Potential Predictability of U.S. Summer Climate with "Perfect" Soil Moisture

FANGLIN YANG

GEST/UMBC, Climate and Radiation Branch, Laboratory for Atmospheres, NASA Goddard Space Flight Center, Greenbelt, Maryland

ARUN KUMAR

Climate Prediction Center, National Centers for Environmental Prediction, Washington, D.C.

K.-M. LAU

Laboratory for Atmospheres, NASA Goddard Space Flight Center, Greenbelt, Maryland

(Manuscript received 13 January 2004, in final form 20 April 2004)

ABSTRACT

The potential predictability of surface-air temperature and precipitation over the United States was assessed for a GCM forced by observed sea surface temperatures and an estimate of observed soil-moisture content. The latter was obtained by substituting the GCM-simulated precipitation, which is used to drive the GCM's land surface component, with observed pentad-mean precipitation at each time step of the model's integration. With this substitution, the simulated soil moisture correlates well with an independent estimate of observed soil moisture in all seasons over the entire U.S. continent. Significant enhancements for the predictability of surface-air temperature and precipitation were found in boreal late spring and summer over the U.S. continent. Anomalous pattern correlations of precipitation and surface-air temperature over the U.S. continent in the June–August season averaged for the 1979–2000 period increased from 0.01 and 0.06 for the GCM simulations without precipitation substitution to 0.23 and 0.31, respectively, for the simulations with precipitation substitution. The results provide an estimate for the limits of potential predictability if soil-moisture variability is to be perfectly predicted. However, this estimate may be model dependent and needs to be substantiated by other modeling groups.

1. Introduction

It is well known that tropical sea surface temperature (SST) anomalies have substantial influence on the climate variability over the North Pacific and North America in boreal winter through teleconnections (e.g., Wallace and Gutzler 1981). Many authors (e.g., Kumar and Hoerling 1998; Trenberth et al. 1998; Shukla et al. 2000) have explored the potential predictability of the North American winter climate simulated by atmospheric general circulation models (GCMs) forced with observed SSTs. During boreal summer, however, the influence of tropical SSTs on midlatitude climate variability is weak and is primarily limited to the zonal mean component of the extratropical height field (Schubert et al. 2002). Although a few studies have found that SST anomalies outside of the Tropics may be of certain predictive value (e.g., Ting and Wang 1997; Lau et al. 2004), a robust link between SST anomalies and the U.S. summertime climate has yet to be established. The impact of SSTs is often blurred due to local processes and feedbacks, such as those associated with changes in low-level jet streams and soil moisture content. The influence of soil moisture on precipitation and surface temperature has long been noticed and is drawing even wider attention in recent years (e.g., Delworth and Manabe 1988; Atlas et al. 1993; Wang and Kumar 1998; Fennessy and Shukla 1999; Hong and Kalnay 2000; Koster et al. 2000; Schlosser and Milly 2002; Koster and Suarez 2001, 2003; Kanamitsu et al. 2003; Mo 2003).

Soil-moisture content is primarily determined by groundwater holding capacity, precipitation, runoff, and evaporation (Delworth and Manabe 1988; Koster and Suarez 2001). In turn, soil moisture affects surface-air temperature and humidity by modifying the release of latent and sensible heat fluxes, and consequently affecting atmospheric circulation and precipitation. The process involves many feedbacks and is so complicated that often it is impossible to identify the cause and effect from the analysis of observational records alone. To

Corresponding author address: Fanglin Yang, Climate and Radiation Branch, NASA Goddard Space Flight Center, Code 913, Greenbelt, MD 20771.
E-mail: fyang@climate.gsfc.nasa.gov

circumvent this problem, atmospheric GCMs have been used by many authors to understand the process.

So far, there have been two major kinds of GCM studies. The first kind treats soil moisture as a boundary condition problem. Either model-generated or idealized soil-moisture anomalies were specified and maintained during model integrations to study the impact of soil-moisture anomalies on the simulations of observed flood and drought conditions (e.g., Atlas et al. 1993; Hong and Kalnay 2000) or on the interannual variability of model-generated precipitation and/or surface temperature (e.g., Koster and Suraez 1995; Koster et al. 2000; Dirmeyer 2000). No feedback processes associated with soil moisture were included since the prescribed soil moisture does not respond to changes in atmospheric conditions. The second kind treats soil moisture as an initial value problem. These studies examined how initial soil-moisture anomalies, once initialized, affect the predictability of precipitation and/or surface temperature. The feedbacks between soil moisture and the atmospheric conditions were included. Often, the predictability of soil moisture itself (or soil-moisture memory) was also investigated. Most of the studies relied on idealized model-generated soil-moisture anomalies (e.g., Wang and Kumar 1998; Schar et al. 1999; Schlosser and Milly 2002). Attempts have also been made to initialize the models with more realistic soil-moisture anomalies, either by using soil-moisture analyses (Fennessy and Shukla 1999; Kanamitsu et al. 2003) or by performing spinup simulations for which observed atmospheric conditions were used to force the model's land surface component before formal predictions start (Koster and Suraez 2003). These studies emphasized the importance of initial soil-moisture anomalies. The degree to which the initialization can enhance the predictability of summertime precipitation and temperature is mixed, varying among models and with locations.

The potential predictability in association with observed SST anomalies has been explored in-depth using GCM results from Atmospheric Model Intercomparison Project (AMIP)-type experiments (e.g., Kumar and Hoerling 1998; Straus et al. 2003). A similar investigation on the predictability in association with ''observed'' soil-moisture anomalies has not been attempted, primarily because of the lack of global-scale long-term observations of soil moisture. Various ongoing Land Data Assimilation Systems (LDAS) are filling this gap by running retrospective and near–real time LDAS (e.g., Mitchell et al. 1999; Cosgrove et al. 2003). Satellite observations have also started to produce soil-moisture estimates. However, there are inherent problems when independent soil-moisture observations or analyses are used as initial or boundary conditions for GCM experiments. A variety of land surface models are now being used by different GCMs, and often they are also different from those used in Land Data Assimilation Systems. These differences cause incompatibility in soil types, layers, and field capacity, and consequently lead to different definitions of ''dry'' and ''wet'' conditions in the models. For example, Fennessy et al. (2000) used the soil-moisture analysis of Huang et al. (1996) as initial conditions to perform near–real time seasonal prediction by the Center for Ocean–Land–Atmosphere Studies GCM. They found several adjustments have to be made with the soil-moisture data for compatibility.

In this study, we propose first a simple method to generate GCM soil moisture that is fairly realistic. We substitute the model-simulated precipitation with observed precipitation during model integrations to force the model's land surface component. By doing so the incompatibility issue is avoided, and the feedbacks between soil moisture and the atmospheric conditions are also retained. Results show that the simulated soil moisture matches well with the Huang et al. (1996) analysis in all seasons. Then, the potential predictability of precipitation and surface-air temperature over the continental United States in boreal summer is explored using a set of ensemble GCM simulations, which are forced by observed SSTs and the almost ''perfect'' soil-moisture content.

A brief outline of this paper is as follows. Section 2 describes the National Centers for Environmental Prediction (NCEP) GCM and the observed SSTs and precipitation used to force the GCM. Given the fact that observational precipitation analyses are often presented as daily, pentad, or monthly means, a choice has to be made of the kind of precipitation data to use. Following a perfect model approach, different options are evaluated in section 3. It is found that using pentad-mean precipitation can reproduce well the land surface features that the NCEP GCM simulates when no alteration of precipitation is made. Section 4 compares the GCM-simulated soil moisture with an observational analysis. The potential predictability of U.S. summertime climate is examined in section 5. The conclusions and discussions are presented in section 6.

