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Seasonal Forecasts of Precipitation Anomalies for North American and Asian Monsoons

T.N. KRISHNAMURTI, L. STEFANOVA, Arun CHAKRABORTY, T.S.V. Vijaya KUMAR, Steve COCKE, David BACHIOCHI, and Brian MACKEY

Department of Meteorology, Florida State University, Tallahassee, FL, USA

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Abstract

In this paper model-generated data sets are examined to address the question of seasonal precipitation forecast skill of the Asian and the North American monsoon systems. In this context the seasonal climate forecast data from a set of coupled atmosphere-ocean models were used. The main question we ask is if there is any useful skill in predicting seasonal anomalies beyond those of climatology. The methodology for prediction is the 'FSU Superensemble', which is applied here to the anomalies of the predicted multimodel data sets and the observed (analysis) fields. The skills of seasonal forecasts are evaluated using two different types of parameters: anomaly correlations and root mean square errors. Comparison of skill of the coupled model forecasts and the AMIP hindcasts yields encouraging results. It is noted that the superensemble based anomaly forecasts have somewhat higher skill compared to the bias-removed ensemble mean of member models, individually bias removed ensemble mean of the member models and the climatology. This skill comes partly from the forecast performance of multimodels and partly from the training component built into this system that is based on past collective performance of these multimodels. These components are separated to assess the improvements of the superensemble. Though skill of the forecasts from the superensemble is found to be higher than that of the bias-removed ensemble mean and has shown some usefulness over the climatology, the issue of forecasting a season in advance in quantitative terms still remains a challenge and demands further advancement in climate modeling studies.

1. Introduction

The Asian-Australian and the North American monsoon systems are major components of the world's monsoon systems. These two systems include major components of the low-latitude atmospheric heating field and the seasonally varying local Hadley circulations. During almost all the years, the dominant feature of the low-latitude Hadley circulation is a single direct cell that links the two hemispheres by descending motion in the winter hemisphere and ascending motion in the summer hemisphere. In a similar way, the regional monsoon components of the Hadley circulation link the winter monsoon circulation of one hemisphere with its summer monsoon counterpart. The size, shape, and location of the landmasses and surrounding oceans involved in the Asian-Australian and American monsoon system have important differences.

The current state of prediction over the monsoon region is not much better than the prediction of long-term mean climate, and there is almost no skill in the prediction of seasonal anomalies, Palmer et al. (2000). The use of an ensemble mean of seasonal forecasts, generated

Corresponding author: T.N. Krishnamurti, Department of Meteorology, 4520, Florida State University, Tallahassee, Florida 32306-4520, USA.
E-mail: tnk@io.met.fsu.edu

from adjacent start dates, also appeared to perform very close to a climatological forecast, Palmer (1994), thus showing almost no skill for the prediction of seasonal anomalies. Gadgil and Sajani (1998) examined the performance of seasonal climate prediction using atmospheric general circulation models in the context of the Atmospheric Model Inter-comparison Project (AMIP) data sets, Gates et al. (1999). The examination of monthly and seasonal forecasts from a number of research and operational atmospheric general circulation models showed very low skill for the prediction of precipitation.

Several recent studies have emphasized the extreme sensitivity of seasonal monsoon forecasts to the choice of cumulus parameterization algorithms. It is becoming increasingly clear that this will remain a major scientific issue for climate modeling. Some recent studies revealed that the results from the use of two or more simple cumulus parameterization algorithms have led to drastically different seasonal monsoon simulations (Slingo et al. 1994, Pattanaik and Satyan 2000).

It is a well established fact that currently realistic simulations/forecasts of seasonal climate are best done by coupled atmosphere-ocean models since they do not rely on prescription of future SSTs. The prime objective of this study is to evaluate results of the seasonal precipitation anomaly forecasts of several versions of the Florida State University (FSU) coupled atmosphere ocean model employing different combinations of cumulus parameterization and radiation schemes in conjunction with the superensemble forecast method. This paper focuses on the results from four different versions of FSU coupled model and evaluation of superensemble based on these coupled model results. Some comparisons are shown with results from multimodel seasonal hindcasts of precipitation anomalies using the AMIP data sets. It has to be noted here that in this study we added a few more models from AMIP II to the AMIP I models used in our earlier publications and reconstructed the superensemble forecasts (hindcasts). Another important aspect of this study is that this paper deals with anomaly forecasts instead of full fields of precipitation, because the statistics based on anomalies show the skill of forecasts/hindcasts beyond climatology, which is desirable.

2. The concept of the superensemble

The notion of a multianalysis/multimodel superensemble is presented in some recent publications by the research group at FSU, Krishnamurti et al. (1999, 2000a,b, 2001). In these studies, seasonal climate hindcasts were addressed using the AMIP data sets provided by the Lawrence Livermore National Laboratory in California. Here the construction of superensemble included a training phase where past seasonal forecasts and analysis were used to construct bias stabilities on the performance of the multimodels. This method differed from the conventional ensemble averaging methods by invoking a training period from a subset of these forecasts of the multimodels. The purpose of that was to evaluate model biases geographically, vertically, and for each variable. The knowledge of model biases was later used in another subset of forecasts by the multimodels for the construction of what has been designed as a superensemble.

