Prospects for Dynamical Prediction of Meteorological Drought

XIAO-WEI QUAN,* MARTIN P. HOERLING,* BRADFIELD LYON,[+] ARUN KUMAR,[#] MICHAEL A. BELL,[+] MICHAEL K. TIPPETT,[+,@] AND HUI WANG[#]

* *NOAA/Earth System Research Laboratory, Boulder, Colorado*
[+] *International Research Institute for Climate and Society, Columbia University, Palisades, New York*
[#] *NOAA/Climate Prediction Center, Camp Spring, Maryland*
[@] *Center of Excellence for Climate Change Research/Department of Meteorology, King Abdulaziz University, Jeddah, Saudi Arabia*

(Manuscript received 12 September 2011, in final form 21 February 2012)

ABSTRACT

The prospects for U.S. seasonal drought prediction are assessed by diagnosing simulation and hindcast skill of drought indicators during 1982–2008. The 6-month standardized precipitation index is used as the primary drought indicator. The skill of unconditioned, persistence forecasts serves as the baseline against which the performance of dynamical methods is evaluated. Predictions conditioned on the state of global sea surface temperatures (SST) are assessed using atmospheric climate simulations conducted in which observed SSTs are specified. Predictions conditioned on the initial states of atmosphere, land surfaces, and oceans are next analyzed using coupled climate-model experiments. The persistence of the drought indicator yields considerable seasonal skill, with a region's annual cycle of precipitation driving a strong seasonality in baseline skill. The unconditioned forecast skill for drought is greatest during a region's climatological dry season and is least during a wet season. Dynamical models forced by observed global SSTs yield increased skill relative to this baseline, with improvements realized during the cold season over regions where precipitation is sensitive to El Niño–Southern Oscillation. Fully coupled initialized model hindcasts yield little additional skill relative to the uninitialized SST-forced simulations. In particular, neither of these dynamical seasonal forecasts materially increases summer skill for the drought indicator over the Great Plains, a consequence of small SST sensitivity of that region's summer rainfall and the small impact of antecedent soil moisture conditions, on average, upon the summer rainfall. The fully initialized predictions for monthly forecasts appreciably improve on the seasonal skill, however, especially during winter and spring over the northern Great Plains.

1. Introduction

Increasing demand for water resources is a ubiquitous concern, but stress is exacerbated during periods of drought such as witnessed recently in the U.S. Southwest during that region's prolonged dry spell (Pulwarty et al. 2005). The socioeconomic costs of drought in North America can be enormous (e.g., the estimated costs of the 1988 U.S. drought alone are more than U.S.$5 billion; Wilhite 1993), and it is becoming increasingly clear that mitigating the hazards of drought impacts will require both proactive planning and developing new capacities for drought early warning (e.g., Wilhite et al. 2000; Wilhite and Pulwarty 2005).

Current national drought monitoring and forecasting efforts take place through a multiagency partnership that produces the U.S. (and North American) Drought Monitor and the regular production of seasonal drought outlooks (Svoboda et al. 2002; Hayes et al. 2005). While these efforts are providing benefits to decision-making communities vulnerable to drought, the National Integrated Drought Information System implementation plan (NOAA 2007) stresses the need to develop new, objectively based approaches to drought prediction that allow for robust verification, are transparent to users, and have sufficient flexibility so as to generate probabilistic drought-related information across different

Corresponding author address: Dr. Xiao-Wei Quan, NOAA/Earth System Research Laboratory, University of Colorado/CIRES, 325 Broadway, PSD1, Boulder, CO 80309.
E-mail: quan.xiao-wei@noaa.gov

DOI: 10.1175/JAMC-D-11-0194.1

time scales (monthly, seasonal, etc.) to address specific decision-making needs.

This study examines prospects for objective drought forecasting over the contiguous United States. It seeks to build upon current drought prediction capabilities embodied in the U.S. Drought Outlook. This product is informed by expert assessment that benefits from the existing knowledge base and typically relies on empirical associations with drought, including the consequence of persistent high pressure that can impede moisture delivery via redirection of migratory storms (e.g., Namias 1983; Lyon and Dole 1995), suspected land surface feedbacks in which antecedent soil conditions resulting from the cumulative effects of drought are believed to affect event persistence (e.g., Oglesby and Erickson 1989; Koster et al. 2004, 2006), and anomalous states of the tropical Pacific Ocean sea surface temperatures (SSTs) that can remotely affect atmospheric circulation patterns over North America and induce long-term sustained droughts (e.g., Hoerling and Kumar 2003; Schubert et al. 2004, 2008; Seager et al. 2005). Also, whereas the seasonal cycle of a region's rainfall is not a cause for drought per se, it is nonetheless relevant to the probability for recovery from the antecedent moisture deficits (Karl et al. 1987).

The National Oceanic and Atmospheric Administration's (NOAA) current drought prediction method begins with the construction of the latest Drought Monitor (Svoboda et al. 2002), a map of the United States (since 2002, NOAA has also provided an experimental North American Drought Monitor that includes Canada and Mexico) that describes the initial state of drought. This assessment uses various drought indicators, including the Palmer drought severity index (PDSI; Palmer 1965), the standardized precipitation index (SPI; McKee et al. 1993), the surface water supply index in semiarid regions where storage is important, and others. The Drought Outlook is a forecast product that propagates the existing monitored drought state into the next season using monthly and seasonal predictions of precipitation and surface air temperature combined with other relevant knowledge base as mentioned. The Drought Outlook thus identifies regions expected to experience improving/deteriorating conditions and regions in which currently existing drought is likely to persist. The forecast is couched in subjective language that is not readily amenable to verification, however. Given that much is at stake when weighing hazard mitigation options associated with potential drought impacts, it is important to explore objective forecast methods that can be verified to build the level of confidence that decision making requires.

Here we evaluate prospects for objective drought forecasts by diagnosing climate-model simulations and predictions of a selected drought indicator. Our approach involves an objective analysis of the initial state of moisture balances (akin to the Drought Monitor), and combines that information with an objective prediction of precipitation for the subsequent season that is based on dynamical model output. As described in section 2, different suites of model integrations are employed to isolate particular factors that can contribute to drought forecast skill. Uninitialized atmospheric model simulations forced by specified observed SSTs are studied to determine the effect of oceans on drought. These simulations also include land surface coupling and thus have the ability to represent the surface feedbacks that may influence intensity and persistence of drought solely due to the remote ocean forcing, although they are not initialized with observed soil moisture conditions. Initialized coupled atmosphere–land–ocean model runs of the NOAA Climate Forecast System (CFS) that are based on an ensemble of historical hindcast experiments are also examined. At the beginning of the forecast these have information of the initial states of land surface, soil moisture, and atmospheric circulation in addition to ocean conditions. Drought forecast skills are calculated for monthly and seasonal mean conditions using the 6-month standardized precipitation index (SPI6) as the predictand to indicate drought severity. The SPI6 is utilized as one of the principal metrics for drought severity in the current Drought Monitor and is a suitable drought indicator for the seasonal time scales addressed in this study.

Results for seasonal skill in predicting SPI6 are presented in section 3. An empirical baseline for seasonal drought forecast skill that is derived from unconditioned, simple persistence of the drought indicator is first derived. It is next demonstrated that the seasonal skill in an uninitialized atmospheric model conditioned solely upon the state of global SSTs exceeds this baseline skill, principally during the cold season over regions of the United States where precipitation is sensitive to El Niño–Southern Oscillation (ENSO). Seasonal drought forecast skill using predictions from an initialized, fully coupled model is subsequently diagnosed. Although these results reproduce the pattern of skill enhancement above the baseline found in the Atmospheric Model Intercomparison Project (AMIP) simulations, little additional skill for seasonal drought forecasts is found. Initialized coupled predictions for monthly drought conditions are also examined, and these show considerable skill enhancement beyond the dynamical methods for seasonal drought prediction. The results are summarized in section 4, including a discussion of their relevance to current Drought Outlook activities.

