Comparison of Daily Precipitation Statistics for the United States in Observations and in the NCEP Climate Forecast System

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ABSTRACT

An intercomparison of the statistics of daily precipitation within seasonal climate over the conterminous United States is carried out using gridded station data and output from the NCEP Climate Forecast System (CFS). Differences in the occurrence of daily precipitation between the observations and a set of CFS reforecasts are examined as a function of forecast lead time for 1982–2005. Difference patterns show considerable evolution depending on season and lead time, with positive biases in CFS at most locations and leads except along the southern tier of states during the spring and summer months.

An examination of differences in daily precipitation statistics by ENSO phase and in the frequencies of wet and dry spells is also conducted using a longer period of gridded daily station data (1948–2006) and a pair of 100-yr CFS coupled simulations. These comparisons expose additional details of the regional and seasonal dependence of the bias in the CFS simulations and reforecasts over the conterminous United States. The analysis motivates additional synoptic studies aimed at improving the linkage between daily precipitation and related circulation features in CFS. Prospects for using this information to develop more reliable ensemble-based probabilistic forecasts in real time at leads of 2–4 weeks (e.g., risks of heavy rain events) are also considered.

1. Introduction

A major challenge for the climate community is to provide information that decision makers can directly apply to reduce vulnerability to climate risk. While probabilistic forecasts of seasonal mean quantities (such as precipitation and surface temperature over the conterminous United States) have proven utility, they do not address questions relating to the specific character of the daily weather statistics within the season. User requests for products that expand beyond averages to extremes, and that project changes with more spatial and temporal detail and real-time access are increasingly common. Very often these requests are for detailed deterministic forecasts (e.g., for the start and ending dates of the rainy season at specific locations, or for products that elucidate the risk of high-impact weather events within a month or season).

Our current understanding of the climate system suggests that it may not be possible to meet all of these requests. There is evidence, however, of some progress in understanding and predicting the statistics of daily weather within seasonal climate. For example, recent studies utilizing daily station data (both gridded and raw) for the United States (Higgins et al. 2007) and South America (Ropelewski and Bell 2008) suggest significant differences in the character of rainy seasons (e.g., histograms of daily rainfall) conditional on ENSO phase. In South America, Ropelewski and Bell (2008) found evidence of shifts in the histograms of daily precipitation over seasons not only in regions traditionally identified with ENSO but also in regions and for seasons where, historically, there are not significant differences in seasonal rainfall totals. For the conterminous United States as a whole, Higgins et al. (2007) documented increases in the annual numbers of wet days and heavy precipitation days, and in the mean daily and annual total precipitation since 1950 over portions of the United States, consistent with conclusions of the Intergovernmental Panel on Climate Change (IPCC) Working Group I (WGI) Fourth Assessment Report (Solomon et al. 2007). These and other studies also find that numerical models have difficulty replicating the

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gridded station results, but that they may be useful for identifying candidate regions for further analysis with station data.

To characterize the statistics of weather within seasonal climate, we confront the historical climate record to determine what has happened and use this information to employ model simulations and predictions to consider why it happened and what is likely to happen next. Despite the fact that there have been many studies focused on relationships between daily precipitation statistics and climate variability (e.g., Gershunov and Barnett 1998; Groisman et al. 1999; Karl and Knight 1998; Gershunov and Cayan 2003; Higgins et al. 2007), it is fair to conclude that our understanding of what has happened is far from perfect, including over the United States where the observed climate records are relatively complete and of relatively long duration.

In this study we intercompare the statistics of daily precipitation within seasonal climate over the conterminous United States using gridded station data and output from the National Centers for Environmental Prediction (NCEP) Climate Forecast System (CFS; Saha et al. 2006). Differences in the occurrence of daily precipitation between the observations and a set of CFS reforecasts are examined as a function of forecast lead time for 1982–2005. Differences in the daily precipitation statistics by ENSO phase and in the frequency of wet and dry spells (i.e., periods of consecutive wet or dry days) are also examined using a longer period of gridded station data (1948–2006) and a pair of 100-yr Coupled Model Intercomparison Project (CMIP) simulations. The comparisons expose the regional and seasonal dependence of the bias in the CFS reforecasts and simulations over the conterminous United States. Prospects for using this information to develop more reliable ensemble-based probabilistic forecasts in real time at leads of 2–4 weeks (e.g., risks of heavy rain events) are considered.

