US National Multi-Model ENSO Prediction with CFS and CCSM3

Ben P. Kirtman[1,2,]* and Dughong Min[1]
[1] *Center for Ocean-Land-Atmosphere Studies, Calverton MD*
[2] *RSMAS/MPO, University of Miami, Miami, FL*

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1. Introduction

Seasonal-to-interannual climate predictions are now made routinely at a number of operational centers around the world, using comprehensive coupled models of the atmosphere, oceans, and land surface (e.g. Leetmaa and Ji 1989, Ji et al., 1994; Stockdale et al. 1998, Kanamitsu et al. 2002, Wang et al., 2002, Alves et al. 2002, Saha et al. 2006). These comprehensive coupled models are also being used for prediction and predictability research at various research centers around the world (Kirtman et al., 1997; Rosati et al. 1997, Schneider et al., 1999; Kirtman 2003; Schneider et al., 2003; DeWitt 2005; Stan and Kirtman 2007). This rapid growth in the use of comprehensive coupled models is due to the convergence of many factors including a concerted international effort to observe (i.e., McPhaden et al. 1998) and understand coupled ocean-atmosphere dynamics (Philander et al., 1984, Schopf and Suarez 1988, Battisti and Hirst 1989; Kirtman 1997). These efforts have led to the development and application of models that accurately simulate the observed variability (Neelin et al. 1992, Mechoso et al., 1995, Schneider et al. 1997; Davey et al., 2001, Kirtman et al. 2002, Collins et al., 2006, Delworth et al., 2006, Wittenberg et al., 2006).

Despite the advances noted above, real-time seasonal-to-interannual prediction efforts have not met expectations. For example, according to Barnston et al. (1999) and Landsea and Knaff (2000), the performance of many different prediction systems during the 1997-1999 ENSO episode was mixed. Arguably, there were substantial qualitative forecasting successes - almost all the models predicted that the boreal winter of 1997/98 would be a warm event one to two seasons in advance. But, there were also some striking quantitative failures. For instance, none of the models predicted the early onset or the amplitude of that event, and many of the forecast systems had difficulty capturing the demise of the warm event and the development of cold anomalies that persisted through 2001. Many models failed to predict the three consecutive years (1999–2001) of relatively cold conditions and the development of warm anomalies in the central Pacific during the boreal summer of 2002.

One approach for improving forecast skill that has received considerable international attention emphasizes the use of multiple forecast systems. For example, the studies by Krishnamurti et al. (1999), Palmer et al. (2004), and others have provided compelling evidence that the forecast skill of a multi-model ensemble (MME) system is higher than that of the individual models regardless of whether the skill measure is probabilistic or deterministic. The MME methodology is emerging as a clear strategy for reducing the impact of model error and quantifying forecast uncertainty associated with uncertainty due to differences in model formulation, and has become operational at the European Centre for Medium-Range Weather Forecasts (ECMWF; i.e., Eurosip), the International Research Institute for Climate and Society (IRI) and at the Asia-Pacidic Climate Center (APCC). In fact, it is our assertion that the implementation of a MME prediction system at NOAA is the most direct path to improving operational seasonal-to-interannual prediction given current dynamic modeling capabilities. However, we emphasize that a multi-model prediction strategy does not remove the need to improve models, data streams or initialization strategies. It is important that the members of a multi-model ensemble be of comparably high quality.

There is ample evidence of the need for a US national multi-model seasonal-to-interannual prediction system. It is in the Nation's interest to have a multi-model seasonal-to-interannual prediction capability independent of information that may be available from outside sources. The advantage of a MME prediction system is that it, in addition to providing additional forecast information for the surface air temperature and

*Correspondence to: Ben Kirtman, RSMAS/MPO, University of Miami, 4600 Rickenbacker Causeway, Miami, FL 33149; E-mail: bkirtman@rsmas.miami.edu

precipitation outlooks that are currently products of the Climate Prediction Center (CPC), the MME can also provide information about fields and phenomena that the US has specific interest in predicting (i.e., ENSO cycle, monsoons, intraseasonal variability, the Madden-Julian Oscillation, among others). Finally, by subjecting the CCSM3 to the rigors of routine seasonal-to-interannual prediction, we can calibrate, and potentially gain additional confidence in, our climate change projections (assuming the model performs reasonably well).

