Fundamental challenge in simulation and prediction of summer monsoon rainfall

Bin Wang,[1] Qinghua Ding,[1] Xiouhua Fu,[1] In-Sik Kang,[2] Kyung Jin,[2] J. Shukla,[3] and Francisco Doblas-Reyes[4]

Received 16 February 2005; revised 17 June 2005; accepted 13 July 2005; published 12 August 2005.

[1] The scientific basis for two-tier climate prediction lies in the predictability determined by the ocean and land surface conditions. Here we show that the state-of-the-art atmospheric general circulation models (AGCMs), when forced by observed sea surface temperature (SST), are unable to simulate properly Asian-Pacific summer monsoon rainfall. All models yield positive SST-rainfall correlations in the summer monsoon that are at odds with observations. The observed lag correlations between SST and rainfall suggest that treating monsoon as a slave possibly results in the models' failure. We demonstrate that an AGCM, coupled with an ocean model, simulates realistic SST-rainfall relationships; however, the same AGCM fails when forced by the same SSTs that are generated in its coupled run, suggesting that the coupled ocean-atmosphere processes are crucial in the monsoon regions where atmospheric feedback on SST is critical. The present finding calls for reshaping of current strategies for monsoon seasonal prediction. The notion that climate can be modeled and predicted by prescribing the lower boundary conditions is inadequate for validating models and predicting summer monsoon rainfall.

Citation: Wang, B., Q. Ding, X. Fu, I.-S. Kang, K. Jin, J. Shukla, and F. Doblas-Reyes (2005), Fundamental challenge in simulation and prediction of summer monsoon rainfall, *Geophys. Res. Lett.*, *32*, L15711, doi:10.1029/2005GL022734.

1. Introduction

[2] The atmosphere, by itself, cannot produce random variations that persist for months; the source of predictability beyond two weeks must therefore come from the lower boundary conditions [*Charney and Shukla*, 1981; *Shukla*, 1998]. The ocean has a large heat capacity, giving the climate system a memory that can result in atmospheric deviations lasting for months to years. Thus, current notions on the atmospheric model validation and the two-tier climate prediction, which predicts future atmospheric conditions using an AGCM alone forced by pre-forecasted SSTs [*Bengtsson et al.*, 1993], are based on the premise that the atmospheric models alone should be able to reproduce climate anomalies or capture the predictable portion of climate variations when the models are forced by the observed or "perfectly predicted" SSTs. In a recent assessment of AGCMs performance, *Wang et al.* [2004] challenged this conventional notion. They found that the eleven AGCMs that participate in the Climate Variability and Predictability Program (CLIVAR)/Monsoon Intercomparison Project show no skill in their ensemble simulations of the summer rainfall anomalies during the 1997–1998 El Niño. Different from the previous investigations, they argued that the neglect of air-sea interaction is possibly a major cause of the models' failure. However, their results were obtained for a two-year period during which the unprecedented 1997/98 El Niño might have unusual impacts on the model simulations. Here we further examine the simulation skill of five state-of-the-art AGCMs in seasonal precipitation for a 20-year period of 1979–1998. These models were forced by identical observed SST and sea-ice, following the design of the Atmospheric Model Intercomparison Project (AMIP) [*Gates et al.*, 1999]. Each model made 6 to 10 member integrations to minimize weather noises and enhance climate signal. A multi-model ensemble (MME) mean was made to reduce uncertainties arising from the models' parameterization of sub-grid scale processes.