2. Data and methods

a. Observed precipitation and drought index

The Global Precipitation Climatology Centre analysis (GPCC; Rudolf and Schneider 2005) of monthly precipitation gridded at 1° resolution covering the period 1982–2008 is used for calculating the drought index, estimating the baseline skill of drought predictions, and verifying the predictions from the dynamical models. The drought indicator used herein is the SPI developed by McKee et al. (1993)—a simple index that is a useful proxy for describing surface moisture imbalances having both short-term agricultural and long-term hydrological applications. The focus of this study is on seasonal drought predictability given that NOAA's existing Drought Outlook product applies to the forthcoming seasonal mean condition. We therefore use the SPI for 6-month time scales as our descriptor and predictand of drought severity and overall moisture balances. The choice of such an index is somewhat arbitrary; our use of SPI6 seeks a compromise between the various drought indices (PDSI, SPI-3, SPI-12, etc.) that are blended in operational practices to describe short- and long-term drought in the routine production of the Drought Monitor.

The observed SPI6 is calculated from the monthly precipitation record during 1982–2008, our period of verification. Following the method of Edwards and McKee (1997), the time series of 6-month accumulated precipitation for this period is transformed into a normal distribution so that the mean SPI6 for any grid point is zero. Note that the SPI6 monitors both dry and wet conditions and that the process of normalization allows meaningful intercomparison of precipitation departures across relatively wet and dry climate zones (Guttman 1999). Note also that a longer period for the calculation of SPI is desirable (e.g., Guttman 1999); the use of a 27-yr period herein is based on the fact that model predictions span only this period.

b. Climate-model simulations and hindcasts

Two configurations of climate-model integrations are used to assess drought predictability: an ensemble of uninitialized atmospheric general circulation model simulations and an ensemble of initialized coupled ocean–atmosphere general circulation model hindcasts. For the former, the atmospheric component [Global Forecast System (GFS)] of the coupled model [Climate Forecast System (CFS)] was used and was, in the so-called AMIP mode, subjected to the specified monthly varying observed global SSTs that span the period 1950–2008 (only the data from the 1982–2008 period are used to make a direct and meaningful comparison with the initialized forecasts available for the same period). The ensemble size of the AMIP runs used here is 10 members. Coupled-model runs are diagnosed on the basis of a 16-member ensemble of 0-month lead initialized hindcasts generated by NOAA with the CFS that cover 1982–2008 (CFSv2; see online at http://cfs.ncep.noaa.gov/). The CFS is a fully coupled model that represents the interactions among the earth's oceans, land, and atmosphere and is initialized from a global analysis for the respective component. We use an ensemble set of hindcasts based on 16 different initializations in a calendar month that precedes the target season for which predictions are made. The 16 members of the initialized CFS forecasts are chosen from the available 20-member ensembles, and the choice is made so that none of the 16 members was initialized from any time within the months of a target season. All model data were regridded to match the spatial scale of the GPCC precipitation data.

c. Unconditional drought forecast and baseline skill of drought indicator

As a first step toward quantifying the capability of climate models, an objective baseline for skill in drought forecasts is generated that is based solely upon knowledge of a region's climatological seasonal cycle of precipitation. The baseline skill for predictions of meteorological drought employs the method of Lyon et al. (2012). This method, utilizing the seasonal cycle of precipitation, quantifies the unconditional, inherent persistence of the drought indicator (SPI6). A Monte Carlo resampling (which removes the serial correlation of precipitation) of the historical observational data is employed to generate a synthetic time series of monthly precipitation. For a particular target season [e.g., March–May (MAM)], the prior 3-month [e.g., December–February or (DJF)] observed precipitation is combined with the subsequent 3-month precipitation of the target season to calculate the SPI6, where the monthly precipitation during the target season is randomized. A total of 100 random samples are generated by selecting across the 27 observations (i.e., between 1982 and 2008) for each calendar month, analogous to Lyon et al. (2012). Skill in such a baseline drought prediction is unconditioned by the state of the atmosphere, oceans, or land surface and is dictated only by a region's local precipitation variability as function of the known annual cycle of wet and dry seasons.

d. Dynamical-model forecast skill of drought indicator

Dynamical seasonal forecasts of SPI6 are derived by blending the prior 3-month (e.g., DJF) observed precipitation with the subsequent 3-month (MAM) model precipitation for consequent 3-month seasons from MAM 1982 to DJF 2008. The blending is particularly necessary for drought prediction because prior conditions of surface moisture balance are an important antecedent factor to consider in drought predictions (Wu and Kinter 2009). The blending procedure used here is identical to that employed for calculating the baseline skill. To meaningfully assess the dynamical-model skill relative to the baseline of unconditioned forecasts, however, it is necessary to calibrate the model precipitation before merging with observations. The procedure used herein is to add the *percent increment* of modeled monthly precipitation anomalies to the observed monthly climatological precipitation.

The percent value of model precipitation anomaly P_a^* is first computed as

$$P_a^* = P_a/P_c,$$

where P_a is the model-predicted anomalous precipitation calculated relative to the model's climatological precipitation P_c as follows:

$$P_a = P_T - P_c,$$

where P_T is the total model-predicted precipitation.

The calibrated total model precipitation P_{cal} is then computed according to

$$P_{\mathrm{cal}} = O_c(1 + P_a^*),$$

where O_c is the observed climatological precipitation on the basis of the GPCC data. For a particular 1° grid box, the ''climatology'' is calculated for each calendar month for the 27-yr period 1982–2008 for both model and observations, and the above procedure is applied to each individual model run within the ensemble suite.

The calibration thus principally adjusts for the model climatological mean precipitation bias by computing anomalies relative to model climatology rather than to the observed climatology. Further, it adjusts the model anomalies according to the ratios of observed to model climatological rainfall before constituting the full monthly precipitation. No explicit calibration of model rainfall variance is performed, although the latter step implicitly adjusts for variability in so far as there is a strong correlation between biases in model mean precipitation and its variability. Other procedures were also examined, such as adding P_a directly to the observed climatological precipitation or calibrating P_a by multiplying by the ratio of model to observed rainfall variance, but these approaches were found to generate nonphysical occurrences of negative total rainfall.

The dynamical model skill is then computed by correlating the 27-yr time series of observed and forecast SPI6 for the four target seasons of DJF, MAM, June–August (JJA), and September–November (SON) and for each ensemble member of a particular model. The results shown are of the average correlation among the N-member ensemble, where N is 100 for the unconditional baseline forecast, 10 for GFS AMIP, and 16 for CFS.

3. Results

a. Unconditional seasonal drought forecast skill

The baseline skill for seasonal drought prediction employed herein is based on calculating the persistence of the SPI6 index modified by randomized prediction of precipitation for the target season. Figure 1 presents the spatial maps of the baseline forecast skill of SPI6 for four seasons, the results of which are based on correlating the 1982–2008 time series of observed and forecast SPI6 for each of the 100 synthetic time series and then averaging the skill of the 100 members.

Two outstanding features characterize the baseline correlation skill. First is its positive value during all seasons and in all regions. This reflects the significant persistence of prior accumulated precipitation departures from the antecedent 3-month periods into the subsequent target seasons. Such widespread positive persistence skill of SPI6 resonates with the popular perception of drought and its impacts as being a phenomenon that builds over a period of time and as being a creeping phenomenon that often does not have a sharp ending. The second outstanding characteristic is the strong seasonality in baseline skill for many regions. Over the Great Plains, for instance, skill is greatest during winter, whereas the winter skill is comparatively low along the West Coast and the Gulf of Mexico Coast (Fig. 1, top left). This situation reverses for spring drought prediction skill, which is at a minimum over the Great Plains but is high along the West Coast and Gulf Coast (Fig. 1, top right).