Our recent studies have also shown that the superensemble out-performs the member models and the ensemble mean when standard skill scores, such as the rms error, anomaly correlation, Brier skill scores and equitable threat scores, are used. However, all our studies of seasonal forecasting superensemble so far have been done with hindcasts from the AMIP data sets. The big challenge of seasonal climate forecasting lies in demonstrating that such a foundation as the superensemble has useful skills for the climate anomaly forecasts above those of climatology. If that were generally possible, we could have said something about the recent cold spells, drought, floods, and climate changes. That degree of success is hard to achieve from the present state-of-the-art of the field. In climate modeling, measures of such skills show variability from region to region (Brankovic et al. 1994). We do not even know whether that regional variability is model dependent. It is also not clear why a model exhibits higher skill over a given region and not over other regions. The superensemble appears to exhibit some consistency in successful climate hindcasts as compared to member models, Krishnamurti et al. (2000a). In this paper it is noted that the skill of the superensemble exceeds the ensemble mean of bias-removed member models. This is simply explained by the reasoning that assigning a weight of 1.0 to a poor model (bias corrected) in the construction of the ensemble mean does not qualify it equal to the best model (bias corrected), which is also assigned a weight of 1.0. In this regard, the superensemble is very selective—it even assigns fractional negative weights to the member models, depending on their overall recent past performance. Here reference should also be made to Hasselmann (1979), who notes that under the conditions of optimal combination, equally reliable models need not be weighed equally.

3. Superensemble forecasts from different versions of the FSU coupled model

Combining the FSU atmospheric global spectral model (Krishnamurti et al. 1998) with a Hamburg ocean model (Latif 1987), Larow and Krishnamurti (1998) constructed a coupled climate model that is briefly outlined in Fig. 1a. The atmospheric part of this coupled model is a spectral model with 14 vertical layers and is resolved by 63 waves in the horizontal. The oceanic counterpart of the coupled model is a primitive equation global model with variable meridional resolution (0.5° near the equator and decreasing to 5.0° near the northern and southern boundaries located at 70°N and 70°S respectively). In the zonal direction the resolution is constant at 5.0°. The ocean model contains 17 irregularly spaced vertical levels with 10 levels located within the uppermost 300 meters. Krishnamurti et al. (2000c) recently completed a detailed, 18-month long integration with this coupled model. In that study, the integrations initialized for April 1, 1997 captured the entire life cycle, i.e., the birth and demise of the 1997–98 El Niño. This study included a comprehensive coupled data assimilation phase where physical initialization of observed rainfall estimates, following Krishnamurti et al. (1991), and 'nudging' (only during the assimilation phase) of several variables of the coupled system were included. It was also shown that the coupled model integrations were quite sensitive to the use (versus non-use) of such comprehensive data assimilation. The present modeling starts with a 10-year ocean spin-up phase where the observed winds (and related surface wind stresses) drive the ocean model only. This ocean spin-up is followed by a coupled atmosphere ocean (and land) data assimilation phase, following Larow and Krishnamurti (1998). The three computational phases of FSU coupled model that includes the ocean spin-up, coupled assimilation, and the multimodel seasonal forecasts are shown in Fig. 1b.

In the present study, the multimodels are constructed using two cumulus parameterization schemes (modified Kuo's scheme following Krishnamurti and Bedi (1988) and Arakawa Schubert scheme following Grell (1993)) and two radiation parameterization schemes (an emissivity—absorbtivity based radiative transfer algorithm following Chang (1979) and a band model for radiative transfer following Lacis and Hansen (1974)). Table 1 identifies the four possible permutations that were used to construct four versions of the FSU coupled climate model. Using the forecasts from these four versions, ensemble averages and superensemble forecasts are constructed.

In this study, the superensemble forecast is obtained from the equation:

$$S = \bar{O} + \sum_{i=1}^{N} a_i (F_i - \bar{F_i}). \tag{1}$$

Where F_i is the i^{th} model forecast, $\bar{F_i}$ is the mean of the i^{th} forecast over the training period, $\bar{O}$ is the observed mean over the training period, a_i's are regression coefficients obtained by a minimization procedure during the training period and N is the number of forecast models involved. The coefficients (a_i's) are derived by minimizing the function $G = \sum_{t=1}^{T_{train}} (S_t - O_t)^2$.

A multi-model bias-removed ensemble is given by

$$E = \bar{O} + \frac{1}{N} \sum_{i=1}^{N} (F_i - \bar{F_i}). \tag{2}$$

It is obvious by comparing equation (1) and (2) that, in addition to removing bias, the superensemble scales the individual model forecast contribution according to their relative performance during the training period by mathematically weighing them.

In this study, superensemble forecast computation utilizes the cross-validation approach.

