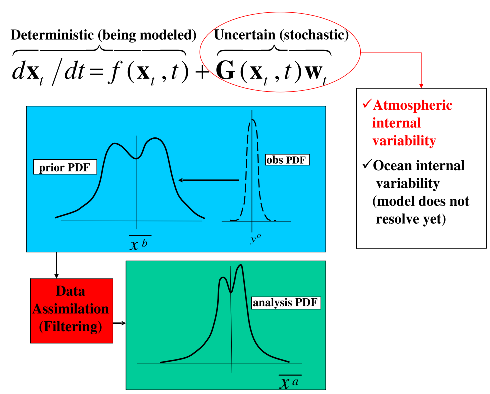

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Figure 1: Cartoon of how an ensemble filter updates the distribution for a scalar variable. The upperleft reprsents the prior distribution derived from model ensemble integrations starting from the previous assimilation results. The upperright represents an observational distribution (usually Gaussian). An ensemble filtering process (lowerleft) combines the observational and prior distributions to form an updated 'analyzed' distribution (lowerright) realized by the ensemble member states that initialize next ensemble integrations.

works. They are: XBTs, CTDs, MBTs, MRBs, OSDs, Gridded sea-surface temperatures (SSTs of the 20th-century and Argo, XBTs, MRBs, Gridded SSTs of the 21st-century. At this time, the altimetric data have not been used.

* *Corresponding author address:* Geophysical Fluid Dynamics Laboratory, PO Box 308, Forrestal Campus, Princeton NJ 08542. USA. Shaoqing.Zhang@noaa.gov

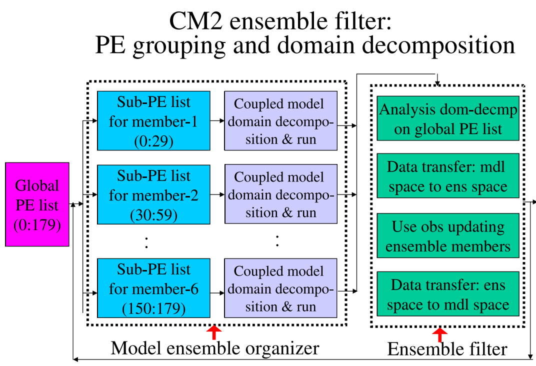

FIGURE 2: Flow-chart of the GFDL's super-parallelized coupled data assimilation system for 180 PEs case. Generally, this system can be scaled for any ensemble size and any big enough processing element (PE) number. But in practice due to efficiency consideration it is currently scaled for running 6, 12, 24 ensemble members.

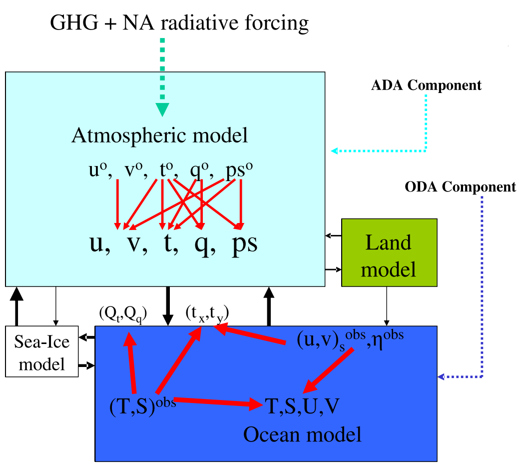

FIGURE 3: Schematic diagram illustrating how the GFDL's coupled model exchanges fluxes between model components (black arrows), and constraints of oceanic/atmospheric observations in this particular climate detection study (red arrows). The dashed green arrow denotes the radiative forcings in the coupled system, and the dashed means that the radiative forcings used during assimilation is set as fixed-year (1860).

Atmospheric data are the NCEP/NCAR-reanalysis gridded atmospheric variables including wind (u,v) and temperature. The specific humidity is a very sensitive variable for the coupled assimilation, and at this time, is not used for the coupled reanalysis.