[3] Figure 1 shows the overall skill of the five-model ensemble simulation measured by the correlation coefficients between the observed and simulated rainfall anomalies. In the Asian-Pacific summer monsoon (APSM) region (5°N –30°N, 70°E –150°E), the skills are very low, which is in sharp contrast to the high skills in the El Niño region (10°S–5°N, 160°E–80°W) where each individual model and MME show a correlation coefficient between 0.6 and 0.8. Figure 2 shows that in the APSM and especially in the tropical western North Pacific (WNP, 5°N–30°N, 110°E – 150°E), all models and their MME have virtually no skills. The poor simulations of the Indian rainfall were previously noted [e.g., *Sperber and Palmer*, 1996; *Gadgil and Sajani*, 1998]. The results here indicate that the performance of AGCMs in the tropical WNP is even worse than over India. The results here also indicate that the failure on monsoon rainfall simulation given by *Wang et al.* [2004] is not specific to the period that is affected by the 1997/98 El Niño episode, rather it is a general 'syndrome' in monsoon climate simulation.

[4] Based on the Climate Prediction Center Merged Analysis of Precipitation (CMAP) data [*Xie and Arkin*, 1997], the June–September rainfall in the APSM region accounts for approximately 30% of the total tropical rainfall, albeit this region occupies only ~10% of the tropics between 30°S and 30°N. The rainfall in this region plays a critical role in maintaining the global energy/water cycle

[1]School of Ocean and Earth Science and Technology, University of Hawai'i, Honolulu, Hawaii, USA.
[2]School of Earth and Environmental Sciences, Seoul National University, Seoul, South Korea.
[3]Climate Dynamics, George Mason University, Fairfax, Virginia, USA.
[4]European Centre for Medium-Range Weather Forecast, Reading, UK.

0094-8276/05/2005GL022734$05.00

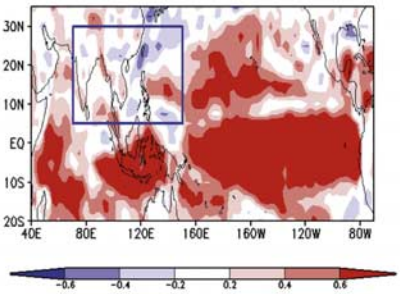

Figure 1. Correlation coefficients between the observed CMAP (1979–1999) and the simulated June–August precipitation anomalies made by five-model multi-ensemble mean. The five models are National Center for Environmental Prediction (NCEP), Japan Meteorological Agency (JMA), Center for Ocean-Land-Atmosphere (COLA), National Aeronautical Space Agency (NASA), and Seoul National University/Korean Meteorological Administration (SNU/KMA).

and driving the monsoon climate variability and has far-reaching impacts on El Niño and global circulation [*Webster et al.*, 1998; *Wang et al.*, 2001]. In this paper, we propose one possible answer to the question of why nearly all AGCMs, when they are given the observed lower-boundary forcing, are unable to reproduce the summer monsoon precipitation anomalies? This question is of fundamental importance to climate simulation and prediction.

2. Observed Relationship Between Rainfall and SST Anomalies

[5] A key to seasonal prediction is to understand the relationship between the slowly varying boundary conditions and rainfall anomalies. Figure 3a shows an observed anomalous rainfall-SST relationship derived from CMAP and Optimal Interpretation SST [*Reynolds et al.*, 2002] for summer seasons (June through August) of 1982–2001. Superposed on these anomaly correlations are the contours of 6 and 10 mm/day rainfall rate that highlight the regions of heavy rainfall. The local SST and precipitation anomalies are positively correlated in the tropical eastern-central Pacific. However, the correlations are negative in the WNP and insignificant in the Bay of Bengal. The SST-rainfall correlations in the MME simulation disagree with observations primarily in the Asian-Pacific monsoon regions where the model rainfall tends to correlate positively with local SST (Figure 3b). In particular, over the WNP the observed area-averaged correlation coefficient is −0.36 while in the MME simulation is 0.24, both statistically significant at the 1% confidence level.