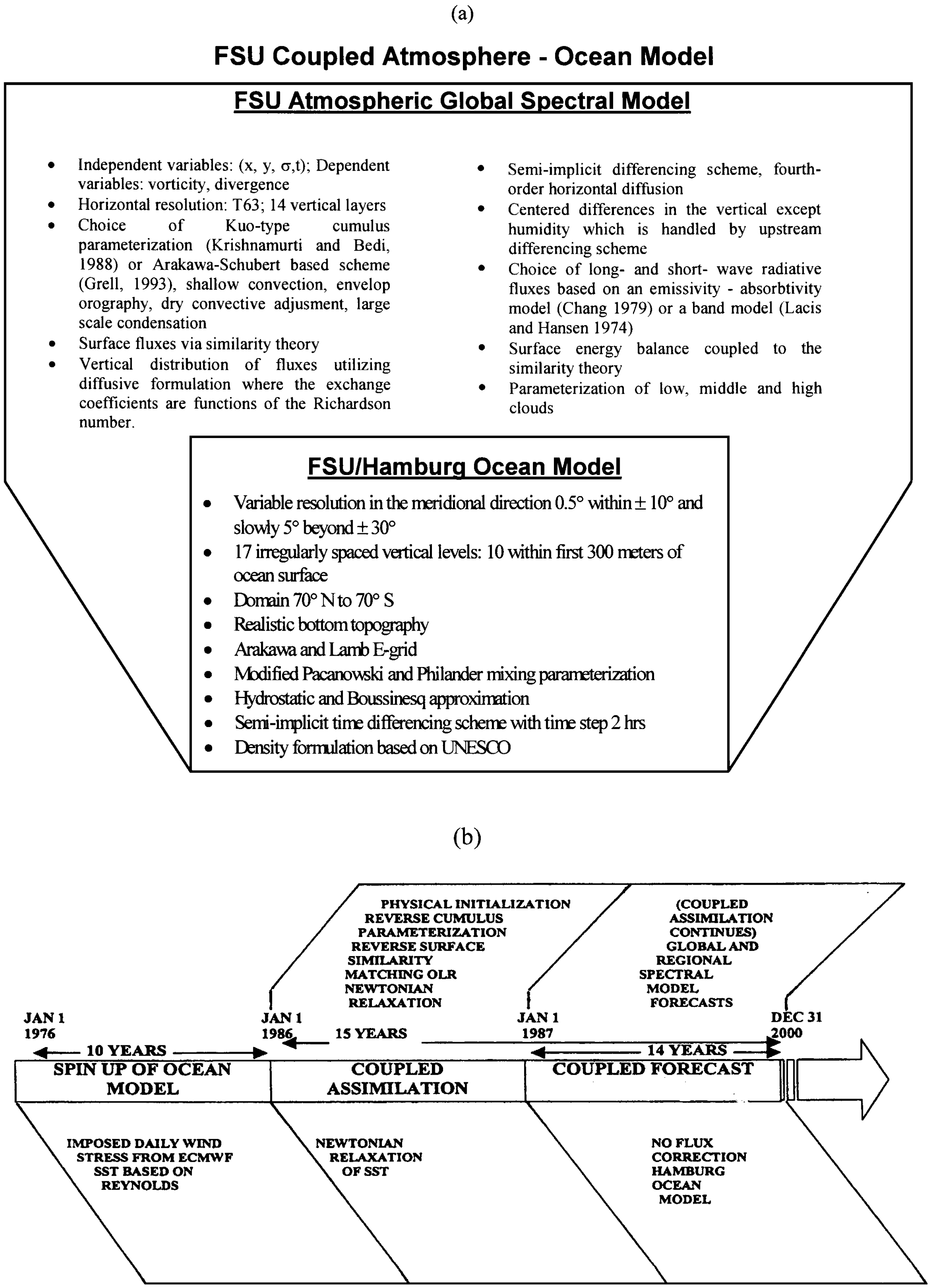


Fig. 1. (a) The ingredients of the FSU global coupled ocean-atmosphere model. (b) An outline of the time line of coupled ocean-atmosphere modeling. The three major time line components are spin up of the ocean model, coupled assimilation and the coupled forecasts.

Table 1. Different Versions of FSU Coupled Model Simulations

C1 Arakawa-Schubert Cumulus scheme	C2 Modified Kuo Cumulus scheme
R1 Emissivity-absorbtivity radiation scheme	R2 Band model radiation scheme

Four models: a) C1-R1, b) C1-R2, c) C2-R1 and d) C2-R2

For each year's forecast, all other years of the data set are used for the training period. The training phase for coupled modeling, central to the design of the superensemble, utilizes eleven years of data assimilation for each member model. The skill of seasonal forecasts in this study is evaluated through calculations of anomaly correlations and rms errors between the forecasts and the observations (analysis).

4. Results from modeling studies

In this section the results of seasonal forecasts of precipitation from superensemble forecasts based on the four versions of the FSU coupled model for the Asian summer monsoon and the North American monsoon are presented. The majority of the results shown here are for the anomalies obtained after removal of temporal mean fields, because they provide more insight in to the skills of superensemble forecasts better than those of the total fields. The temporal means are automatically subtracted while constructing the superensemble of the anomalies (which are in fact departure from the time mean).

Skill scores, such as the correlation of modeled rain (and of rainfall anomalies) to the 'observed' seasonal (and anomaly) estimates, and corresponding rms errors, are also presented in this section.

4.1 Asian monsoon forecasts

Results of seasonal rainfall forecasts over the Asian monsoon domain from the four versions of FSU Coupled model are presented in this section. The total rainfall from these four models, ensemble mean (e), climatology (clim), superensemble (s), and the observed estimates (o) based on Xie and Arkin (1996) data sets, are examined for one season, June through September 1997. The patterns of seasonal predicted rainfall distributions for the ensemble mean, climatology, and the superensemble appear quite similar to the observed estimates (not shown here), whereas the member model rainfall totals generally appear to have larger errors. These results support the premise that some improvement of the skill for total seasonal rainfall can be achieved for the coupled models from the proposed FSU superensemble.