The seasonal variability in baseline skill is fundamentally determined by the seasonal cycle of a region's climatological precipitation. Figure 2 displays the seasonal cycle by expressing each season's mean rainfall as a departure relative to 25% of annual totals that would occur in the absence of any seasonality. Thus, wet seasons (shown in green) receive appreciably more than 25% of annual totals, with the dark green regions indicating that upward of 43% of annual precipitation falls during that season. Dry seasons (shown in red) receive appreciably less than 25% of annual totals, with red regions indicating that only about 7% of annual precipitation falls

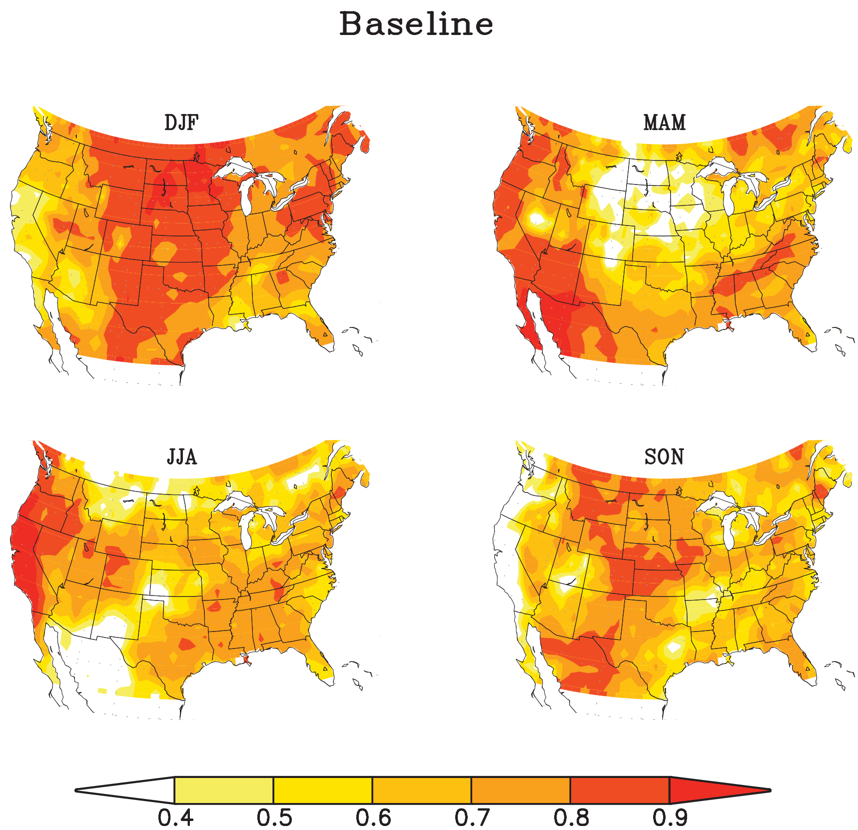

FIG. 1. The ''baseline'' skill of SPI6 in which random forecasts of target-season precipitation using observed historical values are combined with prior observed seasonal precipitation. Shown are the 0-lead seasonal forecasts for the target seasons of boreal (top left) winter (DJF), (top right) spring (MAM), (bottom left) summer (JJA), and (bottom right) autumn (SON). The skills are the average of 100 members of blended SPI6 calculated on the basis of randomizing the time sequence of monthly mean precipitation from GPCC for the period 1982–2008.

during that season. A visual comparison of Figs. 1 and 2 reveals that for most regions the seasons of high baseline forecast skill for SPI6 are when the target season corresponds to a climatological dry period. In this situation, drought (or wet) conditions prevailing in the prior season because of accumulated rainfall deficits (surpluses) are very likely to persist through the subsequent climatological dry season. This is also the situation during near-normal-precipitation seasons in a few areas, such as spring over the Pacific Northwest, owing to the very high abundance of rainfall in the prior season. In effect, there is insufficient variance of precipitation during a season that is drier than its prior season to appreciably alter the sign of the prior season's accumulated moisture anomalies whose magnitude can be very large when originating during a climatological wet period. The outcome is a high skill for persistence. Likewise, the baseline skill is low for target seasons that are the wet periods of a region's annual cycle, a consequence of the high variance of wet-season precipitation that has the potential to overwhelm moisture surpluses (or deficits) accumulated in the prior season. Overall, the seasonal variation in the baseline correlation skill ranges from a maximum of 0.9 to a minimum of less than 0.4, with the range being largest in the semiarid and arid regions west of the Mississippi River where the annual cycle exhibits distinct wet and dry seasons.

It is helpful to summarize particular shortcomings of these unconditional baseline forecasts because these provide foci for assessing dynamical-model performance. Most notable is the low skill during wet seasons in the baseline predictions—for instance, spring and summer over the northern and central Great Plains, winter over the West Coast, and summer over the southern plains and Southwest. The physical reasons for these shortcomings were discussed above, and here we add the practical consideration that the value of drought forecasts is likely to be greatest for a region's upcoming rainy season since its failure could either greatly exacerbate the social impact of antecedent moisture deficits or

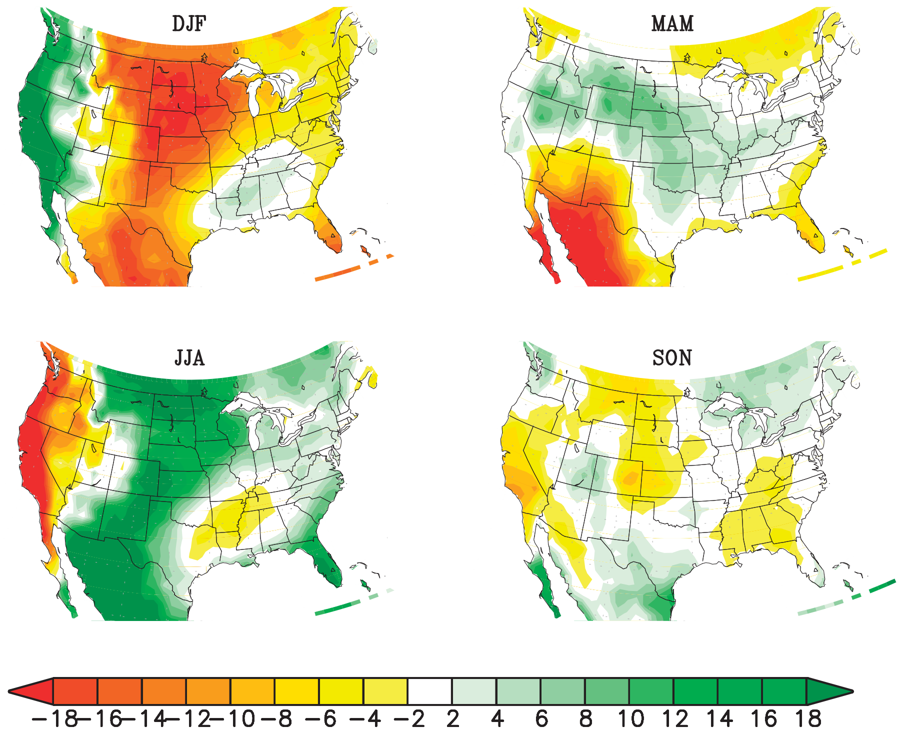

FIG. 2. The 1982–2008 climatology of seasonal precipitation. The values shown are the percentage of seasonal total precipitation with regard to 25% of annual total precipitation amount. Wet seasons are shown in green, with the dark-green regions indicating that upward of 43% of annual precipitation falls during that season. Dry seasons are shown in red, with dark-red regions indicating that only about 7% of annual precipitation falls during that season.

initiate a new drought event. From a hazard mitigation perspective, one might argue that the unconditional baseline skill has the *unfortunate attribute* of exhibiting high skill during dry seasons (when skill is less critical) yet low skill during wet seasons (when skill is more critical). This section thus explores especially the extent to which precipitation during a region's wet season can be predicted skillfully using dynamical models.

b. Dynamical-model seasonal drought forecast skill—AMIP

Figure 3 shows the skill for all four seasons derived from the AMIP simulations, and the differences (AMIP − baseline) in correlation skills are presented in Fig. 4. The appreciable correlation skill of persistence forecasts for SPI6 presents a high benchmark for dynamical-model forecasts to outperform; nonetheless there are widespread areas of statistically significant skill improvements. The procedure for calculating the significance of differences in correlation skill is given in Appendix B. Enhanced skill (i.e., exceeding the baseline) is generally found across the United States in winter, notably over the West and South. Over California in particular and also along the Gulf Coast, a statistically significant enhancement of skill is found, the pattern of which is consistent with the known wintertime impact of ENSO on seasonal precipitation variability over the southern United States (e.g., Ropelewski and Halpert 1987; Kiladis and Diaz 1989) and the skill of AMIP models in predicting such SST impacts (Quan et al. 2006). Figure A1 in appendix A shows the AMIP simulation skill for seasonal precipitation during the 1982–2008 period, from which one can discern that the pattern of improved SPI6 skill during winter is consistent with the pattern of the AMIP seasonal precipitation skill. Thus, one of the critical gaps in the baseline skill is at least partially filled by the use of SST-conditioned climate information.