2. Model and data

The atmospheric GCM used in this study is the NCEP seasonal forecast model. It has been described in detail by Kanamitsu et al. (2002). In brief, the GCM has a spectral triangular truncation at wavenumber 42, and has 28 levels in the vertical direction. The horizontal grid spacing is approximately 3° in latitude and longitude. In the model, surface temperature is predicted and governed by a surface energy budget equation. Surface momentum and sensible and latent fluxes are parameterized using the Monin–Obukov similarity profile (Miyakoda and Sirutis 1986). A two-layer soil model (Mahrt and Pan 1984) is used to predict soil-moisture fraction, soil temperature, and canopy water content. The top layer extends from the surface to 10 cm, and the deep layer extends from 10 to 200 cm. Vegetation type and cover and soil type are taken from the Simple Biosphere model climatology (Dorman and Sellers 1989). When rain falls, a portion proportional to the vegetation fraction is intercepted by the leaves and converted into canopy water content. The canopy water then evaporates. If the final canopy water content exceeds the canopy water capacity, the excessive part drops to the ground. Water on the ground is either absorbed by soil or becomes runoff depending upon the ground wetness and soil types.

For all GCM experiments we present here, the model was forced by the observed monthly mean SSTs for the period from 1979 through 2000 (Smith et al. 1996). For the experiments described in section 4 in which the observed precipitation was inserted to replace model-predicted precipitation, we used the Experimental Global Precipitation Climatology Project (GPCP) Pentad Precipitation Analysis, created and maintained at NCEP (P. Xie 2002, personal communication). This dataset was defined by merging gauge and satellite observations and has a resolution of 2.5° latitude × 2.5° longitude. At the time these experiments were carried out, this dataset was the only one available that had a fine temporal resolution, covered the globe, and extended back to 1979. More recently, Huffman et al. (2001) produced a 1° daily mean precipitation dataset. In section 3, in the context of a perfect model approach, we demonstrate that results drawn from this study are not biased because of the use of the pentad-mean precipitation instead of other types of precipitation with higher temporal resolutions.

3. Choice of mean precipitation for substitution—A perfect model assessment

Ideally, the best choice for GCM precipitation substitution is to have an observational precipitation dataset whose temporal resolution matches the time step of the model's land surface physics. However, observational precipitation analyses are often presented as daily, pentad, or monthly means. Are the modeled soil-moisture content and surface climate affected by the use of time-averaged precipitation instead of the precipitation produced by the model at each time step? We assess this impact from a set of different GCM experiments.

We first performed a 22-yr simulation for the 1979–2000 period forced by observed SSTs, a standard AMIP-type simulation. We refer to this simulation hereinafter as Cntl. Daily mean precipitation was saved during the Cntl run. Pentad and monthly means were subsequently derived. Then, three more GCM experiments were performed for the 1979–2000 period starting from the same single initial condition and forced by the same SSTs, except that for the land surface component of the GCM, the saved daily, pentad, and monthly mean precipitation were inserted into the GCM to replace the model-predicted precipitation (referred to as Daily, Pentad, and Monthly experimental runs, respectively). To elaborate, for instance, the Pentad run was carried out in such a way that the pentad precipitation derived from the Cntl run was divided equally and inserted into the soil-moisture budget equation at each model physical step to update canopy water content, runoff, and soil-moisture fraction. The precipitation predicted by the model itself was ignored. The insertion is made only if the model-predicted precipitation is in liquid phase; that is to say, snow is still predicted by the model itself. For illustration, the daily, pentad, and monthly precipitation averaged over the U.S. continent for 1979 are plotted in Fig. 1.

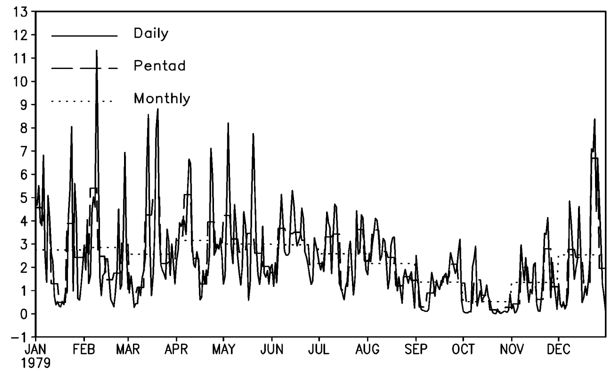

FIG. 1. Daily, pentad, and monthly mean precipitation averaged over the U.S. continent, derived from the Cntl run for 1979. Large variations of daily and pentad precipitation are superimposed on the monthly means.

The focus of this study is on summertime surface climate in monthly to seasonal time scales. To understand to what extent the substitution of modeled precipitation with time-averaged precipitation replicates the soil-moisture evolution, we compared a few land and near-surface properties from the experimental runs (Daily, Pentad, and Monthly) with those from the control run (Cntl).

Shown in Fig. 2 are the percent differences of the top-layer (0–10 cm) soil volumetric wetness (cm) and surface-air temperature (°C) in July averaged for the 1979–2000 period between the experimental runs and the control run. Figure 3 shows local correlations for the 22-yr period in July. For all three experimental runs, the biases in soil-moisture content and surface-air temperature are less than 10% everywhere over the U.S. continent. Local correlations are generally larger than 0.9 for soil moisture and larger than 0.8 for surface-air temperature. The results from the Pentad run are rather close to the Daily run. Larger biases are found for the Monthly run. For other months in the warm season, we found similar results (not shown). For the cold season, even though the simulated soil-moisture content from the experimental runs still matches rather well with that from the control run, surface-air temperature shows almost no correlation, indicating much stronger dynamical control of the atmosphere on surface-air temperature in winter than in summer.

These tests indicate that monthly mean statistics of the modeled land and near-surface properties in summer