The comparisons in this study are carried out in a manner that builds on our previous studies of relationships between climate variability and daily precipitation over the United States (e.g., Higgins et al. 2007). While our earlier studies emphasized comparisons of raw station data to gridded station data, here the emphasis is on the ability of the CFS to replicate the observed daily statistics based on gridded data in each case. Once these differences are quantified, they can be used to help calibrate real-time probabilistic climate forecasts from CFS, with the assumption being that these biases are a major problem. In a follow-on study we will use bias correction to calibrate the CFS ensembles in an effort to develop new types of outlooks that highlight enhanced risks of heavy rain events or floods at time scales required by users (e.g., weeks 2–4).

A brief summary of the datasets and analysis procedures (section 2) is followed by a comparison of daily precipitation statistics in observations and the CFS reforecasts and simulations (section 3). Influences of ENSO on the daily precipitation statistics are examined in section 4, while wet and dry spells of various durations are compared in section 5. Some considerations for statistical adjustments of the CFS precipitation forecasts are discussed in section 6.

2. Datasets and analysis procedures
   a. Precipitation data

   The daily precipitation analysis is obtained from CPC’s Unified Rain Gauge Database (Higgins et al. 2000). The database contains information from over 8000 stations across the United States. Typically, the station density is highest in the eastern two-thirds of the United States, but coverage over the western United States is relatively good. The database was used to produce a multiyear (1948–2006) daily precipitation analysis (1200–1200 UTC for the conterminous United States. The daily data were gridded at a horizontal resolution of (lat, lon) = (0.25° × 0.25°) over the domain 10°–60°N, 140°–60°W, using a Cressman (1959) scheme with modifications (Glahn et al. 1985; Charba et al. 1992). Several types of quality control were applied including a “duplicate station check” to eliminate duplicates and key punch errors, a “buddy check” to eliminate erroneous extreme values, and a standard deviation check that compares the daily rain gauge data against a gridded daily climatology. The quality controlled daily station data were used to generate the analyzed fields over the United States. Relationships between the spatial distribution and temporal continuity of the station data and errors in the final gridded analysis were examined in Higgins et al. (2007) and Chen et al. (2008).

   b. NCEP CFS retrospective forecasts

   The NCEP CFS is a fully coupled ocean–land–atmosphere dynamical seasonal prediction system that became operational at NCEP in August 2004 (Saha et al. 2006). The current operational version of the CFS is run at a resolution of T62L64. The CFS is a major step forward in dynamical seasonal prediction, having achieved a level of skill in forecasting tropical Pacific sea surface temperatures and surface temperature and precipitation in the United States that is comparable to that of statistical methods currently used in operations.
Table 1. Historical Pacific warm (bold) and cold (bold and italic) episodes during 1948–2006 based on a threshold of ±0.5°C for ONI [3-month running mean of ERSSTv2 SST anomalies (Smith and Reynolds 2003) in the Niño-3.4 region (5°N–5°S, 120°–170°W)], calculated with respect to the 1971–2000 base period. Non-bold and non-italic values did not meet the ±0.5°C criterion. For historical purposes, El Niño and La Niña episodes are defined when the threshold is met for a minimum of 5 consecutive overlapping seasons (e.g., JFM, FMA, MAM, AMJ, MJJ).

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by the NCEP Climate Prediction Center (CPC). The atmospheric component of the CFS is a lower-resolution version of the NCEP Global Forecast System (GFS) that was the operational global weather prediction model at NCEP during 2003. The ocean component is the Geophysical Fluid Dynamics Laboratory (GFDL) Modular Ocean Model version 3. For the land surface hydrology the two-layer model described in Mahrt and Pan (1984) was used.

A set of fully coupled reforecasts covering a 23-yr period (1982–2005), with 15 reforecasts per calendar month out to nine months into the future, have been produced with the CFS. These reforecasts were required for the proper calibration of subsequent operational seasonal forecasts. Only 15 reforecasts were run per month because of limitations in computer time, but care was taken to ensure that the initial conditions span each month and account for the evolution of both the atmosphere and the ocean in a continuous fashion. Detailed discussion of the initialization and sensitivity in the reforecasts is found in Saha et al. (2006).

The atmospheric initial conditions were from the NCEP/Department of Energy (DOE) Atmospheric Model Intercomparison Project (AMIP) II Reanalysis data (Kanamitsu et al. 2002), and the ocean initial conditions were from the NCEP Global Ocean Data Assimilation System (GODAS; Behringer et al. 2005).