During spring, skill is not appreciably greater than the baseline skill. In particular, there is no statistically significant improvement in drought forecast skill over the Great Plains where the baseline skill is particularly low as the wet season emerges over this region in springtime. The only statistically significant enhancements occur over the desert southwestern United States. This result is broadly consistent with what one would expect on the basis of knowledge of the AMIP skill in simulating spring

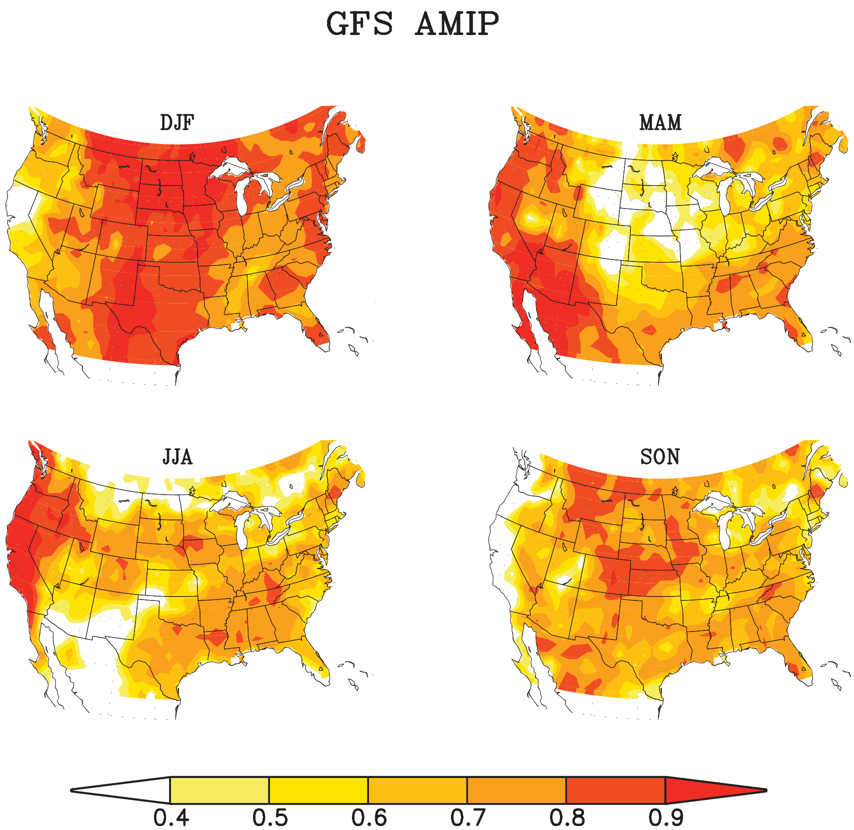

FIG. 3. Skill of the AMIP SPI6 in which AMIP simulations are used for 0-lead seasonal forecasts for the boreal (top left) winter (DJF), (top right) spring (MAM), (bottom left) summer (JJA), and (bottom right) autumn (SON). The skills are the average of a total of 10 members of blended SPI6 calculated on the basis of AMIP simulations using GFS, the atmospheric component of CFS, for the period 1982–2008.

rainfall anomalies over the southwestern United States (see Fig. A1 in appendix A), a result of ENSO impacts.

For summer, the principal feature of the AMIP drought forecast is the significant improvement over the West Coast region (Figs. 3 and 4, bottom left). This is the region's climatological dry season, and the skill of unconditioned persistence is already very high. There is little or no significant increase in skill over the Great Plains during summer when that region experiences its climatological wet season.

For the autumn season there is some indication for statistically significant skill enhancements over central and Southern California and also over portions of the western Gulf Coast. Baseline persistence-based drought forecasts for this region have little skill during autumn, especially over California, and there is considerable AMIP skill in autumn-season rainfall (see Fig. A1 in Appendix A). The latter skill is partly a feature of the emergent impact of ENSO as that influence begins to develop in the southern tier of the United States in the early cold season.

c. *Dynamical-model seasonal drought forecast skill—CFS*

Figure 5 shows the skill for all four seasons derived from the CFS hindcasts, and the differences (CFS − baseline) in correlation skills are presented in Fig. 6. For all seasons, the CFS hindcasts exhibit a pattern of skill improvement relative to the unconditioned baseline forecasts that is not materially different from the skill improvement rendered by the uninitialized AMIP simulations (cf. Fig. 4). The capability of the initialized CFS to capture the SST-conditioned skill enhancement that was indicated by the AMIP results affirms the high skill in predicting global SSTs, and especially those related to ENSO in CFS (S. Saha et al. 2011, unpublished manuscript).

The enhanced skill of CFS-initialized seasonal drought predictions is principally during the cold season along the southern tier of the United States. There is little evidence for a statistically significant improvement, relative to the unconditional baseline, during the warm

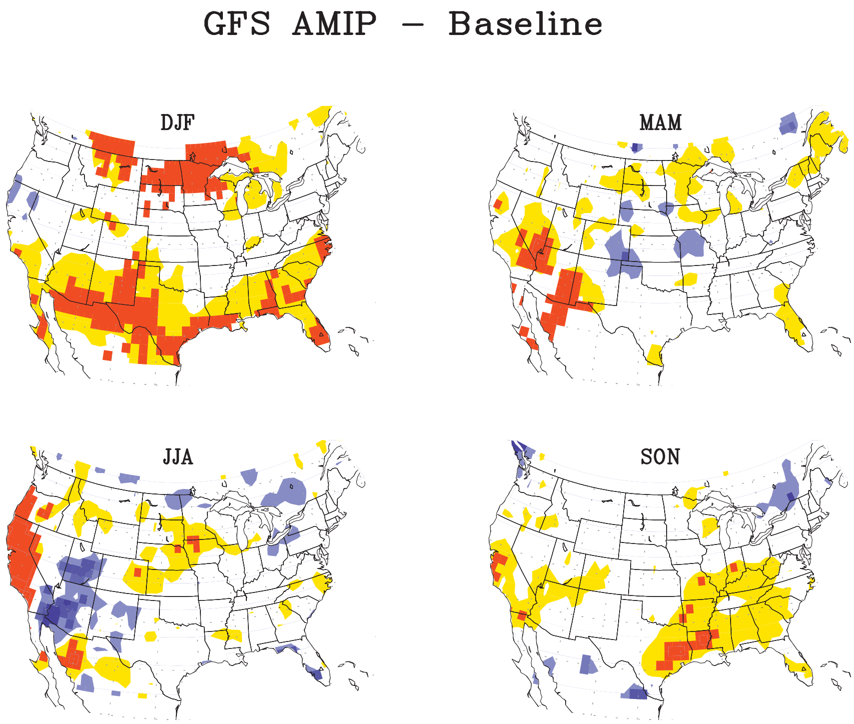

FIG. 4. Difference between the GFS AMIP SPI6 skill and the baseline SPI6 skill. Blue shading indicates values that are less than the baseline skill, yellow indicates values that are higher than the baseline skill, and red indicates values that are higher than the baseline skill at 90% significance level.

season over the Great Plains when that area accumulates the bulk of its annual rainfall. This reflects the apparent lack of an SST-forced impact on warm-season rainfall, at least within the CFS and GFS modeling systems during 1982–2008. Likewise, the lack of significant skill increases in warm-season drought forecasts over the Great Plains in CFS relative to GFS suggests no detectable impact of atmosphere and soil moisture initializations, at least on average.

We explore whether more-frequent initialization of the dynamical model, applied on monthly time scales throughout the target season rather than just once at the beginning of the target season, improves drought forecast skill. Although this is not a practice that can be implemented for making a seasonal-lead prediction, the issue here is to assess at what time scale an initialized drought forecast system might materially improve upon simpler empirical or uninitialized seasonal methods and to gain insight about physical processes rendering drought forecast skill. There are two primary factors that could improve the seasonal mean skill in the average of a forecast constructed from a sequence of three monthly initializations relative to a single (so-called 0 lead) initialized seasonal forecast: 1) information carried by the atmospheric initialization on monthly time scales and 2) information carried in the land surface that is based on prior months' integrated rainfall impact on soil moisture. The results, shown in Figs. 7 and 8, are again based on CFS hindcasts and are verified for the same cardinal seasons. The display is thus identical to that of the 0-lead seasonal CFS drought forecasts (cf. Figs. 5 and 6), but the seasonal predictions are now derived from the average of three consecutive initialized monthly forecasts during each target season.