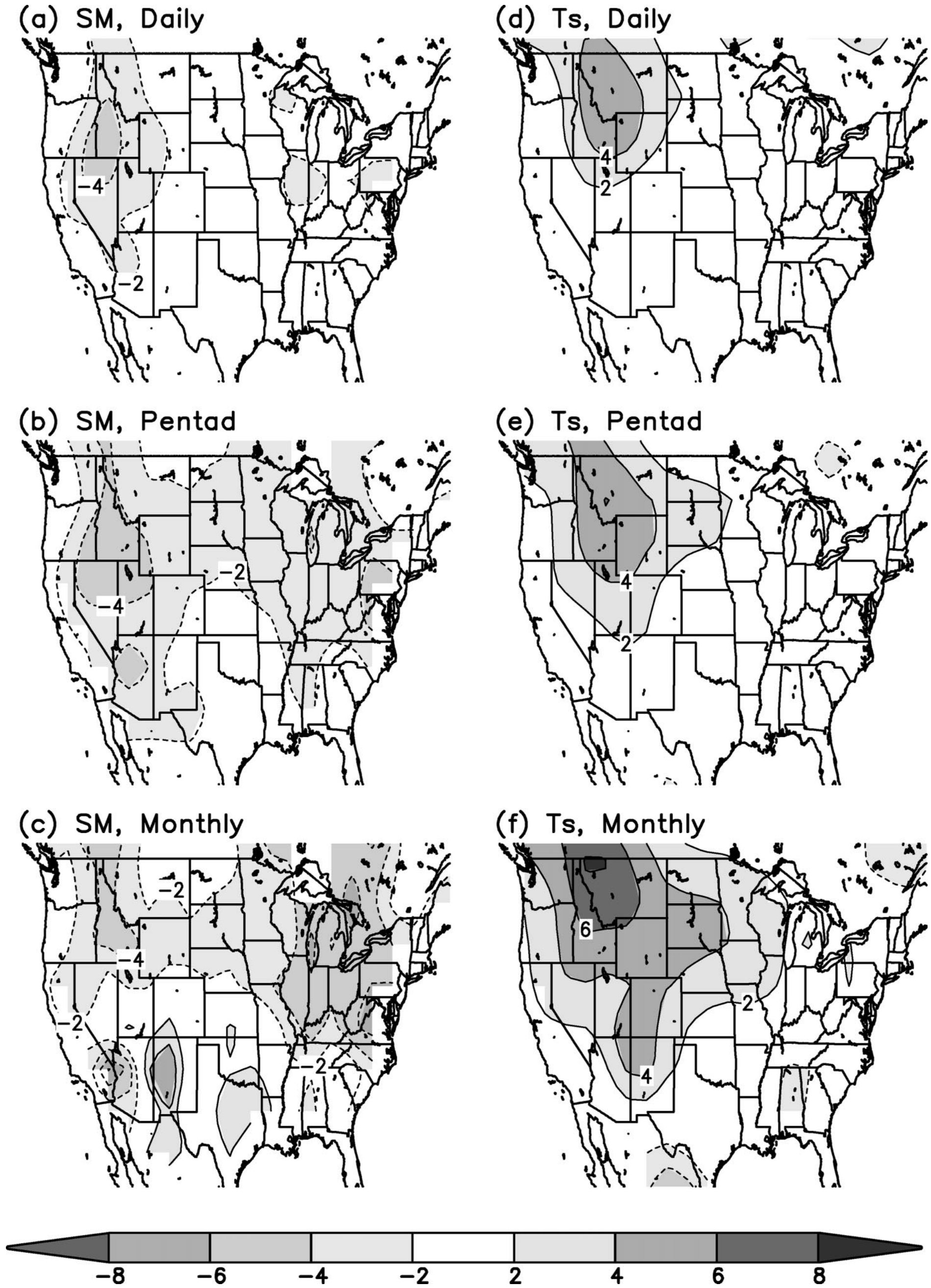

FIG. 2. Percent differences of the GCM-simulated top-layer soil-moisture content in terms of (left) volumetric wetness (cm) and (right) surface-air temperature (°C) between the experimental runs (Daily, Pentad, and Monthly) and the control run (Cntl) in Jul, averaged for the 1979–2000 period.

have not been seriously altered because of the use of time-averaged precipitation as forcing for the GCM land surface component. In section 4, observed pentad-mean precipitation will be used to force the GCM for our investigation of the predictability of U.S. summer climate. Based on the comparisons presented in this section we feel confident that our results are not biased because of the choice of the pentad-mean precipitation.

4. ‘‘Perfect’’ soil moisture from precipitation substitution

Starting from different atmospheric and land surface initial conditions, a set of three GCM simulations were performed for the 1979–2000 period. They were forced by the observed monthly SSTs over the ocean and the observed GPCP pentad-mean precipitation over land.

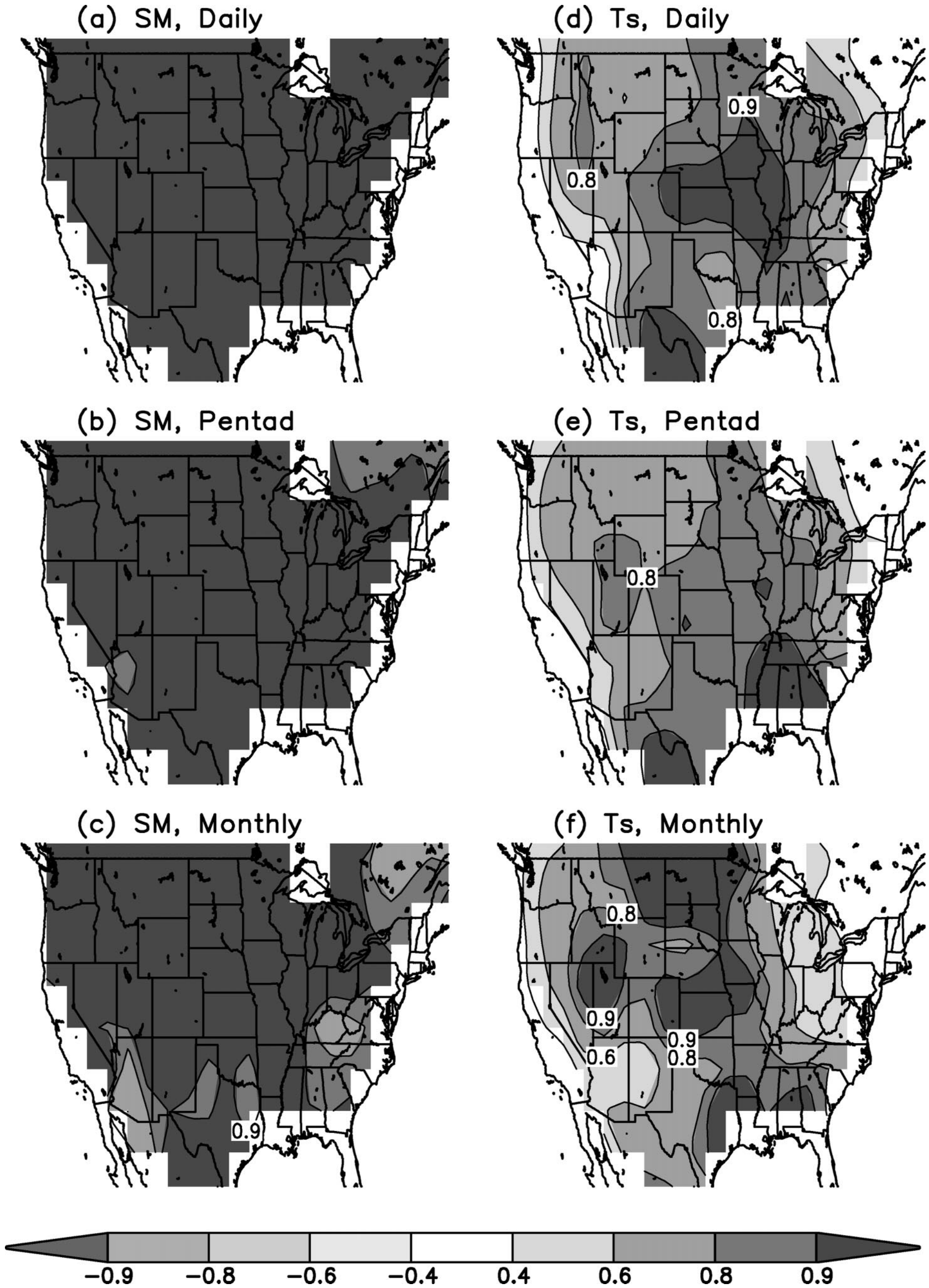

FIG. 3. Local correlations of the (left) GCM-simulated top-layer soil-moisture content and (right) surface-air temperature between the experimental runs (Daily, Pentad, and Monthly) and the control run (Cntl) in Jul for the 1979–2000 period.

We refer this set of simulations as obs_rain. For comparison, another set of three GCM simulations were performed that are the same as the obs_rain except that the land surface component was forced by the model-predicted pentad-mean precipitation. We refer to this set of simulations as gcm_rain. The simulated soil-moisture contents from the two sets of simulations were then evaluated against observations to measure the improvement in soil-moisture simulation by precipitation substitution. All calculations thereinafter are based on ensemble means of the GCM simulations.

Currently, there are still no global and long-term observations, either on the ground or from satellites, of soil-moisture content suitable for climate study. For validation we rely on a model-based soil-moisture analysis over the U.S. continent conducted routinely at NCEP, which is based on the work of Huang et al. (1996). This analysis is performed with a one-layer (0–160 cm) soil-

