CCPP-SciDAC/DOE, 2011, Final

Towards the Prediction of Decadal to Centennial Climate Processes in the Coupled Earth System Model

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Project ID: 0007257
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Award Register#: ER63249 0007257

In this proposal, we have made major advances in the understanding of decadal and long term climate variability. (a) We performed a systematic study of multidecadal climate variability in FOAM-LPJ and CCSM-T31, and are starting exploring decadal variability in the IPCC AR4 models. (b) We develop several novel methods for the assessment of climate feedbacks in the observation. (c) We also developed a new initialization scheme DAI (Dynamical Analogue Initialization) for ensemble decadal prediction. (d) We also studied climate-vegetation feedback in the observation and models. (e) Finally, we started a pilot program using Ensemble Kalman Filter in CGCM for decadal climate prediction.

1. Mechanism of Pacific Decadal Variability

We fully analyzed our CCSM3 modeling surgery experiments and identified for the first time unambiguously the mechanism for Pacific multi-decadal variability is caused by Rossby wave propagation in the subpolar North Pacific (Zhong et al., 2008; Zhong and Liu, 2008, 2009).

We further studied the interaction between decadal variability in the North Atlantic and North Pacific in the observation and the AR4 simulations, in a new colaboration with Drs. T. Delworth and R. Zhang at GFDL. Our analysis confirmed the significant lead of Atlantic decadal variability to the Pacific decadal variability significantly at a 10-year lead time. In the mean time, we also identified a significant correlation when the Pacific decadal variability leads the Atlantic decadal variability by about 2 years, which is caused by the Aleutian Low-Icelantic Low teleconnection (Wu et al., 2011).

2. A New Method for Ensemble Prediction: DAI

Recently, we started exploring a new method for enhanced predictability for weather and climate in a nonlinear regime, the Dynamic Analogue Initialization. Preliminary study in the Lorenze model show that this method can enhance predictability significantly, with the RMSE reduced by 50% (Liu et al., 2010a). Further study suggests that DAI is much better than bred-vector method, and is comparable with EnKF method (Fig.1).

3. EnKF for Coupled Climate Models

A new effort is also initiated to improve coupled climate model and its decadal prediction using a modified Ensemble Kalman Filtering strategy, in collaboration with Drs Shaoqing Zhang and A. Rosati at GFDL and R. Jacob at Argonne National Lab.. In this new method, we will perform traditional EnKF to equilibrium before adjusting model parameters. Our preliminary study in an idealized coupled model suggests a significant improvement of convergence rate of model parameters (Zhang et al., 2010, 2011a,b). Furthermore, we find the assimilation of synoptic atmospheric data is critical for the improvement of initial condition in the coupled model, and in turn climate prediction (Liu et al., 2011). We are in the process of implementing EnKF into a fully coupled CGCM (FOAM) to test these ideas.

4. Long term memory and decadal predictability

A new collaboration is also underway with Prof. K. Fraedrick at Hamburg University to predict future decadal climate change in Greenland using statistical methods on the Greenland ice core data. Climate forecast skills are evaluated for surface temperature time series at grid points of a millennium control simulation from a state of the art global circulation model (ECHAM5/MPIOM). First, climate predictability is diagnosed in terms of potentially predictable variance fractions and the fluctuation power law exponent (using detrended fluctuation analysis). Long term memory (LTM) with a fluctuation exponent (or Hurst exponent) close to 0.9 occurs mainly in high latitude oceans, which are also characterized by high potential predictability. Next, explicit prediction experiments for various time steps are conducted on a grid point basis using an auto-correlation (AR1) predictor: in regions with LTM, prediction skills are beyond that expected from red noise persistence; exceptions occur in some areas in the southern oceans and over the northern hemisphere continents. Extending the predictability analysis to the fully forced simulation shows large improvement in prediction skills.(Zhu et al., 2010).

5. Ocean-atmosphere feedback

We have developed a systematic method known as GEFA (Generalized Equilibrium Feedback Analysis) for the assessment of atmospheric response to global SST variability modes in the observation (Liu et al., 2008; Liu and Wen, 2008; Wen et al., 2010). Our assessment recovers the classical ENSO forcing on the atmosphere. But furthermore, our method is able to, for the first time, separate the SST forcing in the tropical Pacific from that in the tropical Indian Ocean clearly (Fig.2). In addition, we identified a significant North Pacific impact on the remote North Atlantic Oscillation. Further analysis is underway to study the seasonality of the feedback and the mechanism of the feedback. GEFA is now also applied to assess oceanic feedback on US climate (Zhong et al., 2011). We are also developing other methods based on LIM (Linear Inverse Modeling) to identify climate feedback, which potentially provides an independent method for the assessment of climate feedback. We also applied GEFA to study vegetation feedback on climate.

To identify the optimal SST forcing, we also improved the Maximum Covariance Analysis (MCA) with a rotation on the SST field such that the forcing and response can be identified dynamically (Frankignoul et al., 2011). In addition, we also developed the Maximum Response Method and compared MCA, MRE and GEFA-SVD. Each method has its advantage and disadvantages.