During winter and spring, there is some improvement in the overall seasonal skill in the monthly initialized forecasts relative to the 0-lead seasonal forecasts (cf. Figs. 4 and 6 with Fig. 8), mainly over the northern plains. This is consistent with the improved skill of precipitation forecasts using monthly initialization (see Fig. A2 of appendix A). The pattern of statistically significant skill increases (relative to the baseline) in these monthly initialized forecasts is not materially different from that seen in the seasonal initialized forecasts or in the AMIP simulations, however. This affirms once again the dominant contribution of global SST forcing (mainly ENSO) to the predictable component of monthly and seasonal precipitation variability. By summer, there is little indication for a change in the drought forecast skill over the Great Plains in the monthly versus seasonal initializations. There is also little material difference in summer drought skill over the Great Plains between the

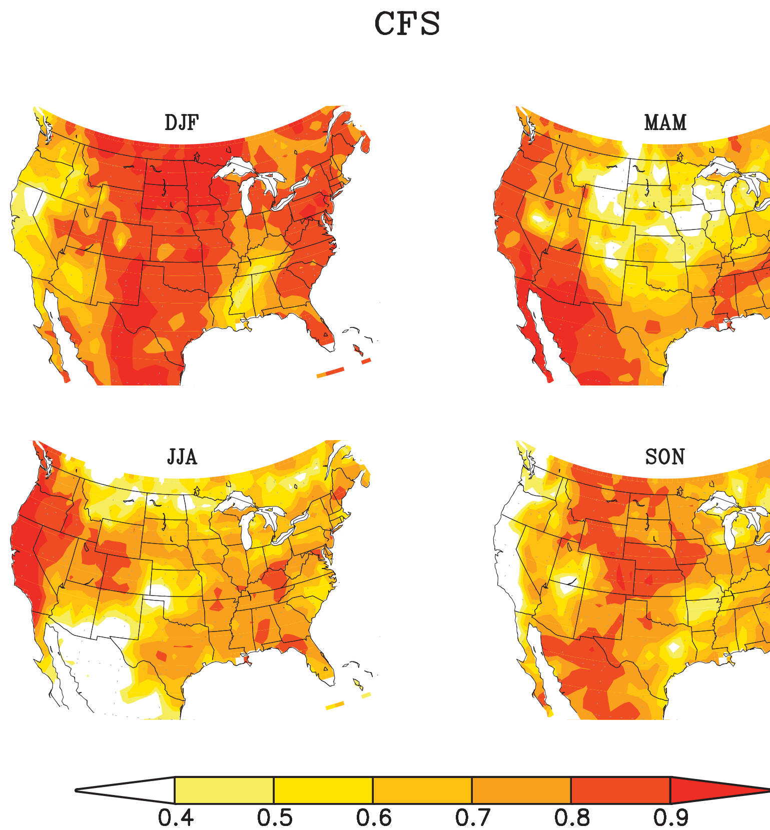

FIG. 5. Skill of the CFS 3-month forecast SPI6 in which the 0-lead seasonal forecasts from CFS are used for 0-lead seasonal forecasts for the boreal (top left) winter (DJF), (top right) spring (MAM), (bottom left) summer (JJA), and (bottom right) autumn (SON). The skills are the average of a total of 16 members of blended SPI6 calculated on the basis of the CFS seasonal forecasts initiated from different initial conditions for the period 1982–2008.

uninitialized AMIP and these initialized hindcasts. Thus, although the monthly initialization integrates the monthly rainfall anomalies into a more-accurate time-evolving soil moisture boundary condition, we do not find strong evidence that this process enhances drought forecast skill during the warm season over the Great Plains. This is not to say that soil moisture–precipitation coupling is absent in CFS; if such coupling exists, however, it apparently fails to enhance precipitation skill at monthly to seasonal time scales, a conclusion also reached in a multi-institutional numerical-modeling experiment that quantified subseasonal (out to 2 months) boreal summer forecast skill for precipitation and air temperature using realistic initialization of land surface states, especially soil moisture (Koster et al. 2011).

4. Summary and discussion

Empirical and dynamical-model methods have been used to quantify the skill of seasonal drought forecasts for the period 1982–2008. Using the 6-month standardized precipitation index (SPI6) as our drought indicator, a baseline forecast was derived that considered only the inherent persistence of that indicator. This simple tool alone was shown to possess considerable seasonal drought forecast skill and provides potentially useful regional information regarding drought evolution. In particular, the baseline skill was shown to exhibit strong regionality and seasonality, the features of which were wholly driven by the complexity of the annual cycle of precipitation across the United States, consistent with results of Lyon et al. (2012). Although serving as a high standard against which to compare the skill of the drought indicator that is based on dynamical-model forecasts, it was found that a simple persistence forecast had particularly low skill during a region's wet season, a time in which accurate drought forecasts would be most consequential for hazard mitigation and related decision making.

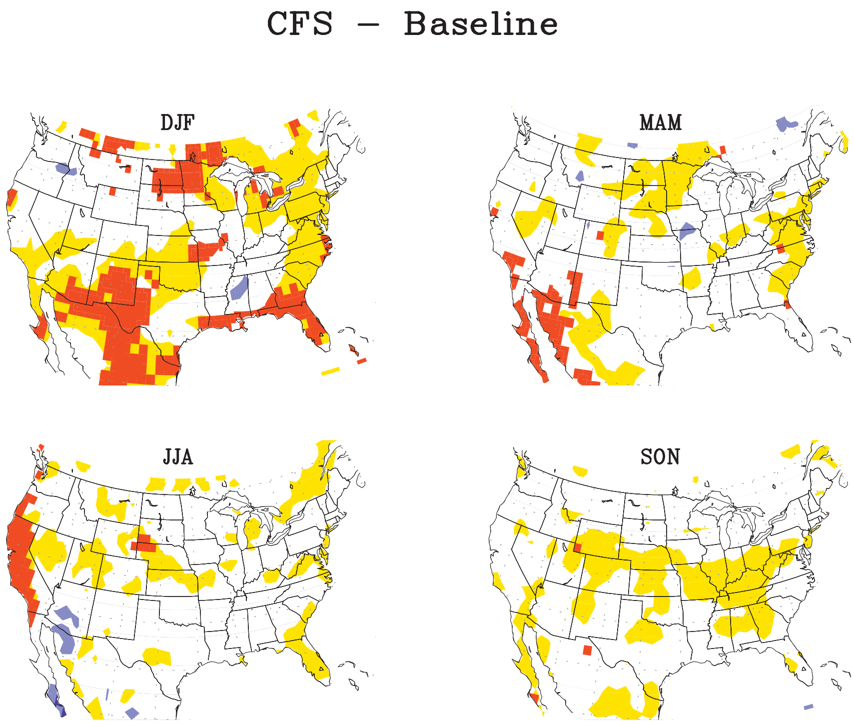

FIG. 6. As in Fig. 4, but between the CFS 3-month forecast SPI6 skill and the baseline SPI6 skill.

Predictions that are based on dynamical models were diagnosed using two configurations that allowed an inference of factors that contribute to seasonal drought forecast skill. Global-model simulations conditioned on the state of specified observed sea surface temperatures were assessed using the atmospheric component (GFS) of the NOAA Climate Forecast System (CFS). Dynamical predictions that were further conditioned on the initial states of atmosphere, land surfaces, and oceans were diagnosed using the fully coupled global-model hindcasts for 1982–2008 generated by NOAA's CFS. It was found that dynamical models forced with observed global SSTs yielded increased skill relative to this unconditional baseline, although improvements were principally realized for the cold seasons over the West Coast and Gulf Coast regions. The improved skill relative to the baseline was attributable to the known impacts of El Niño–Southern Oscillation on those regions' cold-season precipitation. Fully coupled initialized model hindcasts were found to yield little additional skill relative to the AMIP simulations.