2. CCSM as a Seasonal-to-Interannual Prediction System

Both models used in this study, the CCSM3 and the CFS, are coupled ocean-atmosphere-land models whose formulations of dynamics and subgrid-scale physical parameterizations, in both the atmospheric and oceanic component models, are considered state-of-the-art for this generation of models.

a. CCSM3.0

The CCSM3.0 is a global coupled climate model descended from its predecessor version, the Community Climate System Model version 2 (CCSM2; Kiehl and Gent 2004). However, as described by Collins et al. (2006), a number of changes and improvements have been made to the CCSM3.0. In this proposal we use the T85 version of CCSM3.0, with grid points in the atmospheric model [Community Atmospheric Model version 3 (CAM3)] roughly every 1.4° latitude and longitude, and 26 levels in the vertical. The ocean is a version of the Parallel Ocean Program (POP) with a nominal latitude–longitude resolution of 1° (1/2° in the equatorial Tropics) and 40 levels in the vertical, with Gent–McWilliams and *K*-profile parameterization (KPP) mixing. The land surface model is the Community Land Model (CLM), and the elastic–viscous–plastic (EVP) dynamic and thermodynamic sea ice component is the Community Sea Ice Model version 4 (CSIM4). No flux adjustments are used in the CCSM3.0.

b. CFS

Forecasts made with the operational version of CFS (Saha et al 2006) are used for comparisons and for the multi-model combination. The CFS data (i.e., retrospective forecasts) have been made available by NOAA (see http://cfs.ncep.noaa.gov/). The AGCM is the spectral T62 (triangular truncation at total wavenumber 62) version of the NCEP Global Forecast System (GFS; Moorthi et al., 2001) with a finite-differencing discretization on 64 sigma vertical layers between the Earth's surface and 0.2 hPa. The solar radiation parameterization is the scheme developed by Chou (1992); Chou and Lee (1996) and Chou and Suarez (1999). The parameterized physical processes include horizontal and vertical diffusion (Kanamitsu et al., 1991; Troen and Mahrt, 1986), gravity wave drag (Alpert et al., 1988; Kim and Arakawa, 1995). Deep convection is an implementation of Arakawa-Schubert as reported in Hong and Pan (1998). The model documentation is given in the technical note by the Global Climate and Weather Modeling Branch, EMC (2003) and in Wang et al., 2005.

The OGCM is the GFDL modular Modular Ocean Model version 3 (MOM3) described in Pacanowski and Griffies (1998). The numerical model is a finite-difference treatment of the primitive equations describing the oceanic circulation in spherical coordinates. The domain is that of the World Ocean between 74° S and 65° N. The coastline and bottom topography are realistic except that the ocean depths less than 100 m are set to 100 m. The zonal resolution is 1.0 ° and the meridional resolution is variable. Between 10° S and 10° N is 1/3°, gradually increasing poleward throughout the tropics. Beyond 30° N and 30° S the meridional grid spacing is fixed at 1.0°. In the vertical there are 40 time-independent levels with 27 layers in the upper 400 m. The vertical resolution is 10 m from the surface to the 240-m depth, gradually increasing to 511 m in the bottom layer. The vertical mixing scheme is the non-local K-profile parameterization of Large et al. (1994). The horizontal mixing of tracers and momentum is Laplacian. The momentum mixing uses the space-time-dependent scheme of Smagorinski (1963) and the tracer mixing uses Redi (1982) diffusion along with Gent and McWilliams (1990) quasi-adiabatic stirring.

c. Ocean Initialization

Here we briefly describe how we have initialized the ocean component of CCSM3 (POP) in our preliminary retrospective prediction experiments. The ocean initialization uses data assimilation products made available by GFDL (Rosati and Harrison, 2002; personal communication). The GFDL ocean data assimilation system is based on MOM3 using a variational optimal interpolation scheme (Derber and Rosati, 1989). The GFDL ocean initial states are interpolated to the POP grid, and since the CFS Reanalysis and Reforecast (CFSRR) project uses MOM4, we expect that the overall process will be similar in the proposed experiment, although some modifications may be required.