[6] In general, a negative correlation between the seasonal-mean SST and rainfall anomalies may indicate that the atmosphere affects SST more than SST affects the atmosphere; conversely, a positive correlation means the ocean plays a major role in determining atmospheric response [*Wang et al.*, 2004]. To test this assertion, we computed the lag correlations between monthly mean SST and rainfall anomalies. As shown in Figure 4a, when rainfall leads SST by one month, there is a significant negative correlation in the APSM region, suggesting that the atmosphere has a significant control on SST. Of note is that the simultaneous monthly correlations are also negative though in less degrees. However, when SST precedes precipitation by one month, the correlations in the same region are only marginally positive. Given the persistence of SST anomalies and the rapid response of the atmosphere to SST, the aforementioned results imply that the impact of SST on the atmosphere is weaker than the effect of the atmosphere on SST. Thus, the SST anomalies in the summer monsoon region cannot be interpreted as a forcing; rather the SST anomalies in the WNP are, on an average, determined by the anomalous atmospheric conditions.

[7] The finding that the models are unable to reproduce the actual SST-rainfall relationship provides a clue to why these models are unsuccessful in simulating summer monsoon rainfall. While the models' deficiencies are somewhat to blame (for a detailed discussion, see *Wang et al.* [2004]), we offer that the models' failures are likely due to the lack of atmospheric feedback to the ocean in the experimental design, because in the simulation experiments the SST is prescribed as a forcing.

3. Results of Numerical Experiments With Coupled and Forced AGCMs

[8] If the erroneous positive rainfall-SST correlation in the summer monsoon region results mainly from excluding

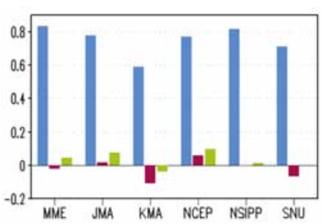

Figure 2. Simulation scales for June–August mean precipitation as measured by area averaged correlation coefficients between the observed CMAP and simulation by five AGCMs and their multi-model ensemble (MME) for regions of El Niño (blue, 10°S–5°N, 80°W–180°W), Asian-Pacific summer monsoon (green, 5°N–30°N, 70–150°E), and WNP summer monsoon (pink, 5°N–30°N, 110–150°E).

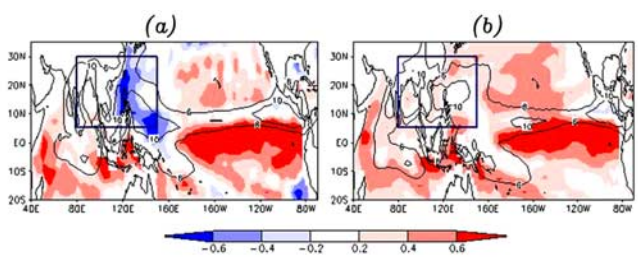

Figure 3. (a) Observed and (b) simulated correlation coefficients between the June–August SST and precipitation anomalies (the color shadings). The contours denote the climatological June–August mean rainfall rate (in units of mm day^{-1}). The observed correlations were computed using 20 years of data (1982–2001) derived from CMAP rainfall and Reynolds SST. The simulated results were made by 5 AGCM's multi-model ensemble simulation.