We have posed the estimates of skills based on construction of the superensemble of predicted seasonal anomalies (i.e., seasonal rainfall anomalies above those of climatology). The distribution of these rainfall anomaly forecasts from the 4 member models, ensemble mean, superensemble, and observed estimates are shown in Fig. 2. Forecasting seasonal rainfall anomalies accurately over the entire domain is a major challenge for climate modeling. During this summer season of 1997, western Indian Ocean, Southeast Asia, and China were wetter than normal, whereas most of India from Southeast to Northwest was drier than normal. As will be seen more clearly from the predicted rainfall correlation and viewing those predicted rainfall distributions, there were rather large errors in the forecasts for almost all models. The distribution of rainfall anomaly forecasts from the superensemble appears to be the best among those realizations, both qualitatively and from the skill perspective. The correlation coefficients in this case, for member models, are -0.10, -0.11, 0.31, and 0.31 while for ensemble mean and superensemble they are 0.14 and 0.48 respectively. The corresponding rms errors are 2.77, 2.12, 1.71, and 1.97 for member models and 1.77 and 1.4 for ensemble mean and the superensemble. It is apparent that the superensemble has highest correlation and lower rms error from seasonal prediction of rainfall anomalies.

Those skills are further elaborated in Figs. 3(a) and (b). In these figures the correlation (Fig. 3a) of model rainfall with respect to the observed estimate is shown for the years 1993 through 1999 (7 summer monsoon seasons). The superensemble has shown somewhat higher skill compared to the other models and the ensemble mean. That improved correlation from the superensemble is only around 0.45 at

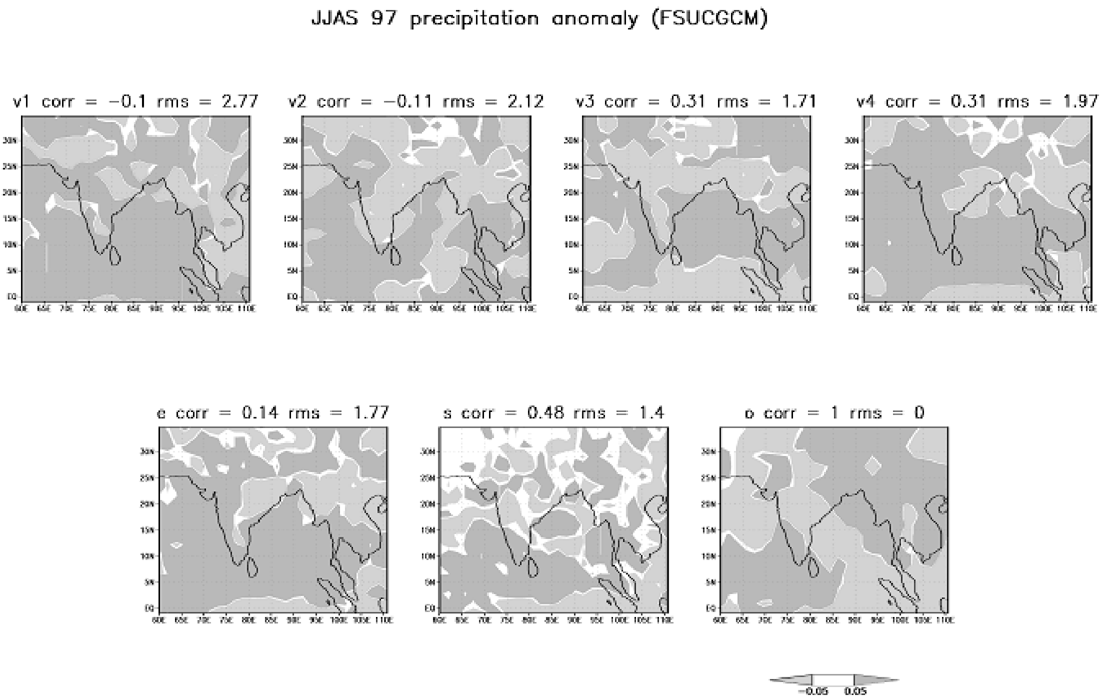


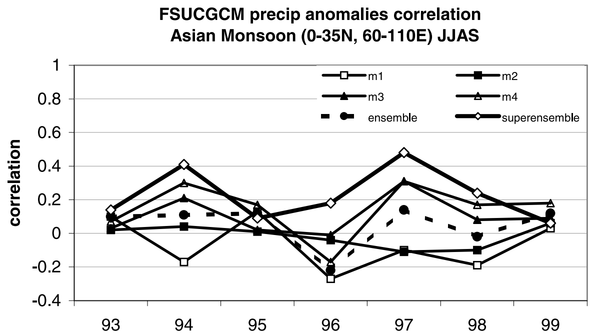
Fig. 2. Coupled model forecasts of precipitation anomalies (mm/day) for June, July, August, and September 1997. Top panel left to right: Four member models. Bottom panel left to right: Ensemble mean, Superensemble, and the Observed precipitation anomalies based on Xie and Arkin (1996). Results pertain to the Asian Summer Monsoon.

best. This is what was obtained from the construction of a superensemble using just four coupled atmosphere–ocean models. The corresponding results for the rms error are presented in Fig. 3b. Here we have also included the results for the skill of climatology. Again, the lowest errors are found for the superensemble, around 1 mm/day. The errors for the member models are as high as 2.5 mm/day.