3 Results of ocean state estmates

The RMS errors of the assimilated SSTs are shown in Fig. 4. The global SST's errors are reduced by 0.7^{o}C from the model simulated 1.8^{o}C. The tropical Pacific SST's errors are reduced by 0.4^{o}C from the

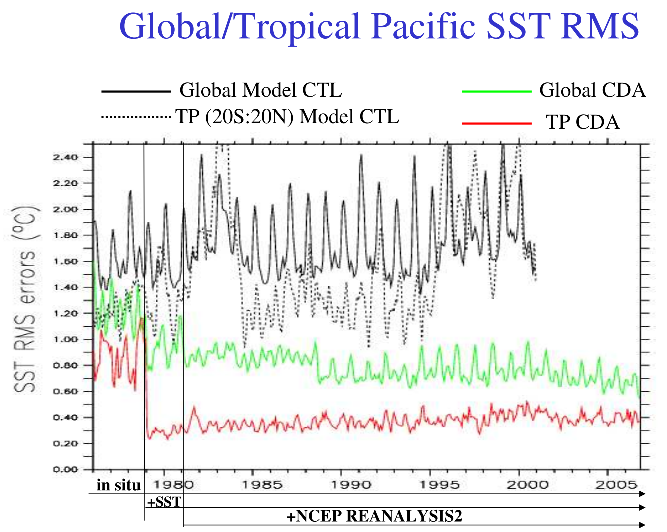

FIGURE 4: The RMS errors of assimilated global (green) and tropical Pacific (red) SSTs. The corresponding free model simulation's RMS errors are plotted by black-solid (global) and black-dashed (tropical Pacific) as the reference. The arrows denote the subsurface data (in situ measurements) are throughout the period and SST observations atmospheric data are used starting from 1979 and 1981 respectively.

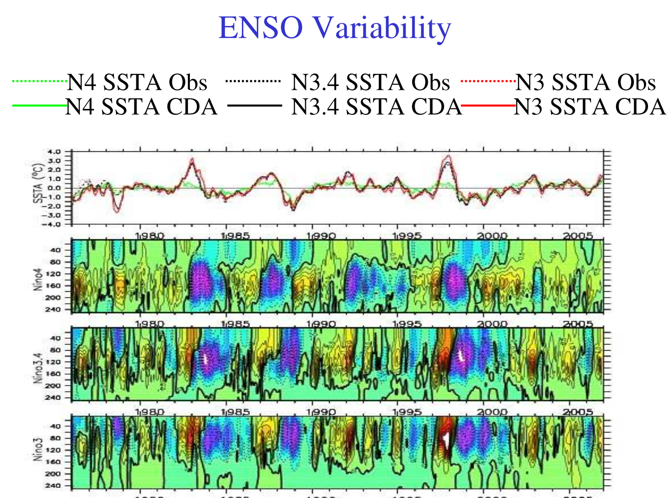

FIGURE 5: Top: Time series of observed (dashed lines) and analysed (solid lines) domain-averaged SST's anomalies in Nino4 (green), Nino3.4 (black) and Nino3 (red). Lower 3 panels: Time series of analysed domain-averaged potential temperature anomalies in Nino4 (upper-middle), Nino3.4 (lower-middle) and Nino3 (bottom). The contour interval is 0.5^{o}C.

4 Impact on ENSO forecasts

25 year (82-06) one-year ENSO retrospective forecasts initialized at each month have been done. The

anomaly correlation coefficients (ACC) of forecasted and observed SSTs and normalized RMS errors of forecasted SSTs are shown in Fig. 6 in forecast leading time and initial time space. Compared to the forecasts initialized from GFDL's old 3D-Var assimilations, the new coupled ensemble assimilation widens the valid forecast area (ACC $>$ 0.6 and the normalized RMS errors $<$ 1.0) tremendously. 4 individual months were selected to represent the forecast skills in different seasons being shown in Fig. 7 and 8. Referred to the persistent forecasts, the new coupled ensemble assimilation improves the short (1-4 months) forecast skills dramatically while extending the valid leading forecast time up to 9 months from the 3D-Var's 3 months.