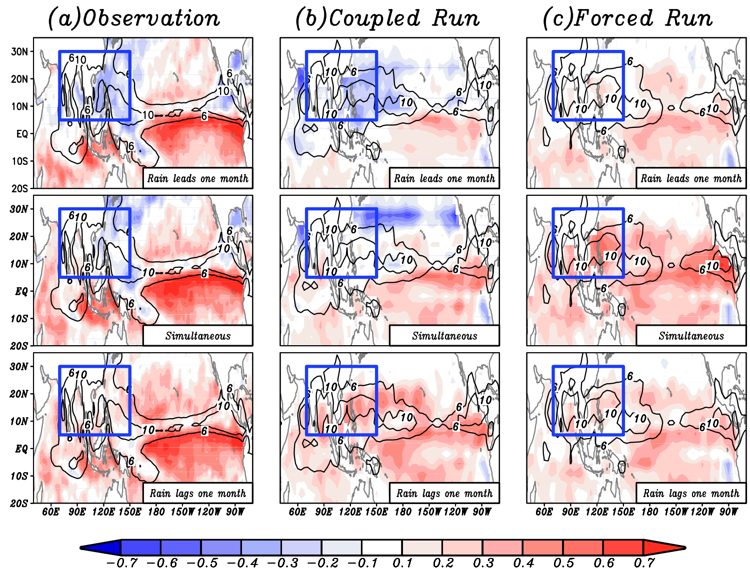

Figure 4. (a) Observed lead-lag correlation between monthly mean SST and precipitation anomalies computed for May through October of 1982–2001. (top) The correlation coefficients when precipitation leads SST by one month, (middle) is concurrent with SST, and (bottom) lags SST by one month. The sample size is 80 for the time series at each grid. (b) The same as in Figure 4a except that the correlations were computed from the coupled ECHAM-ocean model simulation. (c) The same as in Figure 4a except that the correlations were computed from the forced ECHAM simulation.

atmospheric feedback to ocean, then one should be able to reproduce the observed negative correlation with a coupled atmosphere-ocean model. To test this idea, we performed a suite of numerical experiments with a coupled atmosphere-ocean model. The atmospheric component of this coupled model is a T30 version of the ECMWF (European Centre for Medium-range Weather Forecast)-Hamburg (ECHAM4) AGCM [*Roeckner et al.*, 1996]. The ocean component is a $2\frac{1}{2}$-layer tropical upper-ocean model [*Wang et al.*, 1995]. The coupling, namely atmosphere-ocean interaction, was through both the momentum and heat flux exchanges without flux correction. Daily coupling was applied to the global tropics between 30°S and 30°N and climatological SSTs and sea ice outside the tropics were specified. The coupled model was integrated for 50 years, and the last 40 years of data were used for analysis. This coupled model, in general, realistically simulates the climatological mean precipitation and SST, the spatial pattern and temporal characteristics of El Niño, and the tropical intraseasonal oscillation [*Fu and Wang*, 2004].

[9] In the coupled experiment, the AGCM is allowed to interact with the ocean model. In the "forced" experiment the same AGCM was integrated using, as lower boundary forcing, the same SSTs that were produced by the coupled model. The only difference between the coupled and forced experiments is in their initial conditions, which are trivial for climate simulation. The differences in the simulation outcomes between the two experiments are interpreted as being due to the lack of atmospheric feedback.

[10] Figure 4b shows that the coupled run produces lag correlation patterns that bear qualitative similarities with the corresponding observed counterparts. In the Asian-Pacific monsoon region, the correlations change signs from lag −1 to lag +1 month in both the observation and the coupled run, although the simultaneous negative correlations in the coupled simulation are somewhat lower and the positive correlations at lag +1 are higher. When rainfall leads SST by 1-month, the monsoon precipitation and SST are significantly negatively correlated, resembling closely the observations. In contrast, the results obtained from the forced experiment (Figure 4c) show a significant concurrent positive correlation and similar positive, but lower, lead-lag correlations. This persistent positive correlation pattern with a maximum concurrent correlation suggests that slow variations of SST in the model act to regulate local rainfall anomalies: The atmospheric response to the underlying SST forcing is sufficiently rapid, making the maximum monthly correlation occur without a lag.

[11] The results shown in Figure 4 imply that the coupled and forced solutions represent different monsoon climates. This "bifurcation" of solution is essentially caused by the absence of atmospheric feedback in the forced run. Obviously, the errors in the initial conditions trigger how or where the forced and coupled solutions depart.

[12] The coupled model results are compared with the newly released multi-model seasonal prediction experimental results from the European Union-funded DEMETER project (*D*evelopment of a *E*uropean *M*ulti-model *E*nsemble system for seasonal to in*ter*annual prediction). DEMETER was carried out by European partners and coordinated by ECMWF [*Palmer et al.*, 2004]. Seven coupled models participated in this experiment. The coupled model forecasts for May–October season demonstrate that the local SST-precipitation relationships in all the coupled models resemble that shown in Figure 4b, confirming that these coupled models, despite their different physical schemes, are able to produce qualitatively realistic SST-rainfall relationships. In addition, when these atmospheric models are driven by

persistent SSTs, the local SST-rainfall correlations become similar to those found in the forced run (Figure 4c).