The following is the procedure to produce the POP restart file converted from the MOM3 ocean data assimilation restart. The fields of the MOM3 restart file have values at time levels τ and τ+1, while POP has data at time levels τ-1, τ, and τ+1. The τ-1 time level is simple taken from the time level τ data. Both restart files have different resolutions in horizontal and vertical. The MOM3 meridional domain covers 75S to 65N, while the POP domain is global. The MOM3 fields have been interpolated horizontally and vertically using a bi-linear interpolation scheme, which has also been used previously to reduce the resolution in MOM3-based prediction experiments (Kirtman 2003). Climatological data from long simulations of CCSM3 are used in regions where MOM3 data is undefined (i.e., poleward of 65N and 75S). The surface pressure for POP is estimated using the sea surface height and the pressure gradient terms are estimated using centered differencing. As part of the proposed research we will modify the ocean initialization strategy to use the data from the 30-year NCEP CFSRR project.

d. Atmospheric Initialization

The atmospheric initial states are taken from an extended atmosphere-only (CAM3) simulation with observed, prescribed SST. The atmospheric ensemble members were obtained by resetting the model calendar back one week and integrating the model forward one week with prescribed observed SST. In this way, it is possible to generate an unlimited sample of initial conditions that are synoptically independent (separated by one week) but have the same initial date. This procedure was also used by Kirtman (2003) for ENSO prediction and Kirtman et al. (2001) to generate a 100-member ensemble for atmospheric seasonal prediction experiments.

e. Land Initialization

We have adopted an approach that is analogous to the procedure implemented with CAM, namely we use “AMIP”-type initial conditions.

f. Sea Ice Initialization

The sea-ice initial conditions set to the climatological monthly condition based on a long simulation of CCSM3.0. No observational information is included in the sea-ice initial conditions. As part of the proposed research we will modify the sea-ice initialization strategy to use the results from the 30-year NCEP CFSRR project.

g. Retrospective Forecast Experiments

To assess the potential predictive skill of the CCSM3.0, a large sample of retrospective forecast experiments have been made and compared to available observations. The retrospective forecasts cover the period 1982–1998. A 12-month hindcast is initialized each 1 January and 1 July during this 17-yr period. For each initial month, an ensemble of six hindcasts is run, yielding a total of 204 retrospective forecasts to be verified. The hindcast ensembles are generated by atmospheric perturbations only and no attempt has been made to find optimal perturbations. The ocean initial state for each ensemble member is identical. We acknowledge that with this approach we may underestimate the uncertainty in any individual forecast. We emphasize that these particular hindcasts were designed as a “proof of concept” in terms of developing a national multi-model prediction system.

Throughout the ENSO prediction literature there is some confusion regarding the appropriate definition of forecast lead-time. In this discussion, forecast lead-time is defined as in the following example. A CCSM3.0 forecast, initialized on 0000*Z* 1 January 1982, is labeled as being initialized in January 1982. The first monthly mean (i.e., the average of 1–31 January 1982) of the forecast is defined as the 0-month lead forecast. Similarly, the second monthly mean (i.e., 1–28 February 1982) is defined as the first month lead forecast. The CFS hindcast lead-times are defined similarly, but there are notable differences. For example, the forecast where January 1982 is lead-time zero (February 1982 is lead-time one month) is made up of 15 ensemble members.

Five ensemble members are initialized during 9-13 December 1981, 5-members are initialized 19-23 December and 5-members are initialized December 30-January 3, 1982. The remaining lead-times are defined analogously. In the CFS hindcast archive this forecast is referred to the January 1982 case. We have in the deterministic verification discussed below (i.e., Fig. 2) to combine, for example, the five CFS forecasts initialized on 30 December – January 3 with the six CCSM3.0 forecasts initialized on 1 January. There is a trade off here; we have chosen a sub-ensemble so that the multi-model combination is as “clean” as possible. As part of the proposed research the initial condition time and lead-time will follow the CFSRR project strategy thus removing the above confusion and difficulty in formulating the MME.