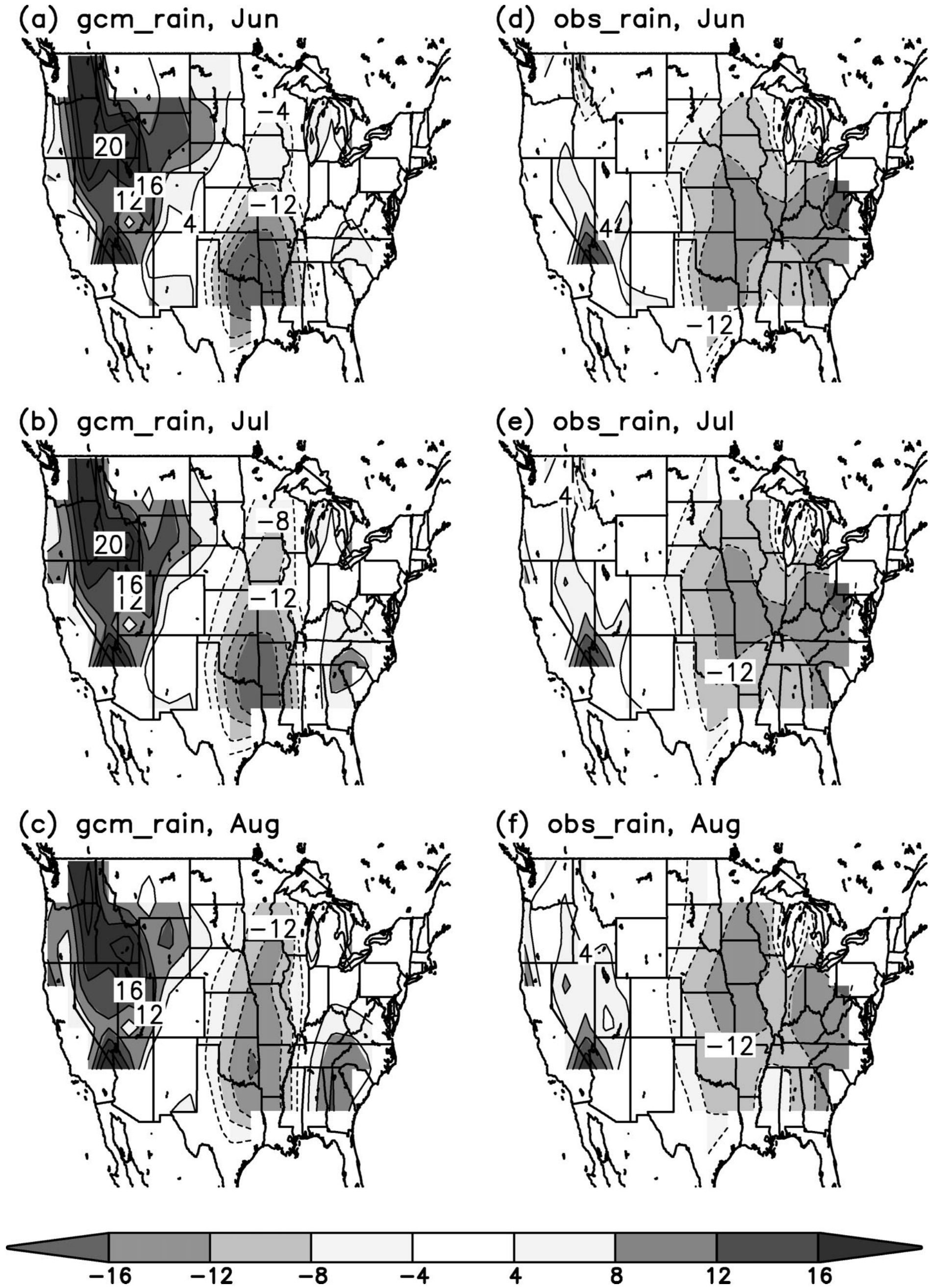

FIG. 4. Differences in soil volumetric wetness (cm) in the top 160 cm of soil between the GCM simulations and the Huang et al. (1996) analysis in JJA, averaged for the 1979–2000 period. (left) The gcm_rain runs in which the GCM was forced by its own pentad-mean precipitation, and (right) the obs_rain runs in which the GCM was forced by the observed GPCP pentad-mean precipitation.

moisture model that computes the water budget in the soil and is forced by observed monthly temperature and precipitation. Huang et al. (1996) showed that their model analysis compared well with the soil-moisture observations in Illinois in terms of climatology and interannual variation. The analysis has been used widely for climate diagnosis and prediction (e.g., Van den Dool et al. 2003; Mo 2003).

The GCM consists of a two-layer soil model, with the top layer extending down to 10 cm and the lower layer from 10 to 200 cm. We derived the GCM soil-moisture content for the top 160 cm by linear scaling. Figure 4 compares the 1979–2000 climate means of soil-moisture content in the top 160 cm over the U.S. continent in boreal summer months (June, July, and August, respectively) between the GCM results and the Huang et al. (1996) analysis. Forced by the GCM's own pentad-mean precipitation (gcm_rain runs), the model is too wet over the northwestern states and too dry over the central and southern states from Iowa down to Louisiana and eastern Texas. These biases are greatly reduced in the obs_rain runs in which the observed GPCP precipitation was assimilated. Over the central to southeastern states, the model suffered from moderate wet biases in the gcm_rain runs and moderate dry biases in obs_rain runs.

Figure 5 presents the local correlations of soil-moisture content between model simulations and the Huang et al. (1996) analysis for the 1979–2000 period. For the gcm_rain runs, the model shows no skill in soil-moisture simulations, with a few exceptions over the southeastern states, the northern part of the Great Plains, and the southwestern states. For the runs forced by the observed GPCP precipitation (obs_rain runs), the correlations between the model-predicted soil moisture and the analysis are generally larger than 0.6 over the entire continent.

The result indicates that even though soil-moisture content is controlled by many parameters and physical processes such as air and ground temperatures, runoff, soil and vegetation types, precipitation and evaporation, and the feedback among the processes (Delworth and Manabe 1988; Koster and Suarez 2001), it is quite effective simply substituting the modeled precipitation with observations if the goal is to obtain a better soil condition to force the atmosphere. We next investigate the potential predictability of U.S. surface climate simulated by the NCEP GCM, given the so-derived ''perfect'' soil-moisture content. This is analogous to the traditional GCM investigation of predictability associated with prescribed SST anomalies (e.g., Kumar and Hoerling 1998; Straus et al. 2003).

5. Potential predictability of U.S. surface climate with ''perfect'' soil moisture

Here the measure of predictability is defined as the contemporary correlations of monthly mean surface-air temperature and precipitation between model simulations and observations. For observations, we use monthly mean precipitation derived from the GPCP daily precipitation (Huffman et al. 2001) and monthly mean surface-air temperature from the global network of surface observations, the Climate Anomaly Monitoring System (CAMS), maintained at NCEP (Ropelewski et al. 1986). Figure 6 presents the correlation maps of monthly mean surface-air temperature over the U.S. continent between the CAMS observation and the two sets of GCM experiments, gcm_rain and obs_rain, respectively, in the three boreal summer months for the 1979–2000 period. Correlation maps for precipitation are presented in Fig. 7. If we regard correlations larger than 0.4 as skillful (at about the 94% significance level for a Student's *t* test), the GCM has skill in predicting the surface-air temperature over only a few states when forced by the model's own precipitation (Figs. 6a–c), such as those over Idaho in June and July and over Georgia and Alabama in July. When forced by the observed GPCP precipitation, the model's prediction skill is enhanced in general over many states (Figs. 6d–f). The areas with the biggest improvement are found over Montana, the Great Plains, the Mississippi Valley, Texas, and New Mexico.

For precipitation (Fig. 7), when the GCM's land surface component is forced by the model-predicted precipitation, the GCM has some prediction skill in the northwest in June and July and in the southeast in July. Over many regions, the correlations are negative (Figs. 7a–c). When forced by the observed GPCP precipitation, the skills are improved over the entire U.S. continent, although in June and July the model became less skillful over a few states in the northwest.

The prediction skill described here is the potential predictability of the NCEP GCM, in the sense that perfect boundary conditions of SSTs and soil-moisture content were used to force the model. Given the chaotic feature of the atmospheric circulation, which is constrained by the specification of soil moisture only to a certain extent, the prediction skill is fundamentally limited. With the foreknowledge of soil moisture in addition to SSTs, the enhancement in the predictions of precipitation and temperature is not uniform in space and time. Koster et al. (2000) demonstrated that for precipitation the enhancement can be detected only in the transition zones between dry and humid climates, where evaporation responds strongly to soil-moisture changes and the variation in evaporation itself is also large enough to affect the overlying atmosphere. They performed two sets of GCM ensemble experiments, one with interactive land surface processes and the other with prescribed interannually varying evaporation efficiency (the ratio of evaporation to potential evaporation). The evaporation efficiency prescribed in the latter was generated by a single randomly chosen member of the former. In this perfect model approach they found (see their Fig. 13) the enhancement in the potential predictability of June–July–August (JJA) precipitation over the United States was measurable only over the northwestern to central southern states and over the southeastern states. Our results based on monthly mean analysis show no such definitive geographical preference in the enhancement of potential predictability of precipitation from month to month (Fig. 7). In June, the enhancement is found in the eastern and southern states. In July, the greatest enhancement is found in the northwestern states. In August, the enhancement occurred in the southeastern and western states. The disagreement between the present study and Koster et al. (2000) may arise from the differences in experimental design and GCM formulation. A small ensemble size of three in the present analysis may also contribute to the large variations in space and time.