4. Concluding Remarks

[13] We have shown that observed seasonal mean rainfall and SST anomalies are negatively correlated in the Asian-Pacific summer monsoon heavy rainfall region, especially when rainfall leads SST by one month, suggesting that SST anomalies are forced by the atmospheric anomalies. We have demonstrated that the coupled models can reproduce the lead/lag correlation between SST and precipitation anomalies realistically. However, if the same atmospheric model is forced by the SST anomalies that are produced by the coupled model, the resulting local SST-rainfall relationships are at odds with observations. The neglect of atmospheric feedback makes the forced solution depart from the coupled solution in the presence of initial noises.

[14] We argue that the unsuccessful simulations of the rainfall variability in the Asian-Pacific summer monsoon under AMIP-type experimental design are partly caused by the neglect of air-sea interaction in the warm Indo-Pacific oceans. In reality and in the coupled model, the SST in the warm pool is primarily a result of atmospheric forcing, thus, the abnormal precipitation and SST are negatively correlated. On the other hand, if the SST is considered as a forcing to the model atmosphere, the atmospheric model would be unable to reproduce the correct rainfall anomalies, because the forced response tends to produce a positive local rainfall-SST relationship.

[15] The present finding suggests that the coupled atmosphere-ocean processes are extremely important in the heavily precipitating monsoon regions. *Kumar et al.* [2005] also demonstrate significant improvements in the skill of Indian monsoon predictions when atmospheric models are coupled with the ocean. Additionally, *Wu and Kirtman* [2005] showed the critical role of Indian Ocean coupling in simulating atmospheric variability over the Pacific Ocean.

[16] The results presented in this study call for rethinking current strategies for validating dynamic climate models and for climate prediction. In contrary to conventional notion, the summer monsoon rainfall cannot be simulated correctly by prescribing lower boundary forcing. While the AMIP has provided a useful benchmark for model sensitivity and predictability experiments to SST forcing, our results reveal an intrinsic limitation in this manner of simulating summer monsoon precipitation. To adequately identify the deficiencies of models in simulating summer monsoon variability, coupled atmosphere-ocean models are needed.

[17] Many operational centers have adopted the two-tier approach for seasonal climate prediction. This approach has been the most important activity in dynamic climate prediction in the past 10–15 years. This strategy works for the most important forcing (equatorial Pacific SST) and for those regions where SST determines the local wind convergence and SST itself is primarily determined by ocean processes. However, in the Asian-Pacific summer monsoon regions, where atmospheric feedback plays a major role in determining local SST, the two-tier approach would yield a forced solution that differs from realistic coupled solutions. Thus, only coupled atmosphere-ocean models or regionally coupled models can provide the necessary condition for being able to correctly forecast the predictable portion of summer monsoon rainfall. Further studies of the nature of the monsoon-ocean interaction and climate predictability in the Asian-Pacific summer monsoon region using multi-model long-term integrations are needed to confirm that the present conclusions are independent of models' physical parameterizations and the simulation skill of rainfall variability over Asian-Pacific monsoon region is improved in coupled atmosphere-ocean models.

[18] **Acknowledgments.** This work is supported by NSF Climate Dynamics program and NOAA OGP/Pacific Program. This is the School of Ocean and Earth Science and Technology publication No. 6639 and IPRC (International Pacific Research Center) publication No. 345. The fourth and fifth authors were supported by Climate Environment System Research Center (CES) sponsored by the Korean Science and Engineering Foundation and the Brain Korea 21 Program. FJDR was supported by the EU-funded DEMETER project (EVK2-1999-00024).

References

Bengtsson, L., U. Schlese, E. Roeckner, M. Latif, T. Barnett, and N. Graham (1993), A two-tiered approach to long-range climate forecasting, *Science*, *261*, 1026–1029.