The capabilities of the CFS to reproduce the statistics of daily precipitation within the season have not been thoroughly examined. Daily precipitation data from the reforecasts were collected into “lead” files (i.e., day 1 forecasts, day 2 forecasts, etc.) for 1982–2005. Twice daily data were averaged into a daily mean. To quantify the bias in the CFS we compare the observations to the CFS reforecasts on grids. For both the CFS reforecasts and the observations, the fraction of the total days with precipitation greater than 1 mm is first computed. Because there are only 45 CFS reforecast days per season,
as compared to ~90 days in the observations, the fraction is then multiplied by the appropriate total number of days per season so that the comparisons can be made.

In addition, the CFS and the observations have different horizontal resolutions, so it is necessary to coarsen the gridded observations from (lat, lon) = (0.25°, 0.25°) to (lat, lon) = (2.5°, 2.5°) to match the horizontal resolution of the gridded dataset from the CFS. This has both positive and negative consequences, as the quantitative nature of the bias in CFS is preserved but some spatial details of the gridded observations are lost. For display purposes the final results (e.g., after differencing the observations and CFS) were regridded back to higher resolution (lat, lon) = (0.25°, 0.25°), although this has no impact on the results.

c. NCEP CFS simulations

Two 100-yr CFS coupled simulations (CMIP1 and CMIP2), run at a resolution of T126L64, are examined in this study. CMIP1 (CMIP2) was initialized on 1 January 2002 and ends on 31 December 2101 (was initialized on 1 January 1984 and ends on 31 December 2083). The first archived day in the CMIP1 (CMIP2) simulations is 2 January 2002 (2 January 1984). Because the first year was not complete, it was not used in the data analysis. At the time that we processed the CMIP runs, the last year in each run was also not complete. For these reasons we used 98 yr for each simulation in the calculations below.

Daily time series of precipitation in GRIB format are converted to a regular (lat, lon) = (2.5°, 2.5°) grid. Daily statistics from the simulations are compared to the observations and to the reforecasts in section 3. Daily precipitation statistics by ENSO phase are compared in section 4 and the occurrence of wet and dry spells of various durations are compared in section 5. Because the comparisons of the observations and simulations are not exact in a temporal sense, we use a longer period of record for the observations (1948–2006) in the comparisons of sections 4 and 5.

Critical differences between datasets (e.g., Figs. 2–4) were evaluated statistically using a t test. In each case statistical significance was assessed relative to the 99% confidence level.

d. ENSO composite analysis

A classification of historical warm (El Niño) and cold (La Niña) episodes developed by the National Oceanic and Atmospheric Administration’s (NOAA) Climate Prediction Center is used to develop composites of the observed daily precipitation statistics by ENSO phase. El Niño and La Niña episodes are identified using the
Oceanic Niño Index (ONI; Kousky and Higgins 2007), which is one of the principal measures used by NOAA for monitoring and assessing ENSO. The ONI is computed from 3-month running mean values of SST departures from average in the Niño-3.4 region using a set of homogeneous historical SST analyses [extended reconstructed SST (ERSST) version 2 of Smith and Reynolds 2003]. The NOAA operational definitions of El Niño and La Niña are keyed to the ONI (Kousky and Higgins 2007):

El Niño is characterized by a positive ONI $\geq +0.5^\circ$C; La Niña is characterized by a negative ONI $\leq -0.5^\circ$C. These definitions properly identify all historical warm and cold episodes (defined as 5 consecutive 3-month seasons in which the El Niño or La Niña definition is satisfied). Historical Pacific warm (red) and cold (blue) episodes during 1948–2006 are indicated in Table 1. We note that CPC forecast operations will implement an improved sea surface temperature analysis product (ERSST version 3) in the near future. This may result in slight changes to the warm and cold episodes identified in Table 1. (For reference, CPC maintains a table of cold and warm episodes by season online at http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml.)
For comparison purposes, a similar procedure is used to identify ENSO events in the CFS coupled simulations. Events are chosen using a threshold of $\pm 0.5^\circC$ for 3-month running mean SST anomalies in the Niño-3.4 region ($5^\circN$–$5^\circS$, $120^\circW$–$170^\circW$). El Niño and La Niña episodes are defined when the threshold is met for a minimum of 5 consecutive overlapping seasons. Because the results are similar whether we use 59 yr (to match the number of years in the observations) or the entire CMIP simulations (98 yr), we elect to use the entire simulations to improve the statistics. For reference, the numbers of warm (El Niño), neutral, and cold (La Niña) episodes in the CMIP1 simulation are given in Table 2; similar results are obtained for CMIP2 (not shown).