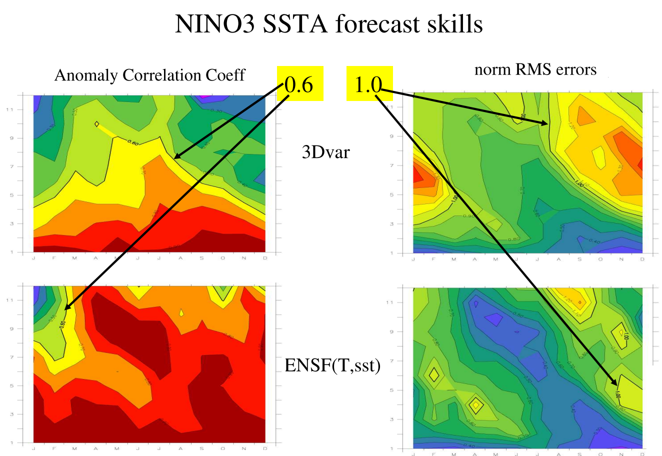

FIGURE 6: Distributions of anomaly correlation coefficients of forecasted and observed SSTs, and the normalized RMS errors of forecasted SSTs in Nino3 produced by GFDL's old 3D-Var system (upper) and the new coupled ensemble filter (ENSF) (lower), in forecast leading time and initial time space. The contour interval is 0.1.

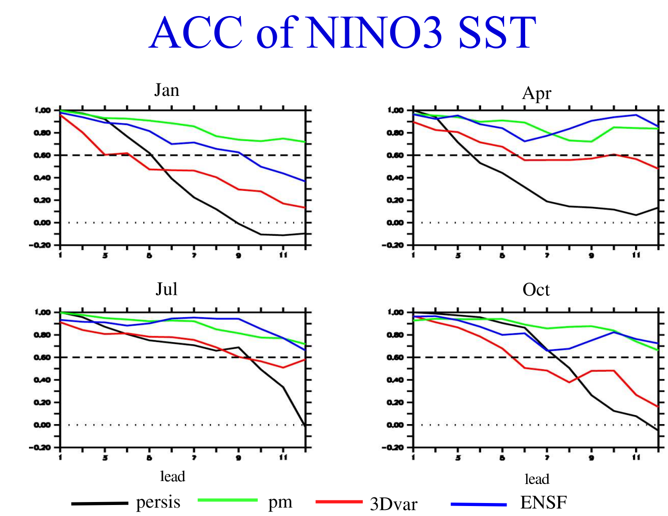

FIGURE 7: Variations of anomaly correlation coefficients of forecasted and observed Nino3 SSTs, produced by persistent forecast (black), 3D-Var (red), ENSF(blue). The green line called the perfect model forecast which sets an individual member as the "truth" and uses the ensemble mean of the rest of members to forecast the truth.

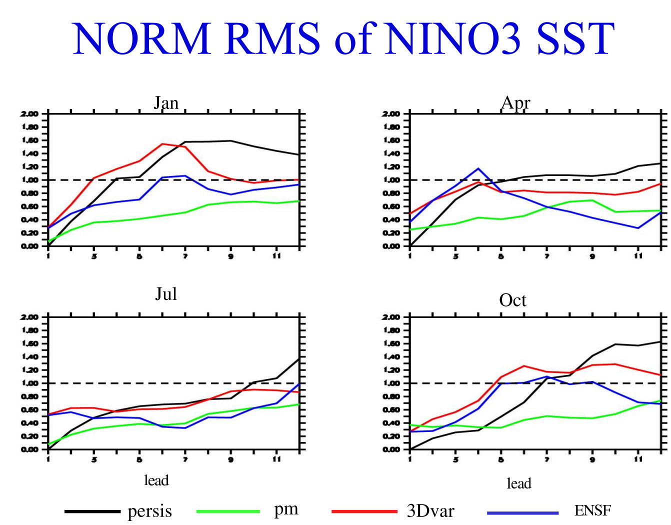

FIGURE 8: Variations of normalized RMS errors of forecasted Nino3 SSTs produced by persistent forecast (black), 3D-Var (red), ENSF (blue) and perfect model forecast (green).

REFERENCES

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