To see the seasonal dependence of the model's prediction skill, we computed the mean correlations shown in Figs. 5–7 over the entire U.S. continent (27°–50°N,

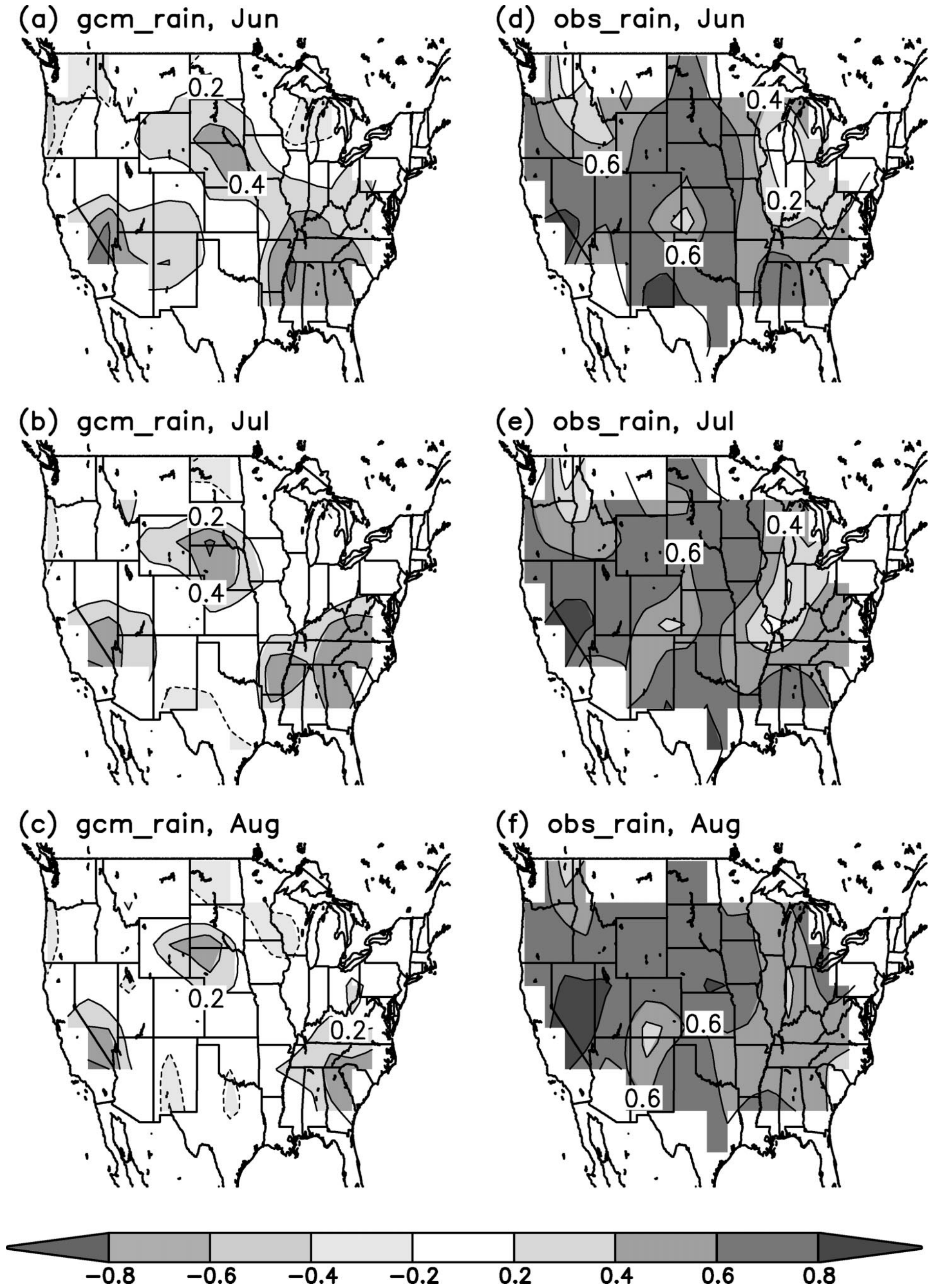

FIG. 5. Anomalous correlations of soil-moisture content in the top 160 cm between the GCM simulations and the Huang et al. (1996) analysis in JJA, for the 1979–2000 period. (left) The gcm_rain runs, and (right) the obs_rain runs.

68°–130°W) and for all 12 months. Presented in Fig. 8 are the spatial mean correlations for soil moisture, surface-air temperature, and precipitation, respectively. The model's simulation skill in soil moisture is greatly enhanced in all months when forced by the observed precipitation. The correlations for soil moisture are raised from below 0.2 for the gcm_rain runs to about 0.6 for the obs_rain in all months. For precipitation and surface-air temperature, better simulation skills are found only in late spring and summer months. The correlations are raised by about 0.1 for precipitation and by up to 0.3 for surface-air temperature. In winter and early spring, snow cover and atmospheric dynamics play more important a role than soil moisture in controlling the land surface processes. In the present study, snowfall was simulated by the GCM without substitution from observations.