The vast majority of dynamical-model improvement in seasonal drought forecast skill relative to the unconditional baseline was due to the ENSO signal, consistent with prior model studies of the SST sources for U.S. seasonal precipitation skill (e.g., Quan et al. 2006; Barnston et al. 2010; Kumar et al. 2011). This skill source for drought was equally well harvested in the AMIP simulations and the seasonal initialized CFS forecasts. Indicated hereby is that the skill of drought predictions during the wet seasons spanning roughly late autumn, winter, and early spring over the far southwestern United States and the Gulf Coast region is significantly improved when conditioned on the state of global SSTs. By comparison, dynamical methods did not significantly enhance skill, relative to the unconditioned baseline performance, over the Great Plains during that region's wet season spanning spring through summer. The modest drought forecast skill associated with simple persistence over this area was not appreciably improved by conditioned dynamical-model information. There appear to be two principal factors that limit the value of dynamical-model information for this Great Plains region. First is that warm-season rainfall was not found to be as sensitive to global SST variability as was the cold-season precipitation over the southern United States. Second, the comparison of uninitialized and initialized seasonal forecasts implies that soil moisture conditions did not materially improve precipitation forecast skill over the Great Plains during the warm season, on average.

This semiarid Great Plains region, where seasonal droughts are often severe and have deleterious impacts on U.S. agricultural production, rangeland management, and livestock health, is particularly vulnerable to failed

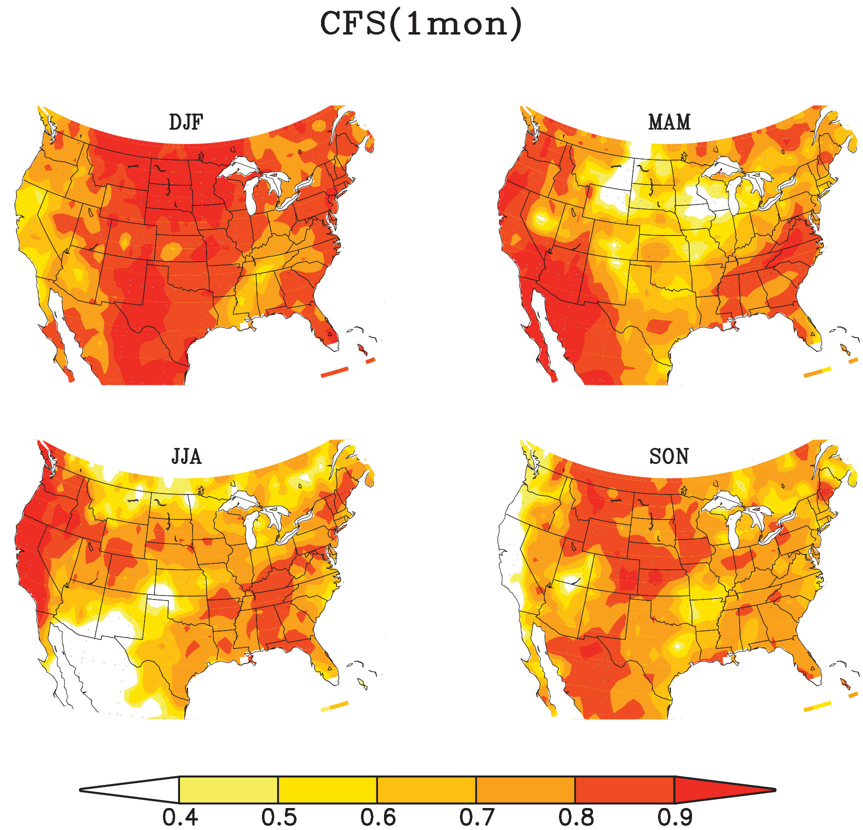

FIG. 7. Skill of the CFS 1-month forecast SPI6, which is calculated in the same way as for the CFS 3-month forecast SPI6 except that the 0-lead seasonal forecasts are replaced with 0-lead monthly forecasts.

rains during spring and summer. This is the region's primary temporal window during the annual cycle for acquiring necessary moisture. Further, contrary to the far West where water supply is drawn from remote mountain runoff and thereby makes local drought conditions less critical, the Great Plains is particularly reliant on local precipitation. Despite some small (but statistically insignificant) skill improvement during the warm seasons over the central and northern Great Plains relative to the baseline, the principal conclusion we draw from the AMIP and 0-lead initialized CFS seasonal forecasts is that neither remote SST impacts nor local soil moisture interactions are particularly efficacious in enhancing skill relative to simple persistence forecasts. Thus, the overall skill of such initialized seasonal forecasts for the Great Plains was not materially better than that rendered by simple persistence.

The prospects for seasonal drought prediction in the Great Plains during the warm season are thus likely to hinge strongly upon the ability to accurately monitor the antecedent precipitation conditions, in so far as simple persistence of such conditions offers moderate skill. We further explored the issue of short-term (monthly) drought predictability over the Great Plains. For this purpose, we studied the results from the CFS model hindcasts on the basis of a sequence of monthly initialized experiments. These exhibited a significant increase in drought forecast skill during spring over the Great Plains relative to the 0-lead seasonal skill, although they showed little improvement during summer. The lack of an improvement during summer, using methods that more frequently initialize soil moisture conditions, indicates a limited impact of soil moisture anomalies on monthly (and seasonal) precipitation variability in the CFS model. Whether this lack of benefit of soil moisture feedbacks on drought predictions is a true indication of the limited memory of land surface conditions, and to what degree it is an indication of CFS model biases that could act to inhibit drought forecast skill, is a key question for future research, although we note that a similar result was also reported recently in other modeling systems (Koster et al. 2011).

Future research should also consider the broader climate context for drought that not only considers the moisture imbalances induced by precipitation conditions alone but also considers the effects related to

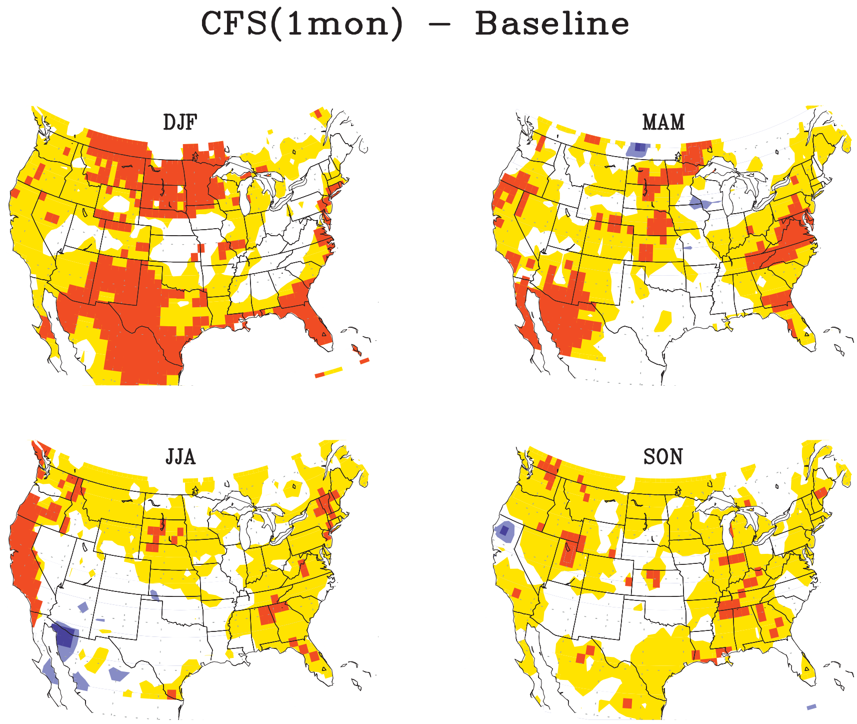

FIG. 8. As in Fig. 4, but between the CFS 1-month forecast SPI6 skill and the baseline SPI6 skill.

temperature conditions. The latter influence surface water balance through the sensitivity of evapotranspiration, and it is widely recognized that increased temperature during periods of reduced precipitation can materially increase overall drought severity (e.g., Palmer 1965). Indeed, Breshears et al. (2005) argued that the more-severe impacts of the western North American drought of the last decade when compared with the 1950s drought was at least in part a consequence of the recent period being appreciably warmer. Land surface feedbacks may be especially important when high temperatures magnify the severity of drought impacts. Vicente-Serrano et al. (2010) recently developed a drought index that is analogous to the SPI but that also attempts to monitor the effect of temperature on water balances. It would be useful to diagnose their so-called standardized precipitation evapotranspiration index (SPEI) for the period studied herein and to further evaluate the skill of dynamical models. It is plausible that model skill attributes for drought using a more general water-balance measure of drought may be somewhat different than those diagnosed herein using precipitation (SPI) alone. Indeed, since the source for U.S. seasonal surface temperature skill is not due to ENSO alone (e.g., Quan et al. 2006), and given that Koster et al. (2011) report that their models show modest but significant skill in predicting surface air temperatures as a consequence of land surface initialization, there is merit in examining the predictability of other physically relevant drought indicators.