[Critical differences between samples of years (e.g., Figs. 6 and 7) were evaluated statistically using a t test. In Fig. 6 (Fig. 7) statistical significance was assessed relative to the 90% (99%) confidence level.]

3. Daily statistics

The annual cycle of the average observed number of days per season with precipitation greater than 1 mm is shown for two periods, specifically 1982–2005 and 1948–2006, in Figs. 1a and 1b, respectively. The shorter period (Fig. 1a) is used for comparisons to the CFS reforecasts in the remainder of this section, while the longer period (Fig. 1b) is used in the comparisons of daily precipitation statistics by ENSO phase (see section 4). The average number of wet days per season is larger at most locations in Fig. 1a than in Fig. 1b suggesting an increasing trend in the number of wet days per season in recent decades. Nevertheless, both results show that precipitation occurs most frequently in the Pacific Northwest during boreal fall and winter and in the Southeast during boreal summer. The Northeast experiences its most frequent rainfall during boreal spring, while the Southwest has its highest frequencies during the summer monsoon season. While annual precipitation totals are greatest in the Southeast, annual numbers of days with precipitation are greatest in the Northwest (not shown).

An examination of the average number of days per season with precipitation greater than 1 mm expressed as the difference between the CFS reforecasts at forecast lead times of 1, 10, and 100 days and the observations during 1982–2005 (Fig. 2) shows a considerable evolution of the difference patterns depending on the season and the forecast lead. During boreal winter the CFS overestimates the number of wet days along the northern tier of states at all leads, with a tendency to underestimate the number of days in the Southeast.

During boreal spring the positive bias in the number of wet days in the CFS is primarily restricted to the western third of the nation, and there is a tendency for this bias to increase with increasing forecast lead. There is a negative bias in the number of wet days in the central and southern Great Plains that decreases with forecast lead, while a negative bias persists at all leads along the immediate Gulf Coast.
In boreal summer the CFS underestimates the number of days with precipitation in the Great Plains, Southwest and along the Gulf Coast; the largest underestimates are in the Southwest and along the Gulf Coast where the CFS averages more than 20 fewer wet days per season than the observations. During boreal fall the CFS exhibits a negative bias in the number of wet days along the West Coast that diminishes with forecast lead and a positive bias in the number of wet days in the northern and central Great Plains that increases with forecast lead.

An examination of the difference between the CFS reforecasts (based on 1982–2005) and the CFS coupled simulations (based on 98 yr of simulation) and the CFS coupled simulations (denoted either CMIP1 or CMIP2). Results are shown for (a) CFS CMIP1 and (b) CFS CMIP2. The CFS reforecast results are based on the 1982–2005 and the CMIP results are based on 98 yr of coupled simulation. In both (a) and (b) results are shown for (top to bottom) JFM, AMJ, JAS, and OND. Shading as in Fig. 2.
results at the shorter leads (Fig. 4). There are obvious differences in the patterns when we compare day 1 to day 10, but differences are less apparent when we compare day 10 to day 100. The larger differences between day 1 and day 10 indicate possible spinup effects.

The preceding results illustrate that bias in the number of days with precipitation in CFS has considerable spatial and temporal variability through the annual cycle. To examine regional characteristics of the bias, four regions were selected based on areas of large bias in the spatial difference (CFS minus observations; e.g., Figs. 2 and 3). Care was taken to choose areas with bias of one sign or the other in order to avoid combining areas of positive and negative biases when taking area averages. The four regions are

Interior Pacific Northwest (PNW): (42.5°–47.5°N, 115°–120°W);
North-central Great Plains (NC): (45°–47.5°N, 95°–100°W);
Southwest (SW): (32.5°–37.5°N, 107.5°–112.5°W);
Southeast (SE): (30°–35°N, 82.5°–87.5°W).