We computed further the pattern correlations over the

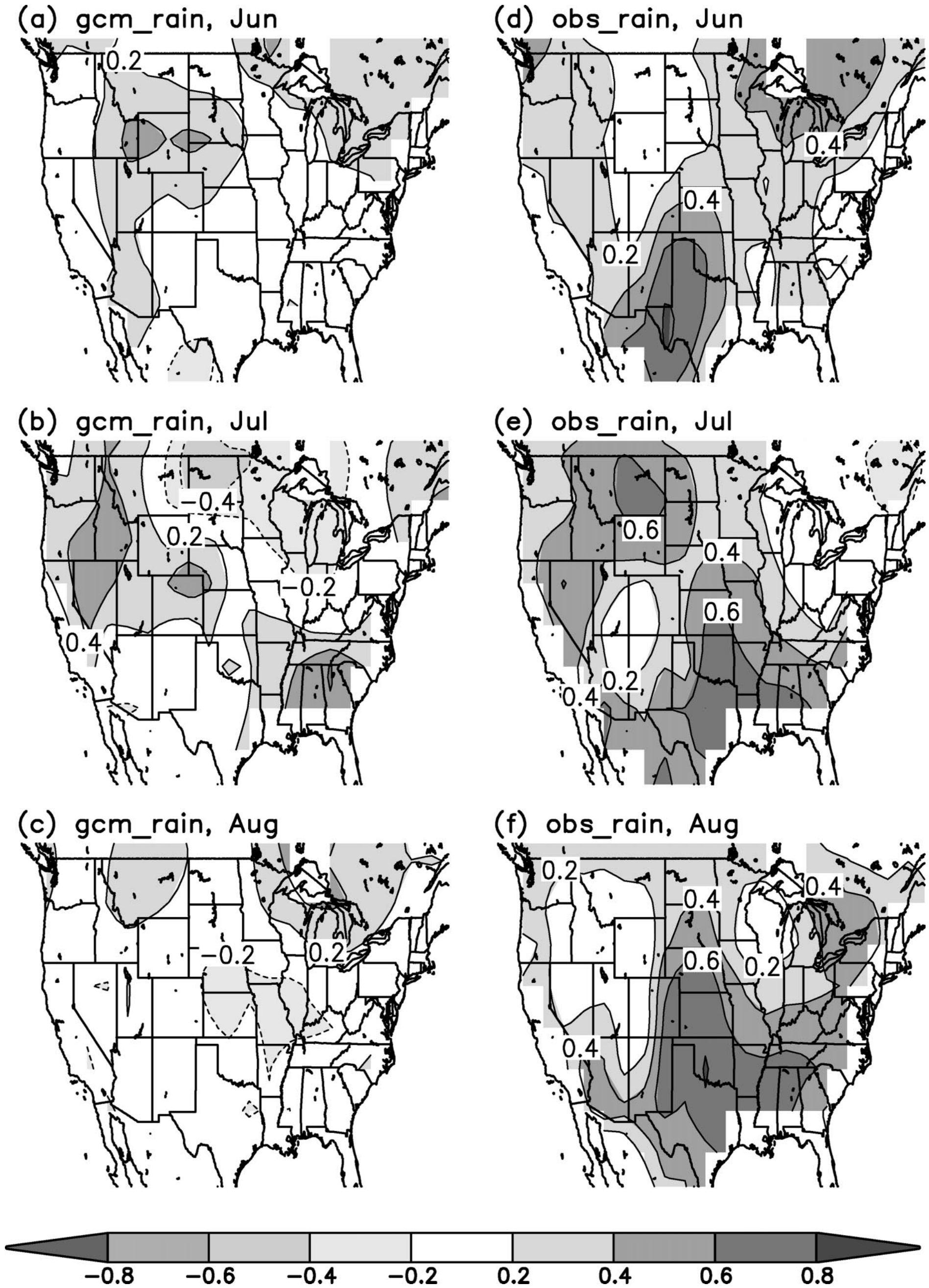

FIG. 6. Local correlations of surface-air temperature between the GCM simulations and the CAMS observations in JJA, averaged for the 1979–2000 period. (left) The gcm_rain runs, and (right) the obs_rain runs.

U.S. continent for June–August averaged anomalies of soil moisture, precipitation, and surface-air temperature between model simulations and the corresponding observations for the years from 1979 through 2000. For the traditional AMIP-type simulations (gcm_rains, solid bars in Fig. 9), the NCEP GCM has some skill in simulating soil moisture in most of the years. The skill for surface-air temperature is appreciable for some years, but is very low when averaged over all the years. For precipitation, there is basically no skill. For the AMIP simulations with precipitation substitution (obs_rains, gray bars in Fig. 9), the anomalous pattern correlations for the three variables are much higher and are positive for all years. Consistent with the mean temporal correlations shown in Fig. 8, the most significant improvement is found for soil moisture. The simulations for precipitation and surface-air temperature are also improved considerably. However, the greatest improve-

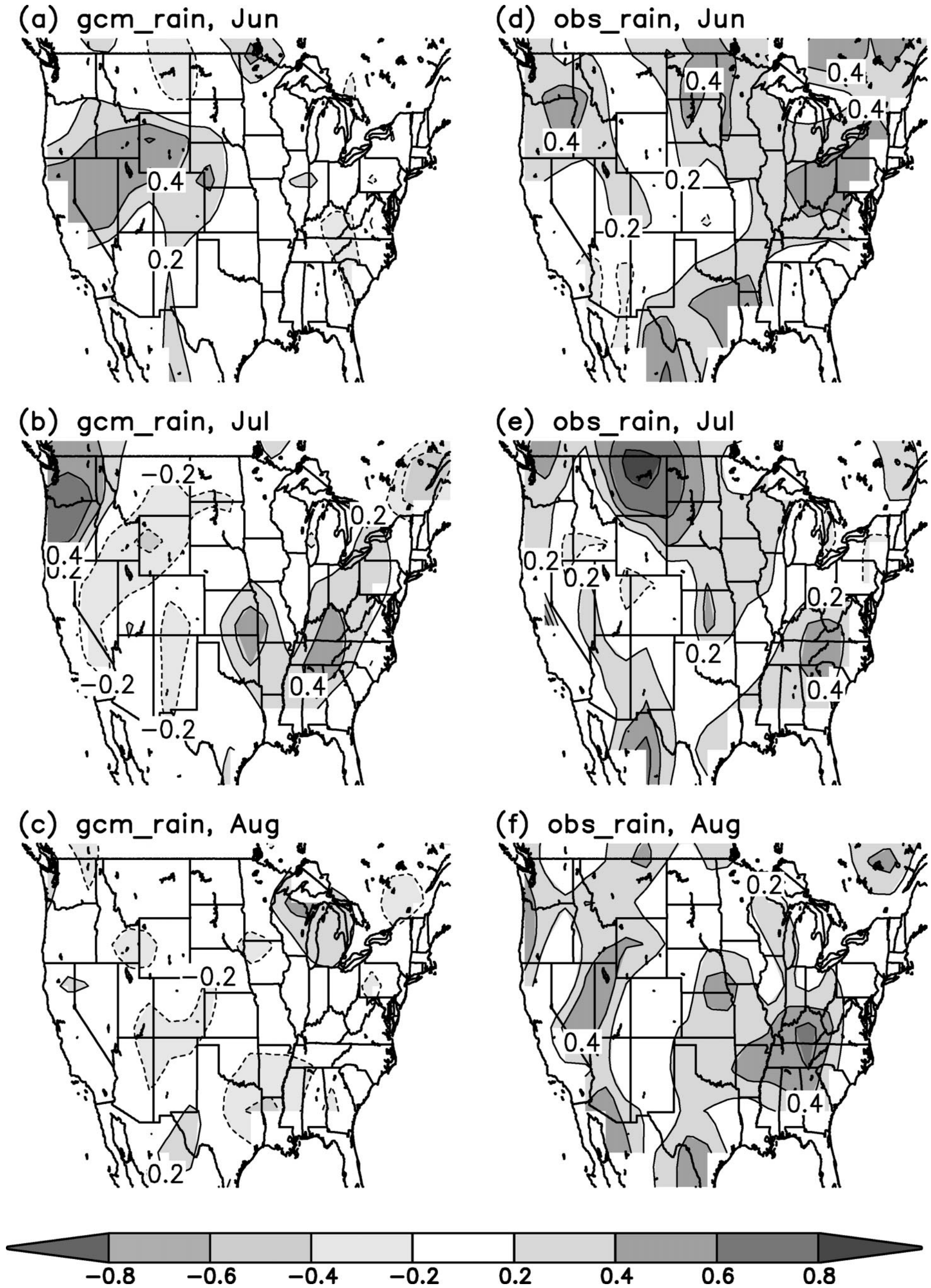

FIG. 7. Local correlations of precipitation between the GCM simulations and the GPCP observations in JJA, averaged for the 1979–2000 period. (left) The gcm_rain runs, and (right) the obs_rain runs.

ment in soil moisture (e.g., 1988) did not always transform into the best prediction skill of precipitation and surface-air temperature. On the contrary, in certain years such as 1996 and 1997 a small improvement in the simulation of soil moisture transformed into a large increment of the prediction skill for precipitation. This indicates that in addition to soil moisture the conditions of large-scale circulation and SSTs are also important factors that determine the overall prediction skill of precipitation and surface-air temperature.