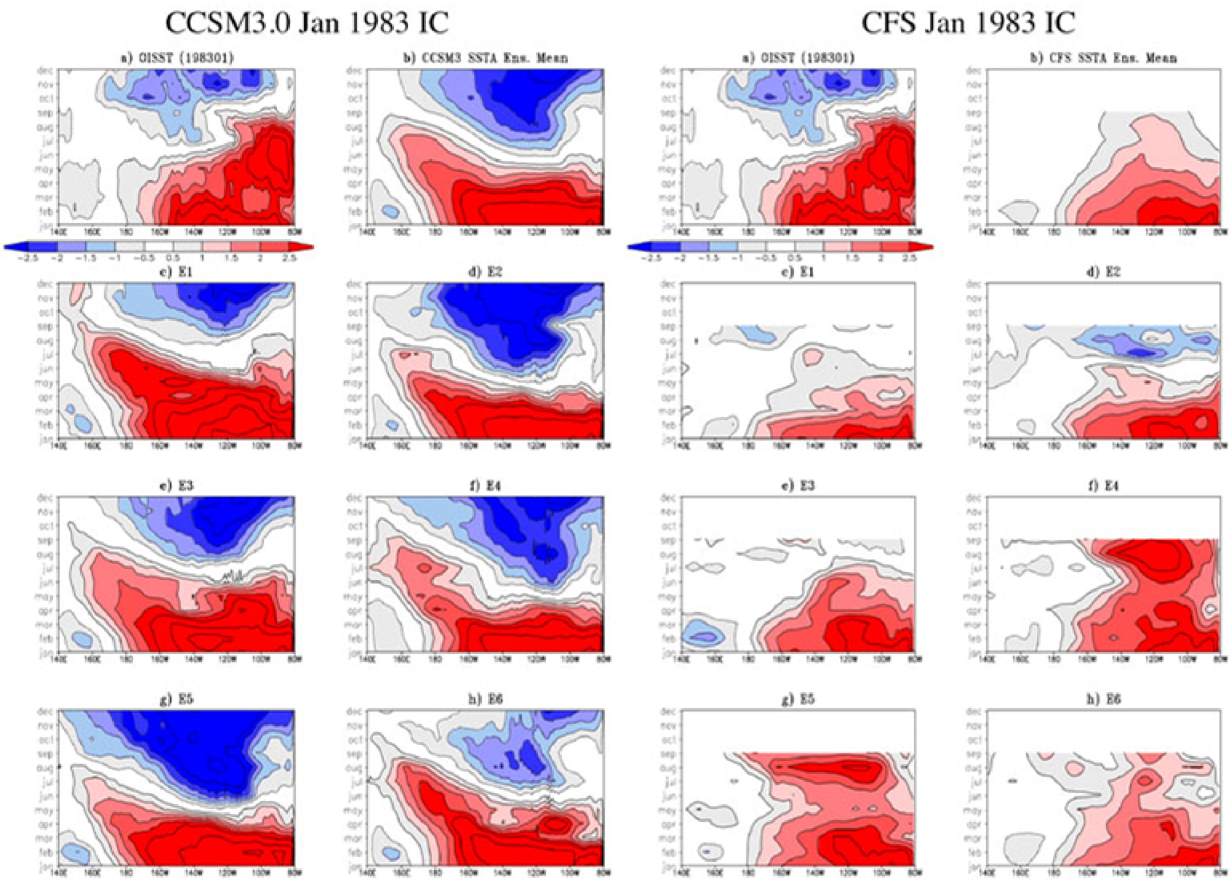

Figure 1 Time-longitude equatorial Pacific SSTA cross-sections for each CCSM3.0 ensemble member and for six randomly chosen ensemble members from the CFS hindcast data set. In each set of panels the top left is the observed SSTA and the top right is the ensemble mean model SSTA. In this example, the first full forecasted month is January 1983.

h. Deterministic Verification

Figure 1 shows the evolution of the SSTA along the equator in the Pacific in 1983 as an example. The figure has time-longitude sections for each of the six CCSM3.0 ensemble members and for six CFS ensemble members randomly chosen from the 15 hindcast members verifying at the same target month and lead time. The CCSM3.0 SSTA forecasts have notable westward phase propagation, which *may* be ameliorated in CCSM3.5. This is consistent with the errors in the “free running” model. Other examples (not shown), suggest that the CCSM3.0 forecasts appear to do a better job on the transition from warm to cold SSTA. This is probably due to the fact that the CFS tends to persist warm events longer than observed. The CCSM3.0 also appears to be more confident in forecasting cold events. This may be a weakness. Both models are quite weak for the forecast of the 1997 warm event (not shown).