Acknowledgments. The authors thank Dr. Sergio M. Vicente-Serrano at Spanish National Research Council and two anonymous reviewers for their helpful reviews. This study is supported by funds from the NOAA Climate Program Office.

APPENDIX A

Correlation Skill of Seasonal Mean Precipitation

The figures in this appendix show the spatial pattern of the correlation skill of seasonal mean precipitation in the uninitialized GFS (AMIP simulations, shown in Fig. A1) and the initialized CFS (hindcasts, shown in Fig. A2) for 1982–2008.

APPENDIX B

Significance of Difference between Two Pearson Correlation Coefficients

To determine the statistical significance of differences between two Pearson correlation coefficients (i.e., the

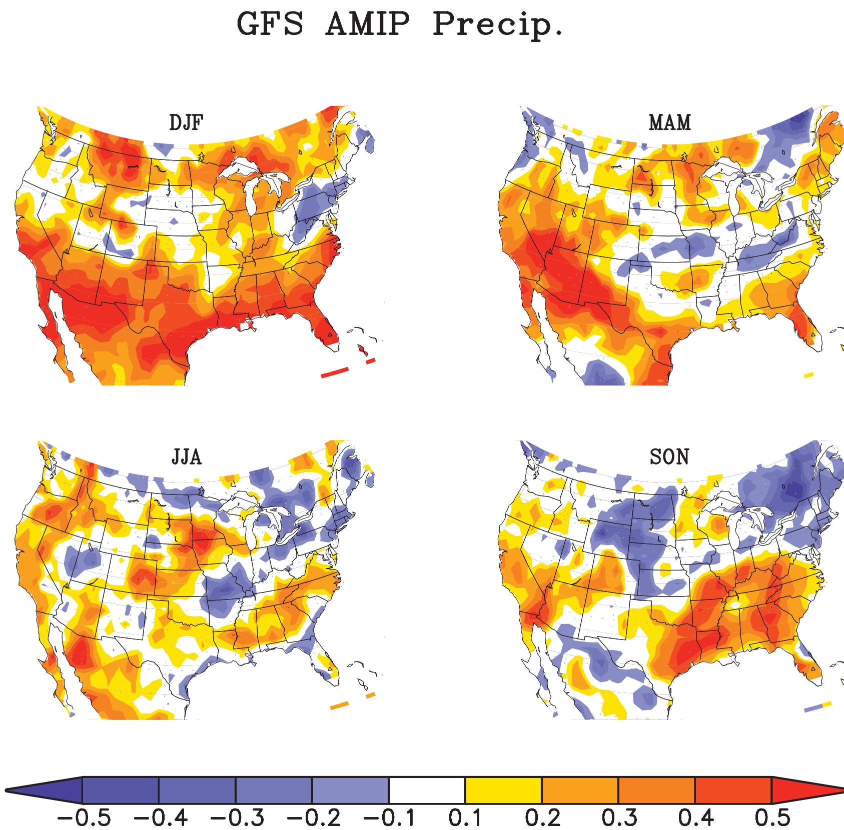

FIG. A1. Correlation skill of the 10-member ensemble average of 3-month mean precipitation anomalies from the GFS AMIP simulations.

correlation skill in this paper), the one-tailed confidence interval d_α of a correlation coefficient value r can be estimated as follows:

$$d_\alpha = \frac{1}{2}(r_\alpha^+ - r_\alpha^-), \quad r_\alpha^- < r < r_\alpha^+, \tag{B1}$$

where

$$r_\alpha^\pm = \tanh(z \pm z_\alpha/\sqrt{N-3}), \tag{B2}$$

$$z = \frac{1}{2}\log\frac{1+r}{1-r}, \tag{B3}$$

N is the number of samples, and $\tanh(x) = (e^x - e^{-x})/(e^x + e^{-x})$. The so-called Fisher's z is asymptotically normally distributed with a mean of 0 and a standard deviation of $(N-3)^{-1/2}$, and z_α is a constant determined by the significance level α (Anderson 1958). For the significance level of $\alpha = 90\%$, $z_\alpha = 1.28$. The estimated confidence interval as function of r on the basis of Eqs. (B1)–(B3) is shown as the solid line in Fig. B1.

For a given value of the Pearson correlation coefficient r_0, its confidence interval may also be estimated directly from the distribution of possible values r around r_0. The dashed curve in Fig. B1 shows an estimate of the confidence interval that is based on the distribution function given by Hotelling (1953):

$$p(r, r_0) = \frac{N-2}{\sqrt{2\pi}}\frac{\Gamma(N-1)}{\Gamma(N-\frac{1}{2})}(1-r_0^2)^{[(N-1)/2]}(1-r^2)^{[(N-4)/2]}(1-r_0 r)^{-N-(1/2)}F\left(\frac{1}{2}, \frac{1}{2}; N-\frac{1}{2}; \frac{1+r_0 r}{2}\right), \tag{B4}$$

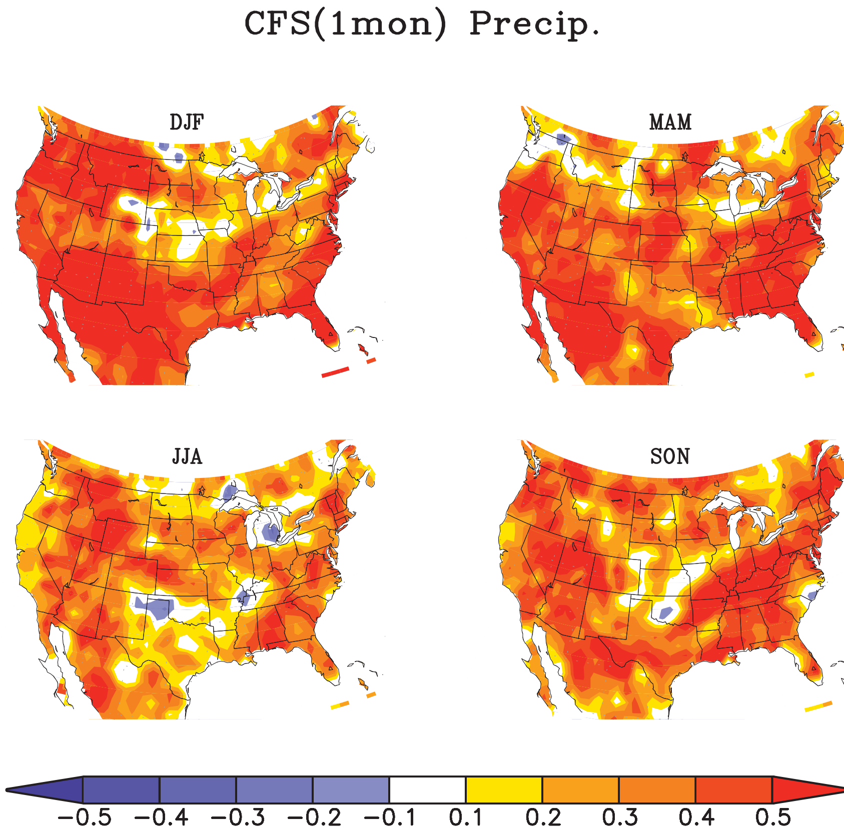

FIG. A2. Correlation skill of the 16-member average of 3-month mean precipitation anomalies from the 0-lead CFS monthly forecasts.