6. Conclusions and discussion

It is still a big challenge for current atmospheric GCMs to simulate accurately atmospheric precipitation and hence the soil-moisture content. Previous studies (e.g., Fennessy and Shukla 1999; Kanamitsu et al. 2003; Koster and Suarez 2003) have demonstrated that GCMs initialized with realistic soil-moisture content can improve the prediction skill of U.S. summer climate over certain regions. The potential predictability associated

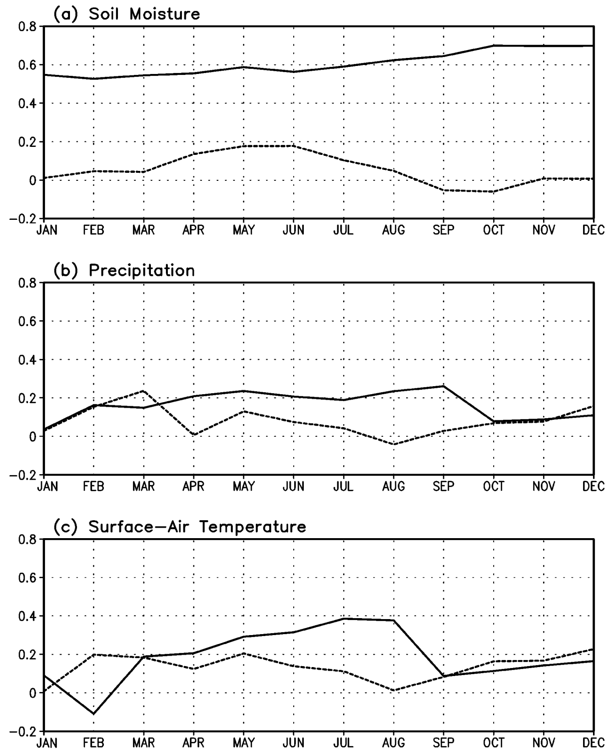

FIG. 8. Mean correlations between prediction and observations averaged over the entire U.S. continent, for (a) soil moisture, (b) precipitation, and (c) surface-air temperature, as shown in Figs. 5–7 except for all months. Dotted lines are for the correlations between the gcm_rain runs and observations, and bold lines are for those between the obs_rain runs and observations.

with observed soil moisture as a boundary forcing instead of an initial value problem has not been explored because of the scarcity of soil-moisture observations.

In this study, the potential predictability of precipitation and surface-air temperature over the U.S. continent in boreal summer is estimated using the NCEP operational seasonal forecast model with precipitation substitution over the land and with the observed SSTs as boundary forcing over the oceans. The observed GPCP pentad-mean precipitation was used during model integrations to replace the model-predicted precipitation as input to the land surface component of the GCM. Soil-moisture content simulated by the GCM with this simple precipitation substitution match well with the Huang et al. (1996) soil moisture analysis over the U.S. continent in all seasons in terms of climate mean, and almost ''perfectly'' well in terms of temporal and anomalous pattern correlations. The potential prediction skill of precipitation and surface-air temperature are also greatly improved in late spring and summer months over many states in the continent. Averaged for all years, the anomalous pattern correlations (Fig. 9) for precipitation and surface-air temperature in JJA are 0.01 and 0.06, for the runs without precipitation substitution, and are raised to 0.23 and 0.31, respectively, for the runs with precipitation substitution. This indicates that even though the potential predictability of U.S. summer climate associated with SST anomalies is low, better prediction skill can still be achieved with improved modeling of soil-moisture content.

Now the question is how to improve the simulation of soil moisture in GCMs. One way is to initialize the GCM with realistic soil-moisture content (e.g., Fennessy and Shukla 1999; Schlosser and Milly 2002; Kanamitsu et al. 2003; Koster and Suarez 2003). But the persistence or memory of soil-moisture anomalies is usually small in spring and summer over the U.S. continent (Wang and Kumar 1998; Schlosser and Milly 2002). Schlosser and Milly found for the Geophysical Fluid Dynamics Laboratory climate model the predictability time scale of soil moisture measured as *e*-folding time is about 2 weeks or less in midlatitudes during summer. Seasonal prediction skill of U.S. summer climate with soil-moisture anomalies treated as an initial value problem is limited because of the short memory of soil moisture in summer and the inability of current GCMs to simulate precipitation accurately. Results from previous studies showed that the degree to which the initialization can enhance the predictability of summertime precipitation and temperature is limited and mixed, varying among models and with locations.

In this study we treat soil moisture as a boundary value problem and demonstrate the appreciable prediction skill of U.S. summer climate. Similar studies can be carried out using soil moisture from Land Data Assimilation Systems (e.g., Mitchell et al. 1999; Cosgrove et al. 2003) to better understand the potential predictability of U.S. summer climate for other GCMs. However, this approach is not practical for operational forecasts because we do not know soil moisture or precipitation beforehand. On the other hand, given the strong dependence of soil moisture on precipitation as found in this study, it might be helpful to apply bias corrections, in terms of not only mean but also spatial patterns, on GCM-predicted precipitation during real-time seasonal forecasts based on antecedent statistical relations between model-predicted precipitation and observations. The reduction in precipitation bias might lead to improved simulation of soil moisture, and possibly better prediction skill of surface-air temperature and, in turn, precipitation itself. This kind of model-output-statistics (MOS) adjustment has been applied to, for instance, surface winds, for the dynamical forecast of tropical SSTs, and proved to be effective in improving the forecast skill of SSTs (Ji et al. 1994). A proper soil-moisture initialization combined with precipitation MOS correction might further enhance the seasonal forecast skill of U.S. summer climate.

Finally, we note that our analysis only provides an estimate for the potential predictability related to the interannual variability of soil-moisture anomalies. Such estimates can easily be biased by the GCM characteristics and remain to be substantiated by other modeling

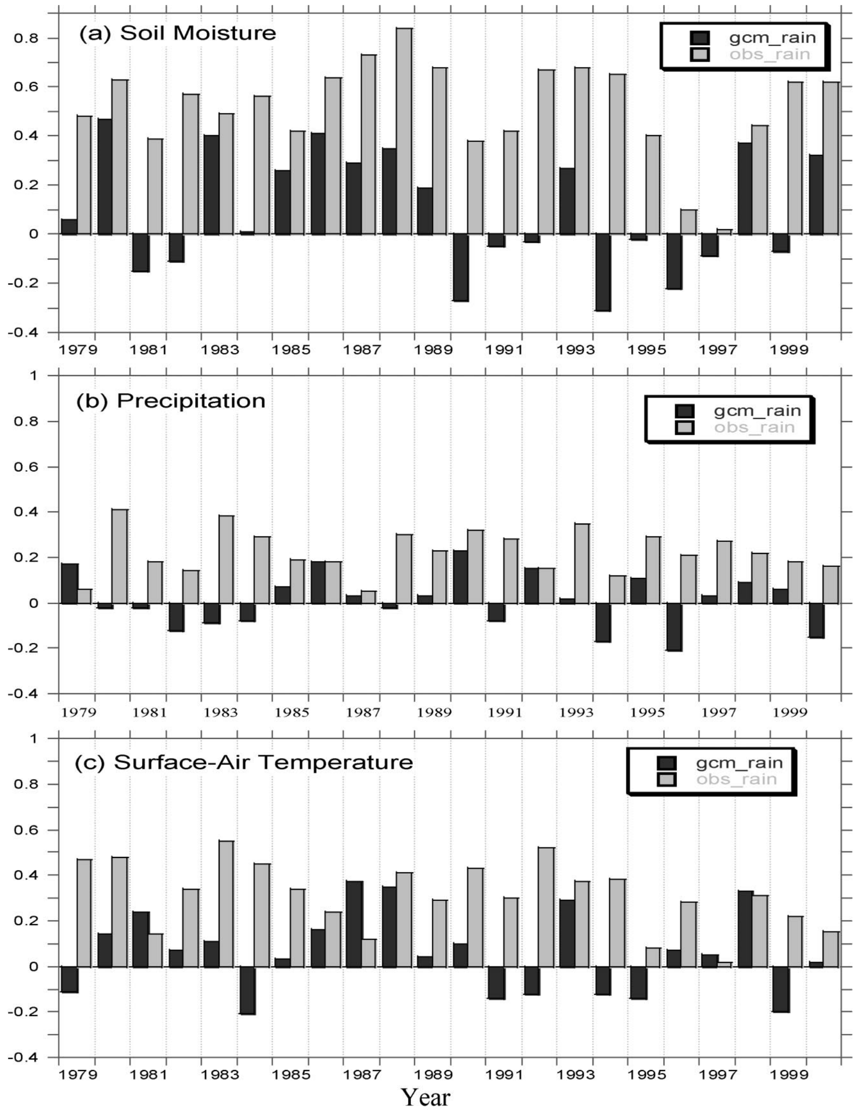

FIG. 9. Pattern correlations of JJA mean anomalies for (a) soil moisture, (b) precipitation, and (c) surface-air temperature over the U.S. continent from 1979 through 2000 between the NCEP GCM simulations and the observations as described in the text. Black bars are for the gcm_rain runs for which precipitation assimilation was not applied. Gray bars are for the obs_rain runs for which the observed GPCP pentad-mean precipitation was used to force the land surface component of the GCM.

systems. Another factor that might have influenced our estimates for the potential predictability is the small ensemble size of three used in this study. As was shown by Kumar and Hoerling (2000), the expected level of skill depends on the ensemble size. Given the fact that the expected level of skill progressively increases with increasing ensemble size, potential predictability estimates based on larger ensembles may be slightly higher and more stable in space and time than the ones obtained in the present analysis.