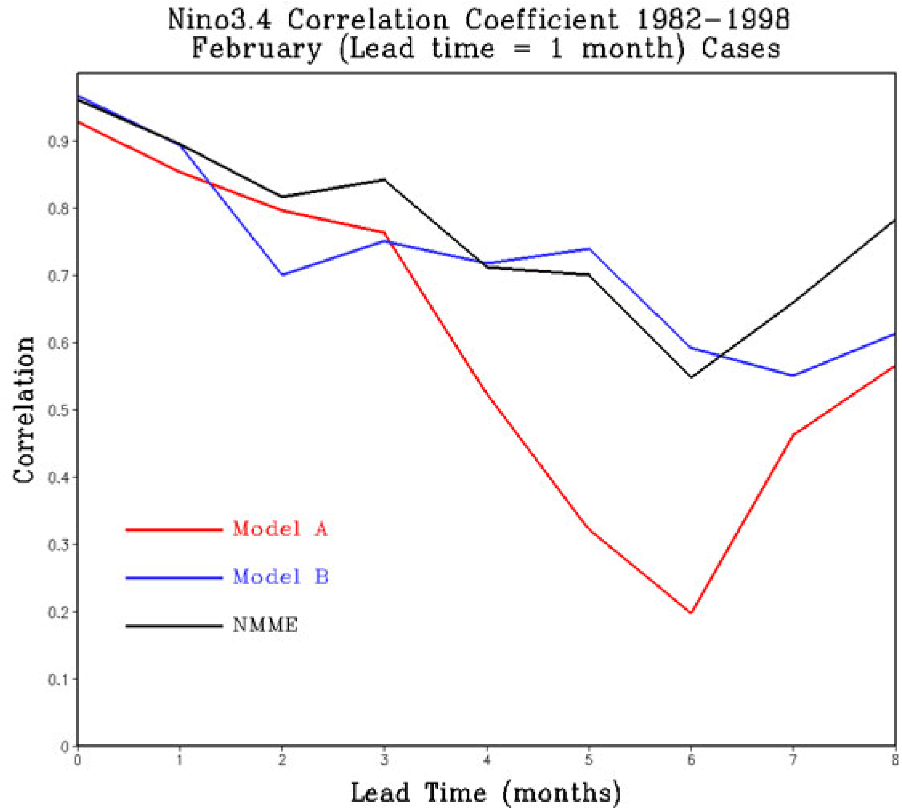

Figure 2 Correlation coefficient of Nino3.4 as a function of lead-time for both models (red and blue curves) and the National Multi-Model Ensemble (NMME; black curve). The removal of the systematic error is based on all 18-years of data for each model.

To form a multi-model ensemble, we use the six CCSM3.0 members initialized on 1 January for each year 1982-1998, and for CFS we use the five ensemble members initialized on 30 December – 3 January for each year 1982-1998. Figure 2 shows the correlation coefficient for each model (we have chosen not to identify which model is which) and the 11-member multi-model ensemble. The systematic error for each model is calculated in the same way as is based on the limited sample from 1982-1998. In calculating the correlation coefficients we use the ensemble means. There are several points to note:

(i) The multi-model ensemble mean (black curve) has the highest correlation for most lead times;
(ii) The multi-model correlation is higher than simply averaging the correlation from the two different models;
(iii) Most notably the large drop in skill for Model A for lead times 4-6 has only a small impact on the multi-model skill;
(iv) Based on 11-member sub-sampling of the CFS data (not shown), the overall multi-model improvement is better than a same-sized ensemble from a single model (this is consistent with the results from the DEMETER project).

This suggests that the correlation coefficient for the multi-model ensemble is generally higher than either model alone, although we need to use larger ensembles, more forecast cases and ensure consist use of lead-time. Moreover, as lead-time increases the multi-model ensemble has a larger impact on the correlation. Similar results are found with the root mean square error. These results are quite encouraging in terms of developing a US national multi-model ensemble prediction system.

References:

Alpert, J. C., and co-authors, 1988: Mountain induced gravity wave drag parameterization in the NMC medium-range model. Preprints. Eight Conf. on Numerical Weather Prediction, Amer. Meteor. Soc., 429-432.

Alves, O., G., and co-authors, 2002: POAMA: Bureau of Meteorology Operational Coupled Model Seasonal Forecast System. Proceedings of the ECMWF Workshop on the Role of the Upper Ocean in Seasonal Forecasting.

Barnston, A. G., M. Glantz, and Y. He, 1999: Predictive skill of statistical and dynamical climate models in SST forecasts during the 1997–98 El Nin˜o and the 1998 La Nin˜a onset. *Bull. Amer. Meteor. Soc.*, **80,** 217–243.