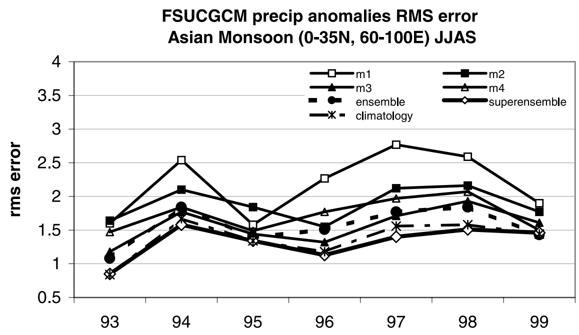
4.2 Asian monsoon hindcasts

Seasonal hindcasts of precipitation anomalies from different AMIP1 and AMIP2 model data sets were also examined in the context of superensemble. In this study, AMIP1 model data sets from BMRC (Australia), ECMWF (European Center, England), GFDL (Princeton, U.S.A), JMA (Japan), CSIRO (Australia), LMD (Paris, France), MPI (Hamburg, Germany), NCEP (U.S.A.), UKMO (England) and AMIP2 model data sets from DNM (Russia), JMA (Japan), NCAR (Boulder, Colorado), UKMO (England), and LLNL (Livermore, California) are utilized to construct the superensemble. The data sets for AMIP1 covered the years 1979 through 1988, and AMIP2 covered the period 1979 through 1995. We have examined these AMIP1 and AMIP2 periods separately and we have also combined the AMIP1 and AMIP2 for the following models: DNM, JMA, NCAR, UKMO and LLNL. The choice of the models was made after examining the rms errors and performance from a total set of 31 models for AMIP1 and 5 models for AMIP2. Details of these model data sets were documented by Gates et al. (1998) and Phillips (1996).

The illustration for the seasonal correlations (of model rainfall anomalies) with respect to the observed anomalies is presented in Fig. 4a. The highest anomaly correlations for the seasonal precipitation forecast are generally seen for the multimodel superensemble (heavy line). The other heavy line shows the results for the ensemble mean, the remaining thinner lines show the skill of the member models of AMIP1 and AMIP2. The calculations carried out here used the cross-validation technique, i.e., all

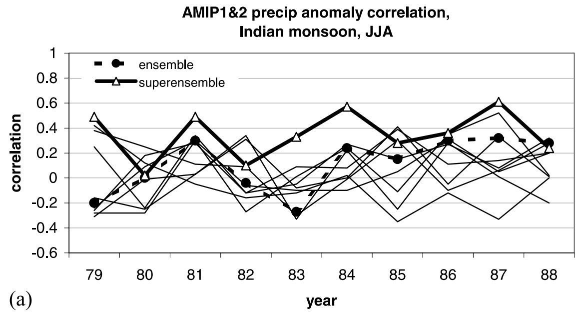


(a)

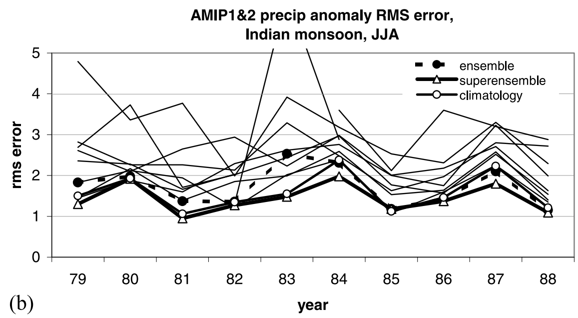


(b)

Fig. 3. (a) Correlation of coupled model forecasts of precipitation anomalies over the summer monsoon domain for June, July, August, and September for the years 1993 to 1999. Results for member models (m1, m2, m3, and m4), the ensemble mean, and the superensemble are shown here. Results pertain to the Asian Summer Monsoon. (b) RMS errors of coupled model forecasts of precipitation anomalies over the summer monsoon domain for June, July, August, and September for the years 1993 to 1999. Results for member models (m1, m2, m3, and m4), the ensemble mean, the superensemble, and the climatology are shown here. Results pertain to the Asian Summer Monsoon.



(a)



(b)

Fig. 4. (a) Correlation of seasonal forecasts of precipitation anomalies with respect to observed anomaly estimates based on Xie and Arkin (1996) over the Asian Summer Monsoon domain from the mix of AMIP I and AMIP II data sets. Heavy line at top: Superensemble. Heavy dashed line: Bias removed ensemble mean. Thin lines: Member multimodels. (b) RMS errors of precipitation anomaly forecasts for a ten-year period from a mix of AMIP I and AMIP II models. Thin lines: Member multimodels. Other lines are described in the inset of the figure.

years (except the one being forecasted) were used to develop the training data statistics. The rms errors for the Asian monsoon domain (Fig. 4b) show errors in excess of 1 mm/day for most models. The thin lines in Fig. 4b show the errors for the AMIP member models and heavy line (at the bottom) with the lowest rms errors show the results for the superensemble. The other heavy line shows the error for the ensemble mean while dashed line depicts the errors for the climatology. It is clear for this representation that the multimodels and their ensemble mean do not perform as well as climatology in these seasonal forecasts. Only the superensemble-based forecasts are superior to those of the ensemble mean.