The CFS reforecasts reproduce the basic characteristics of the observed annual cycle of average number of days with precipitation by categorical amount (Fig. 5) but there are some substantial biases in each region. For example, during fall [October–December (OND)] and winter [January–March (JFM)] the CFS reforecasts have too many daily precipitation events in the PNW for categorical amounts exceeding 4 mm day$^{-1}$. This
FIG. 5. Average number of days per season with precipitation by categorical amount (mm) for (left to right) the PNW, NC, SW, and SE regions. The latitude–longitude coordinates used to define the regions are given in the text. Results are shown (top to bottom) by season for the period 1982–2005. The precipitation categories are 1.01–2 mm, 2.01–3 mm, etc., as indicated along the abscissa. The black line is observations; the red, green, and blue lines are CFS reforecasts at leads of 1, 10, and 100 days, respectively. The dashed line is the CFS CMIP1 simulation.
Bias increases as forecast lead increases indicating possible spinup effects. Because the PNW box is located primarily to the east of the Cascades, the results suggest that orographic influences on precipitation may be showing up too far downstream. Model resolution may also play an important role in this bias, though this has not been investigated. In the NC region there are too many daily precipitation events for all precipitation intensities during fall and winter in the CFS reforecasts. The positive bias in NC suggests that there is overactive shallow convection in this region during the cold season. In the other regions the bias appears to be small during boreal fall and winter.

In the NC region the CFS reforecasts compares well to observations for all precipitation intensities during boreal spring, but there are too few low-intensity precipitation events during boreal summer; this bias decreases somewhat at longer leads. In the SW the CFS

![Fig. 6. Departures from average of the (a) observed and (b) CFS CMIP1 simulated number of wet days ($p > 1$ mm) by season and by ENSO phase (contours). Observed (simulated) ENSO episodes are chosen from 1948–2006 (98 yr). The observed (simulated) base period is 1948–2006 (98 yr). Results are shown for (top to bottom) JFM, AMJ, JAS, and OND. The (left) W, (middle) C, and (right) N labels stand for warm (El Niño), cold (La Niña), and neutral ENSO phases, respectively. Shading indicates areas where the differences are significant at the 90% level [green (+) and brown (−)].]
Reforecasts have a strong negative bias in the number of low-intensity rainfall events during boreal summer [June–September (JAS)], but this bias decreases somewhat as the forecast lead increases. This bias suggests a weak summer monsoon in the CFS reforecasts. Differences in the mean circulation features between the CFS and the NCEP/National Center for Atmospheric Research (NCAR) Reanalysis (Kalnay et al. 1996) are consistent with a weak monsoon circulation and deficient precipitation in CFS (not shown). Of course, this does not explain why the differences are occurring (weaker circulation leading to drier conditions or vice versa), only that they are consistent.

In the SE the CFS reforecasts have a negative bias for the light events (precipitation less than 6 mm day$^{-1}$) and a positive bias for the heavy events (precipitation greater than 6 mm day$^{-1}$) during boreal summer. These biases are greatest at the shortest leads and may result from differences in the strength and timing of the diurnal cycle of precipitation in CFS when compared to observations (e.g., Janowiak et al. 2007).

For comparison, we also examined the characteristics of the observed annual cycle of the average number of days with precipitation by categorical amount in the CFS CMIP1 free run (Fig. 5, dashed lines). In general the biases in the free run are similar to the biases in the reforecasts. In some regions and in some seasons the free run statistics are closest to the day 10 or day 100
reforecast statistics, indicating possible spinup effects within the first 10 days or so. In the SE during JAS, the free run statistics are closer to the observations than to the reforecasts (day 1, day 10, and day 100) for the heavy daily events. There is no obvious explanation for this. Overall, the results also justify use of the CFS CMIP runs to increase the number of cases and hence improve the statistics (e.g., see section 4).

Future research will focus on the possible causes for the CFS reforecast biases, which might include 1) the effects of model resolution over the PNW and SW, 2) overactive shallow convection in the northern Great Plains (NC) during the cold season, and 3) variations in the timing and strength of the diurnal cycle in the SE. An additional potential spinup effect not examined here is the difference between uncoupled and coupled responses of the atmospheric model to the various parameterizations used in the CFS. As with the other contributions mentioned above, inconsistencies in the parameterizations can lead to additional spinup problems.