Battisti, D., and A. C. Hirst, 1989: Interannual variability in a tropical atmosphere–ocean model: Influence of the basic state, ocean geometry and nonlinearity. *J. Atmos. Sci.*, **46,** 1687–1712.

Chou, M. D., 1992: A solar radiation model for use in climate studies. J. Atmos. Sci., **49**, 762–772.

Chou, M. D. and K. T. Lee, 1996: Parameterization for the absorption of solar radiation by water vapor and ozone. J. Atmos. Sci., **53**, 1204–1208.

Chou, M. D. and M. Suarez, 1999: A solar radiation parameterization for atmospheric studies. NASA/TM-1999-104606, **Vol 15**. 40pp.

Collins, W. D., and co-authors, 2006: The Community Climate System Model version 3 (CCSM3). *J. Climate*, **19,** 2122-2143.

Davey, M. K., and Coauthors, 2001: STOIC: A study of coupled model climatology and variability in tropical ocean regions. *Climate Dyn.*, **18**, 403-420.

Delworth, T.L., and co-authors, 2006: GFDL's CM2 Global Coupled Climate Models. Part I: Formulation and Simulation Characteristics. J. Climate, **19**, 643–674.

DelSole, T., 2007: A Bayesian Framework for Multimodel Regression. *J. Climate*, **20**, 2810-2826.

Derber, J., and A. Rosati, 1989: A global oceanic data assimilation system. *J. Phys. Oceanogr.*, **19,** 1333–1347.

DeWitt, D.G., 2005: Retrospective Forecasts of Interannual Sea Surface Temperature Anomalies from 1982 to Present Using a Directly Coupled Atmosphere–Ocean General Circulation Model. Mon. Wea. Rev., **133**, 2972–2995.

Dirmeyer, P.A., Gao, X., Zhao, M., Guo, Z., Oki, T., Hanasaki, N., 2005: The Second Global Soil Wetness Project (GSWP-2): Multi-Model Analysis and Implications for our Perception of the Land Surface, CTR 185, 46 pp.

Gent, P. R. and J. C. McWilliams, 1990: Isopycnal mixing in ocean circulation models. J. phys. Oceanogr., **20**, 150–155.

Hong, S. Y. and H. L. Pan, 1998: Convective trigger function for a mass-flux cumulus parameterization scheme. Mon. Wea. Rev., **124**, 2322–2339.

Ji, M., A. Kumar, and A. Leetmaa, 1994: An experimental coupled forecast system at the National Meteorological Center: Some early results. *Tellus*, **46A,** 398–418.

Kanamitsu, M., and co-authors, 1991: Recent changes implemented into the global forecast system at NMC. Wea. and Forecasting, **6**, 425–435.

Kanamitsu, M., and coauthors, 2002: NCEP-DOE AMIP–II Reanalysis (R-2). Bull. Amer. Meteor. Soc., **83**,1631–1643.

Kiehl, J. T. and P. R. Gent, 2004: The Community Climate System Model, version 2. *J. Climate*, **17,** 3666-3682.

Kim, Y. J. and A. Arakawa, 1995: Improvement of orographic gravity wave parameterization using mesoscale gravity wave model. J. Atmos. Sci., **52**, 1875–1902.

Kirtman, B. P., 1997: Oceanic Rossby wave dynamics and the ENSO period in a coupled model. J. Climate, **10**, 1690–1704.

Kirtman, B. P., J. Shukla, B. Huang, Z. Zhu and E. K. Schneider, 1997: Multiseasonal predictions with a coupled tropical ocean global atmosphere system. *Mon. Wea. Rev.*, **125**, 789-808.

Kirtman, B. P., 2003: The COLA anomaly coupled model: Ensemble ENSO prediction. mon. Wea. Rev, **131**, 2324–2341.

Kirtman, B. P. and P. S. Schopf, 1998: Decadal variability in ENSO predictability and prediction. J. Climate, **11**, 2804–2822.

Kirtman, B. P., D. A. Paolino, J. L. Kinter III and D. M. Straus, 2001: Impact of tropical subseasonal SST variability on seasonal mean climate. *Mon. Wea. Rev.*, **129**, 853-868.