4.3 North American monsoon forecasts

We have examined the results of the four coupled model forecasts over the North American domain in the same manner as in the previous section. The rainfall anomaly forecasts for the summer of 1997 (with respect to the climatology) over the North American region are

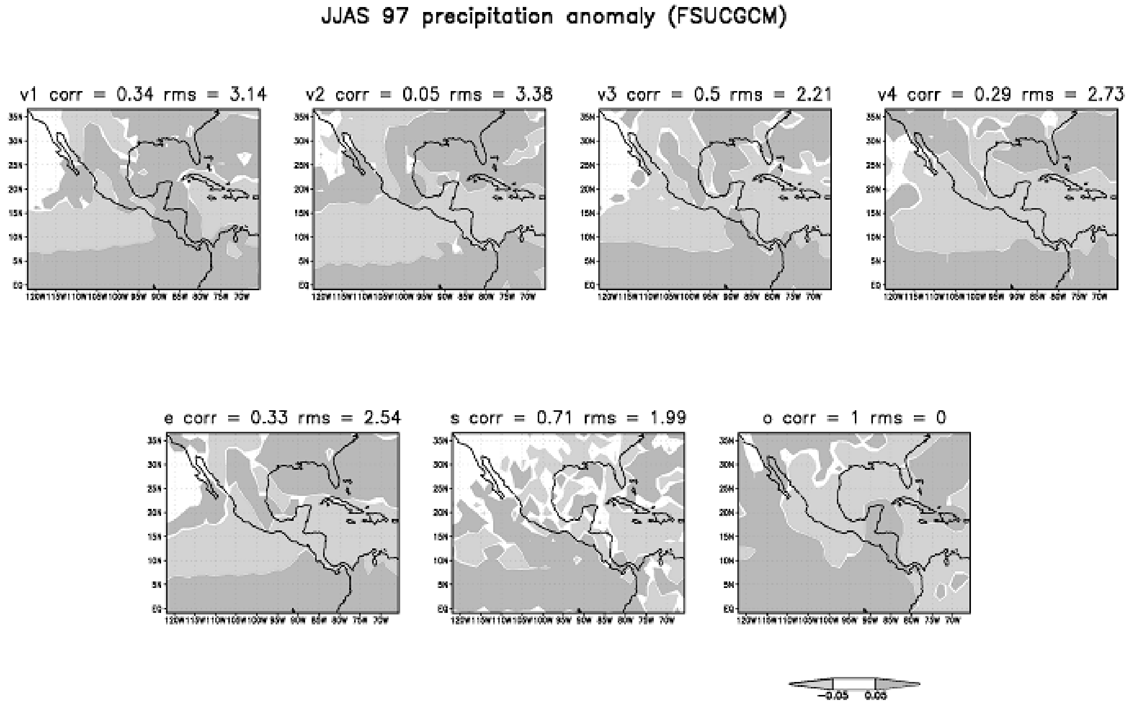


Fig. 5. Coupled model forecasts of precipitation anomalies (mm/day) for June, July, August, and September 1997. Top panel left to right: Four member models. Bottom panel left to right: Ensemble mean, Superensemble, and the Observed precipitation anomalies based on Xie and Arkin (1996). Results pertain to the North American Monsoon.

illustrated in Fig. 5. Most member models predicted a positive anomaly for the seasonal rainfall for the North American monsoon along the Sierra Madre Occidental. The yellow coloring over the Pacific reflects a below average rainfall for all of those member models. The superensemble shows somewhat better results over both of these regions. On the whole, improvement in the prediction of rainfall anomalies is measurable but small. Further details on the time history of correlations and rms error over the North American monsoon domain (covering the years from 1993 through 1999) are shown respectively in Fig. 6 (a) and (b). Clearly the highest correlation and the lowest rms errors are noted for the multimodel superensemble. This is what has been possible from the use of just four member models, each of which includes somewhat different physical parameterizations but essentially carry the same dynamical framework.

Examination of the error statistics for a 7-year period for the seasonal anomaly forecasts over North American Monsoon region reveal that although there is some variability, the overall skills from one year to the next are quite similar. The only exception is found for the year of El Nino 1997–98, where the errors are somewhat larger. This is likely due to the fact that the training period does not include a sufficient number of El Nino years.

4.4 North American monsoon hindcasts

Seventeen years of seasonal anomaly forecasts from the AMIP data sets were examined for the North American monsoon. The performance of a few of the member multimodels (thin black line), the ensemble mean (blue line), the climatology (green line), and the superensemble (red line) are shown in Figs. 7(a) and (b). These illustrations show the correlations and rms errors (of model rain versus observed estimates based on Xie and Arkin, (1996)). The superensemble was constructed using the cross validation technique. The performances of the multimodels over the North American monsoon domain were quite poor during the summer of 1986. The reasons for that poor performance