Acknowledgments. We thank three anonymous reviewers for their constructive and insightful comments. FY and KML were partially supported by the NASA Modeling, Analysis and Prediction program. AK is thankful for the support offered by NOAA's Climate Dynamics and Experimental Prediction Program.

REFERENCES

Atlas, R., N. Woldson, and J. Terry, 1993: The effect of SST and soil moisture anomalies on GLA model simulations of the 1998 U.S. summer drought. *J. Climate,* **6,** 2034–2048.

Cosgrove, B. A., and Coauthors, 2003: Real-time and retrospective forcing in the North American Land Data Assimilation System (NLDAS) project. *J. Geophys. Res.,* **108,** 8842, doi:10.1029/2002JD003118.

Delworth, T. L., and S. Manabe, 1988: The influence of potential evaporation on the variability of simulated soil wetness and climate. *J. Climate,* **1,** 523–547.

Dirmeyer, P. A., 2000: Using a global soil wetness dataset to improve seasonal climate simulation. *J. Climate,* **13,** 2900–2922.

Dorman, J., and P. J. Sellers, 1989: A global climatology of albedo, roughness and stomatal resistance for atmospheric general circulation models as represented by the Simple Biosphere Model (SB). *J. Appl. Meteor.,* **28,** 833–855.

Fennessy, M. J., and J. Shukla, 1999: Impact of initial soil wetness on seasonal atmospheric prediction. *J. Climate,* **12,** 3167–3180.

——, P. A. Dirmeyer, J. L. Kinter III, A. Schlosser, J. Shukla, J. Huang, and L. Sun, 2000: Impact of initial soil moisture anomalies on seasonal atmospheric predictions over the U.S. during March–April–May 2000. *Proc. Climate Diagnostics Workshop,* Palisades, NY, IRI, 239–241.

Hong, S.-Y., and E. Kalnay, 2000: Role of sea surface temperature and soil-moisture feedback in the 1998 Oklahoma–Texas drought. *Nature,* **408,** 842–844.

Huang, J., H. M. Van den Dool, and K. P. Georgarakos, 1996: Analysis of model-calculated soil moisture over the United States (1931–1993) and applications to long-range temperature forecasts. *J. Climate,* **9,** 1350–1362.

Huffman, G. J., R. F. Adler, M. Morrissey, D. T. Bolvin, S. Curtis, R. Joyce, B. McGavock, and J. Susskind, 2001: Global precipitation at one-degree daily resolution from multisatellite observations. *J. Hydrometeor.,* **2,** 36–50.

Ji, M., A. Kumar, and A. Leetmaa, 1994: A multiseason climate forecast system at the National Meteorological Center. *Bull. Amer. Meteor. Soc.,* **75,** 569–577.

Kanamitsu, M., and Coauthors, 2002: NCEP dynamical seasonal forecast system 2000. *Bull. Amer. Meteor. Soc.,* **83,** 1019–1037.

——, C.-H. Lu, J. Schemm, and W. Ebisuzaki, 2003: The predictability of soil moisture and near-surface temperature in hindcasts of the NCEP seasonal forecast model. *J. Climate,* **16,** 510–521.

Koster, R. D., and M. J. Suarez, 1995: The relative contributions of land and ocean processes to precipitation variability. *J. Geophys. Res.,* **100,** 13 775–13 790.

——, and ——, 2001: Soil moisture memory in climate models. *J. Hydrometeor.,* **2,** 558–570.

——, and ——, 2003: Impact of land surface initialization on seasonal precipitation and temperature prediction. *J. Hydrometeor.,* **4,** 408–423.

——, M. J. Max, and M. Heiser, 2000: Variability and predictability of precipitation at seasonal-to-interannual timescales. *J. Hydrometeor.,* **1,** 26–46.

Kumar, A., and M. P. Hoerling, 1998: Annual cycle of Pacific–North American seasonal predictability associated with different phases of ENSO. *J. Climate,* **11,** 3295–3308.

——, and ——, 2000: Analysis of a conceptual model of seasonal climate variability and implications for seasonal prediction. *Bull. Amer. Meteor. Soc.,* **81,** 255–264.

Lau, K.-M., J.-Y. Lee, K.-M. Kim, and I.-S. Kang, 2004: The North Pacific as a regulator of summertime climate over Eurasia and North America. *J. Climate,* **17,** 819–833.

Mahrt, L., and H.-L. Pan, 1984: A two layer model of soil hydrology. *Bound.-Layer Meteor.,* **29,** 1–20.

Mitchell, K., and Coauthors, 1999: GCIP land data assimilation system (LADS) project now underway. *GEWEX News,* Vol. 9, No. 4, Internation GEWEX Project Office, Silver Spring, MD, 3–6.

Miyakoda, K., and J. Sirutis, 1986: Manual of the E-physics. GFDL, 68 pp. [Available from Geophysical Fluid Dynamics Laboratory, Princeton University, P.O. Box 308, Princeton, NJ 08542.]

Mo, K. C., 2003: Ensemble canonical correlation prediction of surface temperature over the United States. *J. Climate,* **16,** 1665–1683.

Ropelewski, C. F., and M. S. Halpert, 1986: North America precipitation and temperature patterns associated with the El Niño/Southern Oscillation (ENSO). *Mon. Wea. Rev.,* **114,** 2352–2362.

Schar, C., D. Luthi, U. Beyerle, and E. Heise, 1999: The soil–precipitation feedback: A process study with a regional climate model. *J. Climate,* **12,** 722–741.

Schlosser, C. A., and P. C. D. Milly, 2002: A model-based investigation of soil moisture predictability and associated climate predictability. *J. Hydrometeor.,* **3,** 483–501.

Schubert, S. D., M. J. Suarez, P. J. Pegion, M. A. Kistler, and A. Kumar, 2002: Predictability of zonal means during boreal summer. *J. Climate,* **15,** 420–434.

Shukla, J., and Coauthors, 2000: Dynamical seasonal prediction. *Bull. Amer. Meteor. Soc.,* **81,** 2593–2606.

Smith, T. M., R. W. Reynolds, R. E. Livezey, and D. C. Stokes, 1996: Reconstruction of historical sea surface temperature using empirical orthogonal functions. *J. Climate,* **9,** 1403–1420.

Straus, D., J. Shukla, D. Paolino, S. Schubert, M. Suarez, P. Pegion, and A. Kumar, 2003: Predictability of the seasonal mean atmospheric circulation during autumn, winter, and spring. *J. Climate,* **16,** 3629–3649.

Ting, M., and H. Wang, 1997: Summertime U.S. precipitation variability and its relation to Pacific sea surface temperature. *J. Climate,* **10,** 1853–1873.

Trenberth, K. E., G. Branstator, G. W. Karoly, A. Kumar, N.-C. Lau, and C. Ropelewski, 1998: Progress during TOGA in understanding and modeling global teleconnections with tropical sea surface temperatures. *J. Geophys. Res.,* **103,** 14 291–14 324.

Van den Dool, H., J. Huang, and Y. Fan, 2003: Performance and analysis of the constructed analogue method applied to U.S. soil moisture over 1981–2001. *J. Geophys. Res.,* **108,** 8617, doi:10.1029/2002JD003114.

Wallace, J. M., and D. S. Gutzler, 1981: Teleconnections in the geopotential height field during the Northern Hemisphere winter. *Mon. Wea. Rev.,* **109,** 784–812.

Wang, W., and A. Kumar, 1998: A GCM assessment of atmospheric seasonal predictability associated with soil moisture anomalies over North America. *J. Geophys. Res.,* **103,** 28 637–28 646.