Kirtman, B. P., Y. Fan and E. K. Schneider, 2002: The COLA global coupled and anomaly coupled ocean-atmosphere GCM. *J. Climate*, **15**, 2301-2320.

Kirtman, B. P., and J. Shukla, 2002: Interactive coupled ensemble: A new coupling strategy for GCMs. *Geophys. Res. Lett*., **29**, 1029-1032.

Kirtman, B. P., K. Pegion, and S. Kinter, 2005: Internal atmospheric dynamics and climate variability. J. Atmos. Sci., **62**, 2220-2233.

Krishnamurti, T. N., and co-authors, 1999: Improved weather and seasonal climate forecasts from multi- model superensemble. Science, **285**, 1548–1550.

Landsea, C. W., and J. A. Knaff, 2000: How much skill was there in forecasting the very strong 1997–98 El Nin˜o? *Bull. Amer.Meteor. Soc.*, **81,** 2107–2120.

Large, W. G., J. C. McWilliams, and S. C. Doney, 1994: Oceanic vertical mixing: A review and a model with a nonlocal boundary layer parameterization. Rev. Geophys., **32**, 363–403.

Leetmaa, A., and M. Ji, 1989: Operational hindcasting of the tropical Pacific. *Dyn. Atmos. Oceans,* **13,** 465–490.

McPhaden, M. J., and co-authors, 1998: The Tropical Ocean-Global Atmosphere observing system: A decade of progress, ournal of Geophysical Research, **103(C7)**, 14,169-14,240 (1998).

Mechoso, C. R., and Coauthors, 1995: The seasonal cycle over the tropical Pacific in coupled ocean–atmosphere general circulation models. *Mon. Wea. Rev.,* **123**, 2825–2838.

Moorthi, S., H.-L. Pan, and P. Caplan, 2001: Changes to the 2001 NCEP operational MRF/AVN global analysis forecast system. NWS Tech. Procedures Bulletin 484, 14pp. (Available online at http://www.nws.noaa.gov/om/tpb/484.htm).

Neelin, J. D., and and Coauthors, 1992: Tropical air–sea interaction in general circulation models. *Climate Dyn.*, **7**, 73–104.

Pacanowski, R. C. and S. M. Griffies, 1998: Mom3.0 manual. NOAA/Geophysical Fluid Dynamics Laboratory, 638pp.

Palmer, T. N., and Coauthors, 2004: Development of a European multimodel ensemble system for seasonal to interannual prediction (DEMETER). *Bul. Amer. Met. Soc*., **85,** 853-872.

Philander, S. G. H., T. Yamagata, and R. C. Pacanowski, 1984: Unstable air–sea interactions in the Tropics. *J. Atmos. Sci.*, **41,** 603–613.

Pegion, K. and B. P. Kirtman, 2007: Internal atmospheric variability and the Madden-Julian Oscillation. J. Climate (submitted).

Pena, M. and H. van den Dool, 2008: Consolidation of Multi Model Forecasts by Ridge Regression: Application to Pacific Sea Surface Temperature. Submitted to J. Climate.

Rosati, A., R. Gudgel, and K. Miyakoda, 1997: The impact of ocean initial conditions on ENSO forecasting with a coupled model. *Mon. Wea. Rev.,* **125,** 754–772.

Redi, M. H., 1982: Oceanic isopycnal mixing by coordinate rotation. J. Phys. Ocean., **12**, 1155–1158.

Saha, S., S., and co-authors, 2006: The NCEP Climate Forecast System. J. Climate, **19**, 3483–3517.

Schneider, E. K., and co-authors, 1997: ENSO variability in a coupled general circulation model. *Mon. Wea. Rev.*, **125**, 680-702.

Schneider, E. K., and co-authors, 1999: Ocean data assimilation, initialization and prediction with a coupled GCM. *Mon. Wea. Rev.*, **127**, 1187-1207.

Schneider, and co-authors, 2003: Retrospective ENSO forecasts: Sensitivity to atmospheric model and ocean resolution. Mon. Wea. Rev., 131, 3038–3060.

Schopf, P. S., and M. J. Suarez, 1988: Vacillations in a coupled ocean– atmosphere model. *J. Atmos. Sci.,* **45,** 549–566.

Smagorinski, J., 1963: General circulation experiments with the primitive equations. I. The basic experiment. Mon. Wea. Rev., **91**, 99–164.