where

$$F(a,b;c;x) = \sum_{j=0}^{\infty} \frac{\Gamma(a+j)}{\Gamma(a)} \frac{\Gamma(b+j)}{\Gamma(b)} \frac{\Gamma(c)}{\Gamma(c+j)} \frac{x^j}{j!}. \quad \text{(B5)}$$

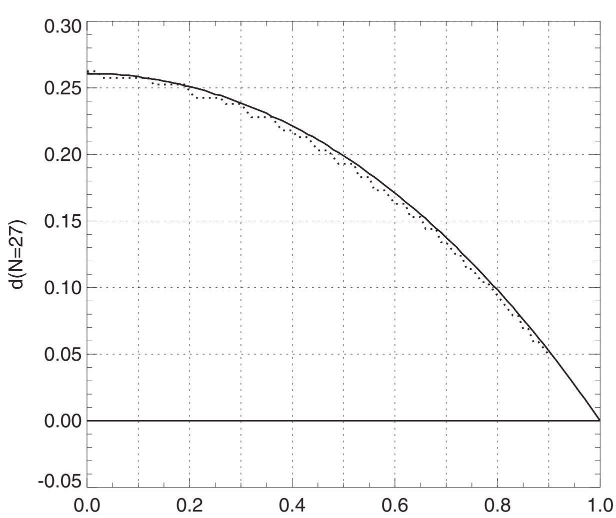

FIG. B1. One-tail confidence interval of the Pearson correlation coefficient at 90% statistical significance level for the sample size of $N = 27$.

In the practice of this study, the significance of a difference between two correlation skills r_1 and r_2 is determined by checking whether the difference $\Delta r = r_2 - r_1$ satisfies the condition $\Delta r > (d_1 + d_2)/2$, where d_1 and d_2 define the confidence interval of r_1 and r_2 as presented in Fig. B1.

REFERENCES

Anderson, T. W., 1958: *An Introduction to Multivariate Statistical Analysis.* John Wiley and Sons, 374 pp.

Barnston, A., S. Li, S. Mason, D. DeWitt, L. Goddard, and X. Gong, 2010: Verification of the first 11 years of IRI's seasonal forecasts. *J. Appl. Meteor. Climatol.,* **49,** 493–520.

Breshears, D., and Coauthors, 2005: Regional vegetation die-off in response to global-change-type drought. *Proc. Natl. Acad. Sci. USA,* **102,** 15 144–15 148.

Edwards, D. C., and T. B. McKee, 1997: Characteristics of 20th century drought in the United States at multiple time scales. Climatology Rep. 97-2, Colorado State University, 155 pp.

Guttman, N. B., 1999: Accepting the standardized precipitation index: A calculation algorithm. *J. Amer. Water Resour. Assoc.,* **35,** 311–322.

Hayes, M., M. Svoboda, D. Le Comte, K. T. Redmond, and P. Pasteris, 2005: Drought monitoring: New tools for the 21st century. *Drought and Water Crises: Science, Technology and*

Management Issues, D. A. Wilhite, Ed., Taylor and Francis, 53–70.

Hoerling, M., and A. Kumar, 2003: The perfect ocean for drought. *Science,* **299,** 691–694.

Hotelling, H., 1953: New light on the correlation coefficient and its transforms. *J. Roy. Stat. Soc., Ser. B,* **15,** 193–225.

Karl, T., F. Quinlan, and D. S. Ezell, 1987: Drought termination and amelioration: Its climatological probability. *J. Climate Appl. Meteor.,* **26,** 1198–1209.

Kiladis, G. N., and H. F. Diaz, 1989: Global climatic anomalies associated with extremes in the Southern Oscillation. *J. Climate,* **2,** 1069–1090.

Koster, R. D., and Coauthors, 2004: Regions of strong coupling between soil moisture and precipitation. *Science,* **305,** 1138–1140.

——, and Coauthors, 2006: GLACE: The Global Land–Atmosphere Coupling Experiment. Part I: Overview. *J. Hydrometeor.,* **7,** 590–610.

——, and Coauthors, 2011: The second phase of the Global Land–Atmosphere Coupling Experiment: Soil moisture contributions to subseasonal forecast skill. *J. Hydrometeor,* **12,** 805–822.

Kumar, A., M. Chen, and W. Wang, 2011: An analysis of prediction skill of monthly mean climate variability. *Climate Dyn.,* **37,** 1119–1131.

Lyon, B., and R. M. Dole, 1995: A diagnostic comparison of the 1980 and 1988 U.S. summer heat wave-droughts. *J. Climate,* **8,** 1658–1675.

——, M. A. Bell, M. Tippett, M. P. Hoerling, A. Kumar, X. Quan, and H. Wang, 2012: Baseline probabilities for the seasonal prediction of meteorological drought. *J. Appl. Meteor. Climatol.,* **51,** 1222–1237.

McKee, T. B., N. J. Doesken, and J. Kleist, 1993: The relationship of drought frequency and duration to time scales. *Proc. Eighth Conf. on Applied Climatology,* Anaheim, CA, Amer. Meteor. Soc., 179–184.

Namias, J., 1983: Some causes of United States drought. *J. Climate Appl. Meteor.,* **22,** 30–39.

NOAA, 2007: The National Integrated Drought Information System implementation plan: A pathway for national resilience. 29 pp. [Available online at http://www.drought.gov/imageserver/NIDIS/content/whatisnidis/NIDIS-IPFinal-June07.pdf.]

Oglesby, R. J., and D. J. Erickson, 1989: Soil moisture and the persistence of North American drought. *J. Climate,* **2,** 1362–1380.

Palmer, W. C., 1965: Meteorological drought. U.S. Weather Bureau Research Paper 45, 58 pp.

Pulwarty, R. S., K. L. Jacobs, and R. M. Dole, 2005: The hardest working river: Drought and critical water problems in the Colorado River Basin. *Drought and Water Crises: Science, Technology and Management Issues,* D. A. Wilhite, Ed., Taylor and Francis, 249–285.

Quan, X., M. P. Hoerling, J. Whitaker, G. Bates, and T. Xu, 2006: Diagnosing sources of U.S. seasonal forecast skill. *J. Climate,* **19,** 3279–3293.

Ropelewski, C. F., and M. S. Halpert, 1987: Global and regional scale precipitation patterns associated with the El Niño/Southern Oscillation. *Mon. Wea. Rev.,* **115,** 1606–1625.

Rudolf, B., and U. Schneider, 2005: Calculation of gridded precipitation data for the global land-surface using in-situ gauge observations. *Proc. Second Workshop of the Int. Precipitation Working Group (IPWG),* Monterey, CA, Naval Research Laboratory, 231–247.

Schubert, S. D., M. J. Suarez, P. J. Pegion, R. D. Koster, and J. T. Bacmeister, 2004: Causes of long-term drought in the U.S. Great Plains. *J. Climate,* **17,** 485–503.

——, ——, ——, ——, and ——, 2008: Potential predictability of long-term drought and pluvial conditions in the U.S. Great Plains. *J. Climate,* **21,** 802–816.

Seager, R., Y. Kushnir, C. Herweijer, N. Naik, and J. Velez, 2005: Modeling of tropical forcing of persistent droughts and pluvials over western North America: 1856–2000. *J. Climate,* **18,** 4065–4088.

Svoboda, M., and Coauthors, 2002: The Drought Monitor. *Bull. Amer. Meteor. Soc.,* **83,** 1181–1190.

Vicente-Serrano, S. M., S. Beguería, J. I. López-Moreno, 2010: A multi-scalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index—SPEI. *J. Climate,* **23,** 1696–1718.

Wilhite, D. A., Ed., 1993. *Drought Assessment, Management, and Planning: Theory and Case Studies.* Kluwer Academic, 293 pp.

——, and R. S. Pulwarty, 2005: Drought and water crises: Lessons learned and the road ahead. *Drought and Water Crises: Science, Technology and Management Issues,* D. A. Wilhite, Ed., Taylor and Francis, 389–398.

——, M. J. Hayes, C. L. Knutson, and K. H. Smith, 2000: Planning for drought: Moving from crisis to risk management. *J. Amer. Water Resour. Assoc.,* **36,** 697–710.

Wu, R., and J. L. Kinter III, 2009: Analysis of the relationship of U.S. droughts with SST and soil moisture: Distinguishing the time scale of droughts. *J. Climate,* **22,** 4520–4538.