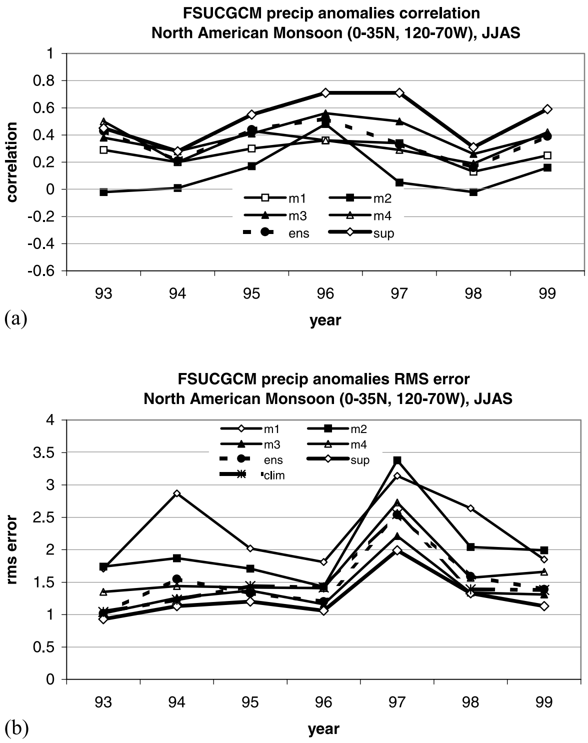


Fig. 6. (a) Correlation of coupled model forecasts of precipitation anomalies over the summer monsoon domain for June, July, August, and September for the years 1993 to 1999. Results for member models (m1, m2, m3, and m4), the ensemble mean, and the superensemble are shown here. Results pertain to the North American Monsoon. (b) RMS errors of coupled model forecasts of precipitation anomalies over the summer monsoon domain for June, July, August, and September for the years 1993 to 1999. Results for member models (m1, m2, m3, and m4), the ensemble mean, the superensemble, and the climatology are shown here. Results pertain to the North American Monsoon.

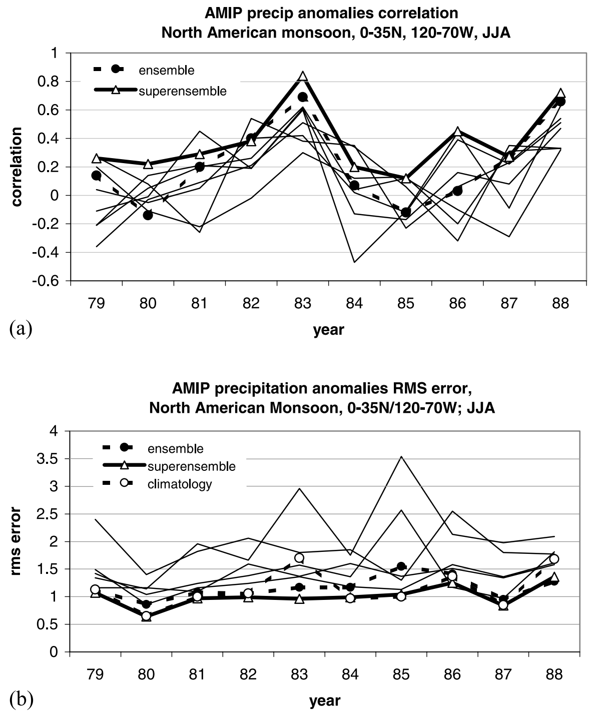


Fig. 7. (a) Correlations of modeled precipitation anomalies with respect to the observed estimates (based on Xie and Arkin, 1996) over the North American monsoon domain for AMIP data sets. Heavy line at top: Superensemble. Heavy dashed line: Bias removed ensemble mean. Thin lines: Member multimodels. (b) RMS errors of modeled precipitation anomalies with respect to the observed estimates (based on Xie and Arkin, 1996) over the North American monsoon domain for AMIP data sets. Thin lines: Member multimodels. Other lines are described in the inset of the figure.

are not entirely clear. As a result, the ensemble mean and the superensemble had rather low negative correlations. For the remaining years, the correlation forecast skill for rainfall anomalies over the North American monsoon domain were as high as 0.6 or higher. These skills were somewhat higher than those over the Asian monsoon domain shown in Fig. 4. The rms errors of the anomaly forecasts for precipitation are shown in Fig. 7b. The skill of the superensemble was clearly higher than those of the member models, the climatology, and the ensemble mean. Over all the results of seasonal forecasts of rainfall anomalies were best for the superensemble compared to the ensemble mean and the member models.

5. Summary and future work

The present study is a new thrust on seasonal climate modeling. It is a first attempt to use multimodels (with different physical parameterizations) with a coupled atmosphere ocean and land system. Our previous climate modeling efforts were, in essence hindcasts, utilizing prescribed SSTs and atmospheric general circulation models, Krishnamurti et al. (2000a). Quoting from the recent results of Palmer (2000), we note that while much progress has emerged on the life cycle progress of El Nino events, (e.g., Krishnamurti et al. 2000c), the overall skill of seasonal forecasts of individual coupled models has been quite marginal. The motivation of this study has been to make a start on coupled model based ensembles and superensemble to explore possible improvements over earlier work.

We have chosen to focus on North American and Asian monsoon systems in this study using the coupled-model-based superensemble approach. Predictability of these monsoon systems over seasonal time scale is low, which was a motivation for starting on a systematic coupled modeling effort following our recent study, Krishnamurti et al. (2000c).

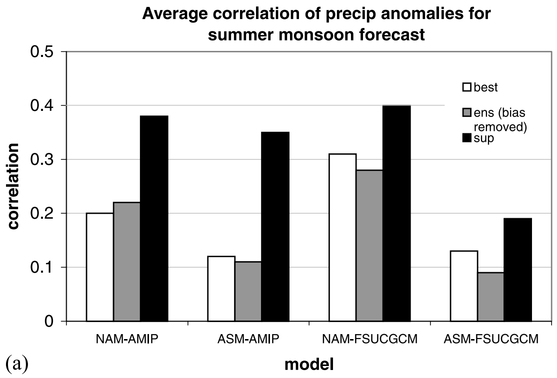
This study substantially differs from our earlier publications using the superensemble; the differences can be seen in the following major areas: (a) design of several coupled models using different physical parameterizations; (b) several years of data assimilation with the coupled model; and (c) use of superensemble methodology for the coupled system.