6. Climate-Terrestrial Ecosystem Interaction

We have studied vegetation feedback in North Africa systematically (Notaro et al., 2008; Notaro and Liu, 2008). This leads us to a recent study exploring the interaction between climate, vegetation and the soil system. We proposed an indirect vegetation feedback that is closely associated with soil moisture. In the coupled FOAM-LPJ, our preliminary application to the arid North Africa region suggests that grassland is less likely than trees in generating positive feedbacks to local rainfall, because of its shallow rooting system and the associated soil moisture feedback of the opposite sign. These studies will have potentially important implications to vegetation feedback in other arid regions. (Liu et al., 2010b). We also discovered a new mechanism for abrupt climate changes in a monostable coupled climate-vegetation model known as the stable collapse. This collapse is caused essentially by the stochastic climate variability and the soil moisture memory which combine to produce a bimodality in a monstable system (Liu, 2010). This new mechanism has significant implications to our study of abrupt climate changes in general, and to other fields related to the abrupt change of nonlinear stochastic dynamic systems.

7: Review of the dynamics of decadal variability

The emerging interest in decadal climate prediction highlights the importance of understanding the mechanisms of interdecadal climate variability. This paper presents an overall review of the understanding of interdecadal climate variability in the Pacific and Atlantic Ocean, in light of the historical development. We first review general mechanisms for interdecadal variability, and the role of ocean dynamics in interdecadal variability, from an unified perspective in a hierarchy of paradigms of increasing complexity, from the simplest red noise to the most complex stochastic-driven coupled ocean-atmosphere mode. We then review the mechanisms of specific decadal and multi-decadal variability in the Pacific, and Atlantic, individually. Our review suggests that in the current understanding, stochastic forcing is the major driving mechanism for almost all interdecadal variability, while ocean-atmosphere feedback plays a relatively minor role. Interdecadal variability can be generated independently in the tropics or extratropics, and in the Pacific or Atlantic, although multi-decadal variability appears to be generated more likely in the subpolar regions. Oceanic wave and circulation are the leading candidates for the mechanism of time scale selection. Interdecadal variability is associated with wind-driven upper ocean circulation in the Pacific, but associated with the AMOC in the North Atlantic, especially for the multi-decadal variability. The time scale of interdecadal variability seems to be determined mainly by the Rossby wave propagation in the extratropics; it could also be determined by the advection of the returning branch of the AMOC in the Atlantic. Finally, remaining questions are also discussed. (Liu, 2011)

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Frankignoul, C., Z. Liu and N. Chouaib, 2011: Estimating the observed atmospheric response to SST anomalies: Maximum Covariance Analysis, Generalized Equilibrium Feedback Assessment, and Maximum Response Estimation, *J. Climate*, in press.

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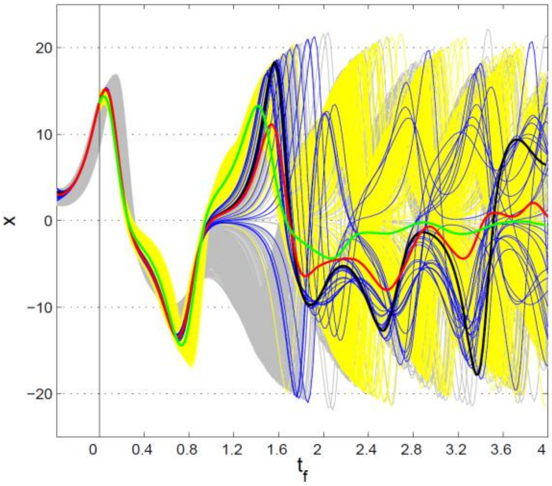
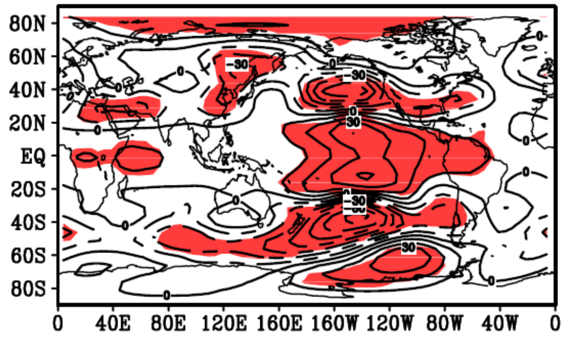


Fig. 1: An example of DAI forecast in the standard experiment (in variable *x*). The truth is in black. Also shown are the ensemble members of the hindcast (initiated at -0.4, grey) and forecast (initiated at 0, yellow) FSE (500 each), the DAI (25, blue), and the ensemble mean of the FSE forecast (green) and DAI (red).

a) GEFA Z250 Rsp to TP1, σ(TP1)=0.42°C



b) GEFA Z250 Rsp to TI1, σ(TI1)=0.23°C

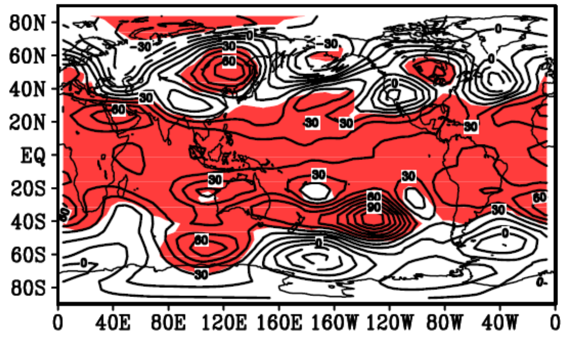


Fig.2: Statistical assessment of atmospheric response (geopotential height at 250 hPa) to (a) Pacific El Nino SST anomaly and (b) tropical Indian Ocean monopole SST anomaly, as identified in NCEP reanalysis. (Wen et al., 2010). (red shade indicate 95% significant with a Monte Carlo test). It is seen that the Pacific SST forces primarily a local response

over the tropical Pacific, while the Indian Ocean SST forces a circumgloble response.