Stan, C., and B. P. Kirtman, 2007: Internal atmospheric dynamics and tropical Pacific predictability in a coupled GCM. *J. Climate* (in press).

Stockdale, T. N., D. L. T. Anderson, J. O. S. Alves, and M. A. Balmaseda, 1998: Global seasonal rainfall forecasts using a coupled ocean–atmosphere model. *Nature,* **392,** 370–373.

Troen, I. and L. Mahrt, 1986: A simple model of atmospheric boundary layer; Sensitivity to surface evaporation. Bound.-Layer Meteor, **37**, 129–148.

Uppala, S.M., and co-authors, 2005: The ERA-40 re-analysis. Quart. J. R. Meteorol. Soc., **131**, 2961-3012.doi:10.1256/qj.04.176

Vikhliaev, Y., and B. P. Kirtman, 2007: Understanding the role of instability and stochastic forcing of ENSO dynamics using the breeding method. J. Climate, in press.

Wang, G., R. Kleeman, N. Smith, and F. Tseitkin, 2002: The BMRC coupled general circulation model ENSO forecast system. *Mon. Wea. Rev.,* **130,** 975–991.

Wang, W., S. Saha, H.L. Pan, S. Nadiga, and G. White, 2005: Simulation of ENSO in the New NCEP Coupled Forecast System Model (CFS03). Mon. Wea. Rev., **133**, 1574–1593.

Wheeler, M.C., and H.H. Hendon, 2004: An all season real-time multivariate MJO index: Development of an index for monitoring and prediction. *Mon. Wea. Rev*., **132**, 1917-1932.

Wittenberg, A.T., A. Rosati, N.C. Lau, and J.J. Ploshay, 2006: GFDL's CM2 Global Coupled Climate Models. Part III: Tropical Pacific Climate and ENSO. J. Climate, **19**, 698–722.

Wu, Z., E. K. Schneider and B. P. Kirtman, 2004: Causes of low frequency North Atlantic SST variability in a coupled GCM. Geophys. Res. Lett., 31, L09210, doi:10.1029/2004GL019548.

Wu, R, and B. P. Kirtman, 2004a: The tropospheric biennial oscillation of the monsoon-ENSO system in an interactive ensemble coupled GCM. J. Climate, **17**, 1623-1640.

Wu, R., and B. P. Kirtman, 2004b: Understanding the impacts of the Indian Ocean on ENSO variability in a coupled GCM. J. Climate, **17**, 4019-4031.

Wu, R., and B. P. Kirtman, 2004c: Impacts of the Indian Ocean on the Indian summer monsoon-ENSO relationship. J. Climate, **17**, 3037-3054.

Wu, R., and B. P. Kirtman, 2005: Role of Indian and Pacific Ocean air-sea coupling in tropical atmospheric variability. Climate Dyn. **25**, 155-170.

Wu, R., and B. P. Kirtman, 2006: Changes in spread and predictability associated with ENSO in an ensemble coupled GCM. J. Climate, **19**, 4378-4396.

Yeh, S.-W., and B. P. Kirtman, 2003: On the relationship between the interannual and decadal SST variability in the North Pacific and the Tropical Pacific Ocean. J. Geophys. Res., **108(D11)**, 4344, doi:10.1029/2002JD002817

Yeh, S.-W., and B. P. Kirtman, 2004a: The impact of internal atmospheric dynamics for the North Pacific SST variability, Climate. Dyn. doi:10.1007/s00382-004-0399-8.

Yeh, S.-W., and B. P. Kirtman, 2004b: The North Pacific oscillation-ENSO and internal atmospheric variability. Geophys. Res. Lett., **31**, doi:10.1029/2004GL019983, 2004.

Yeh, S.-W., B. P. Kirtman, and Soon-il An, 2007: Local versus non-local atmospheric weather noise and North Pacific SST variability. Geophys. Res., Lett., **34**, doi:10.1029/2007GL030206, 2007.

Yeh, S.-W., and B. P. Kirtman, 2004c: Tropical Pacific decadal variability and ENSO amplitude modulation in a CGCM. J. Geophys. Res. – Oceans, **109**, C11009, doi:10.1029/2004JC002442.

Yeh, S.-W., and B. P. Kirtman, 2004d: The North Pacific oscillation-ENSO and internal atmospheric variability. Geophys. Res. Lett., doi:10.1029/2004GL019983.