Individually, the coupled models have low skills in the prediction of seasonal precipitation of the monsoon. The FSU coupled model forecasts were subjected to ensemble averaging and the FSU superensemble forecast. The results from the rms errors of precipitation anomalies show that some measurable improvement in those predictions is possible from the construction of the FSU superensemble.

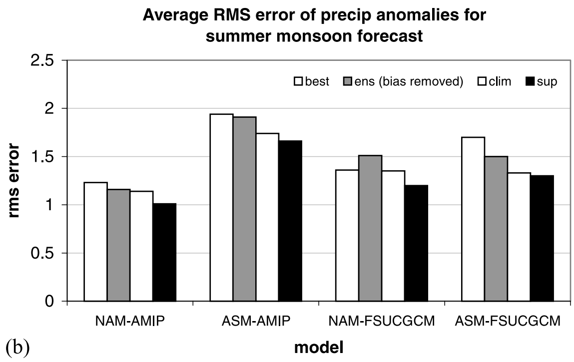
The four versions of the FSU coupled climate model, all running at a resolution of T63 (roughly 1.875° latitude/longitude for the transform grid) were constructed from two different versions of cumulus parameterization algorithms and two different versions of the radiative transfer code. This is a small sample of coupled multimodels, and in that sense this work is somewhat preliminary. However, what is accomplished here is the demonstration that superensemble skills comparable to what were obtained for the AMIP models (where the SST and sea ice were prescribed) are possible from this small family of coupled multimodels.

Looking at the seasonal precipitation anomaly forecasts, it became apparent that much improvement of the member models is needed for an increase in the skill of the superensemble. Our future plans include further improvement in the physical and land-surface parameterizations, resolution, and the number of member models. Our plans also include the possible addition of the results from a number of non-FSU models to bring in a diverse spread in the construction of the ensemble and the superensemble. Given these promising results from a limited number of models, we feel that the proposed extensions may provide further improvement for the seasonal climate anomaly forecasts.

The training phase of the superensemble deserves much further study, since it is that area which provides an edge for its skill. It is important to realize that the bias removal from construction of the superensemble is quite different from the classical method of bias removal. The latter is simply measured as the difference of a forecast time mean field and the observed time mean field. The superensemble bias is given by a summation of the products of weights (determined from past performances of member models) to the difference of forecast and forecast time mean, Krishnamurti et al. (2000a). The difference between the superensemble bias and the classical bias is quite large. This becomes much clearer from a summary of the entire computational results presented here. Figures 8 (a) and (b) present a summary of the correlation and rms errors of the modeled rainfall anomaly and the observed measures of the rainfall anomaly for all the AMIP and the coupled model experiments for the North American and the Asian monsoons. Here all correlations are averaged over the domain of these monsoons shown in Figs. 4 and 6. A comparison of the anomaly correlation forecast skills are shown here for the best model, the ensemble mean of bias removed member models, climatology and the superensemble. Over the entire domain, the superensemble has the highest skill. The member models and the bias removed ensemble mean perform worse than climatology. The bias removed ensemble mean assigns the same weight (i.e., 1.0) to all



(a)



(b)

Fig. 8. Domain averaged seasonal forecast skills—(a) correlation and (b) RMS errors for precipitation anomalies (with respect to climatology) for the North American Monsoon (NAM) and the Asian Summer Monsoon (ASM). Separate results for the AMIP and the coupled models for the best model, the bias removed ensemble mean and the superensemble are shown here.

models regardless of their quality on performance. In that sense the superensemble is more selective based on past performance of the member models and assigns negative, fractional, or positive weights. If all the weights of the member models are set to 1.0, then the classical bias (forecast seasonal mean minus observed seasonal mean) and the superensemble bias become identical. However, there exists a geographical distribution of weights, which makes the superensemble performance different and better with respect to the bias removed ensemble mean.

In this study, we have addressed only rms and correlation measures for the seasonal prediction of rainfall. In this context the superensemble appears to have some skill over climatology. We believe that a larger number of models will firmly establish this possibility, and that would be an important result since at present single models individually or even ensemble averages are not able to convey that message.

The major finding of this work is that the member models (designed for this study) carried a seasonal forecast skill somewhat below the climatology, see Fig. 8, which perhaps suggests that a forecast based on climatology might have been adequate and no model forecasts were needed. The same message would have been conveyed from the ensemble mean as well. However, the training phase of the superensemble provides skills that are in fact slightly above the climatology. This is a positive aspect of this work. Currently we are introducing a twelve member multimodel ensemble with eight FSU models and four external models to provide a greater diversity. It is our hope that with such extension the key issue, i.e., whether a given region will be drier, wetter, warmer, or colder than climatology during the next season, would be answered with some degree of reliability.

Viewing in a real time context, it would be difficult to anticipate in advance which member model would provide the best forecast for any given run. The same can be said for the ensemble mean. From the results of the present study of the AMIP and the coupled model seasonal forecasts of the precipitation anomalies, it appears that there exists an overall consistency in the behavior of the superensemble, i.e., it consistently exhibits a somewhat higher skill than climatology. Out of a total of 20 AMIP forecasts, we noted this to be the case for 15 forecasts. The corresponding figures for the coupled model runs were 12 out of 14 experiments. Thus, are we to conclude that the issue of whether it will be wetter or drier than climatology over the next season can now be addressed by this proposed approach? More tests are clearly needed to establish what appears most promising at this stage. The issue of prediction of very heavy rain (a season in advance) is another milestone requiring further advances in modeling. The quantitative issues of floods or extreme dry spells in this context remain challenges for the future.

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