Charney, J. G., and J. Shukla (1981), Predictability of monsoons, in *Monsoon Dynamics*, edited by J. Lighthill and R. P. Pearce, pp. 99–109, Cambridge Univ. Press, New York.

Fu, X., and B. Wang (2004), The boreal summer intraseasonal oscillations simulated in a hybrid coupled atmosphere-ocean model, *Mon. Weather Rev.*, *132*, 2628–2649.

Gadgil, S., and S. Sajani (1998), Monsoon precipitation in the AMIP runs, *Clim. Dyn.*, *14*, 659–689.

Gates, W. L., et al. (1999), An overview of the results of the Atmospheric Model Intercomparison Project (AMIP I), *Bull. Am. Meteorol. Soc.*, *80*, 29–56.

Kumar, K. K., M. Hoerling, and B. Rajagopalan (2005), Advancing dynamical prediction of Indian monsoon rainfall, *Geophys. Res. Lett.*, *32*, L08704, doi:10.1029/2004GL021979.

Palmer, T. N., et al. (2004), Development of a European multi-model ensemble system for seasonal to inter-annual prediction (DEMETER), *Bull. Am. Meteorol. Soc.*, *85*, 853–872.

Reynolds, R. W., N. A. Rayner, T. M. Smith, D. C. Stokes, and W. Wang (2002), An improved in situ and satellite SST analysis for climate, *J. Clim.*, *15*, 1609–1625.

Roeckner, E., et al. (1996), The atmospheric general circulation model ECHAM-4: Model description and simulation of present-day climate, *Rep. 218*, 90 pp., Max-Planck-Inst. for Meteorol., Hamburg, Germany.

Shukla, J. (1998), Predictability in the midst of chaos: A scientific basis for climate forecasting, *Science*, *282*, 728–731.

Sperber, K. R., and T. N. Palmer (1996), Interannual tropical rainfall variability in general circulation model simulations associated with the Atmospheric Model Intercomparison Project, *J. Clim.*, *9*, 2727–2750.

Wang, B., T. Li, and P. Chang (1995), An intermediate model of the tropical Pacific Ocean, *J. Phys. Oceanogr.*, *25*, 1599–1616.

Wang, B., R. Wu, and K. M. Lau (2001), Interannual variability of the Asian summer monsoon: Contrasts between the Indian and the western North Pacific–East Asian monsoons, *J. Clim.*, *14*, 4073–4090.

Wang, B., I. S. Kang, and J. Y. Lee (2004), Ensemble simulations of Asian-Australian monsoon variability by 11 AGCMs, *J. Clim.*, *17*, 803–818.

Webster, P. J., V. O. Magana, T. N. Palmer, J. Shukla, R. A. Tomas, M. Yanai, and T. Yasunari (1998), Monsoons: Processes, predictability, and the prospects for prediction, *J. Geophys. Res.*, *103*, 14,451–14,510.

Wu, R., and B. Kirtman (2005), Roles of Indian and Pacific ocean air-sea coupling in tropical atmosphere variability, *Clim. Dyn.*, in press.

Xie, P., and P. A. Arkin (1997), Global precipitation: A 17-year monthly analysis based on gauge observation, satellite estimates, and numerical model outputs, *Bull. Am. Meteorol. Soc.*, *78*, 2539–2558.

Q. Ding, X. Fu, and B. Wang, School of Ocean and Earth Science and Technology, University of Hawai'i, 1680 East West Road, Honolulu, HI 96822–2219, USA. (wangbin@hawaii.edu)

F. Doblas-Reyes, European Centre for Medium-Range Weather Forecast, Reading RG2 9AX, UK.

K. Jin and I.-S. Kang, School of Earth and Environmental Sciences, Seoul National University, Seoul 151-742, South Korea.

J. Shukla, Climate Dynamics, George Mason University, Fairfax, VA 22030–4444, USA.