The biases described in Fig. 5 may also be traced to difficulties in using a “one size fits all” approach to parameterizing convection in both weather and climate

**Fig. 7.** Average number of days per season with precipitation >1 mm (contours) by ENSO phase expressed as a difference between the CFS CMIP1 simulation (based on ENSO events during 98 yr of simulation) and the observations (based on 1948–2006). Results are shown for (top to bottom) JFM, AMJ, JAS, and OND. The (left) W, (middle) C, and (right) N labels stand for warm (El Niño), cold (La Niña), and neutral ENSO phases, respectively. Shading as in Fig. 2.
models at NCEP (Pan and Han 2007). In particular, NCEP has adopted an approach in which a coarser-resolution version of the relatively high-resolution global Numerical Weather Prediction model (GFS) is used as the atmospheric component of the global coupled climate model (the CFS). The convective parameterization scheme in GFS has been tuned to simulate the effects of convective clouds and boundary layer and clear air turbulence in order to properly simulate the convective precipitation on a daily basis. However, in the CFS the same convective parameterization has been tuned to have proper feedbacks onto the global circulation on time scales of months to years (e.g., for ENSO). As the resolution of the CFS is increased, however, the convective parameterization scheme must handle both weather and climate, including the possibility that cumulus convection should be directly resolved. At the present time, there are mismatches between the relatively high-resolution GFS and the relatively coarse-resolution CFS that might contribute to the biases in daily precipitation described above. Preliminary tests indicate that these biases are reduced in higher-resolution (e.g., T382) versions of CFS (H. Pan 2008, personal communication).

FIG. 8. Total number of wet spells of at least 5-, 7-, 10-, and 15-days duration for the conterminous United States in the (left) observations expressed as a difference between the number of spells in the CFS CMIP1 simulation and the observations. Results are shown for (a) JFM, (b) AMJ, (c) JAS, and (d) OND. Results are based on 59 yr from the observations (1948–2006) and the last 59 yr from the CFS CMIP1 simulation.
4. Influences of ENSO

The CMIP simulations and 59 yr of observations (1948–2006) are used to examine the seasonal shifts in the number of days with precipitation by ENSO phase over the United States. Ideally the comparisons would involve the same years in the observations and in the model, but this is not possible with the CMIP simulations. Because we compare frequencies instead of simple counts, we use the entire CMIP simulations for the comparison in order to improve the statistical significance of the results. Because the results are similar for CMIP1 and CMIP2, only the results for CMIP1 are shown.

ENSO events from the CMIP simulations are chosen in a manner similar to those in the observations using the Niño-3.4 region (5°N–5°S, 120°–170°W) and an SST anomaly threshold of ±0.5°C based on 3-month running means. El Niño and La Niña episodes are defined when the threshold is met for a minimum of 5 consecutive overlapping seasons [e.g., JFM, February–April (FMA), March–May (MAM), April–June (AMJ), May–July (MJJ)]. The frequencies of warm (El Niño), cold (La Niña), and ENSO-neutral episodes in the CMIP1 simulation are given in Table 2; similar results are obtained for the CMIP2 simulation (not shown).

Departures from average of the number of observed wet days (precipitation greater than 1 mm) per season are shown in Fig. 6a. For reference, the average observed number of wet days per season was shown in Fig. 1b. Relative to the climatological (1948–2006) mean, El
Niño features an increase in the number of wet days per season along the southern tier of states during boreal winter, spring and fall, and a decrease in the number of wet days per season in the Ohio Valley and Northeast during boreal winter (Fig. 6, left column). El Niño also features an increase in the number of wet days per season along the northern tier of states during boreal summer; an examination of the associated circulation features revealed that the jet stream tends to be shifted south of its climatological mean position (not shown), resulting in more frequent cold frontal passages and wetter-than-average conditions in this region. Consistent with this, El Niño also tends to feature a weaker North American monsoon during boreal summer in the southwestern United States.

Relative to the climatological mean, La Niña features a decrease in the number of wet days per season in much of the Southwest and along portions of the Gulf Coast during boreal winter, in the Pacific Northwest during spring, and in portions of the northern tier of states during spring and summer (Fig. 6a, center column). The smallest departures from the climatological mean are for the ENSO neutral years, and in general they are slightly negative (fewer-than-average wet days).

While the CFS CMIP1 simulation reproduces many of the classical features of the ENSO precipitation anomaly patterns (Fig. 6b), the difference patterns between the CFS CMIP1 simulation and the observations show that CFS has a generally positive bias in the num-
ber of wet days per season independent of ENSO phase (Fig. 7). We note that base period means were removed from each panel shown in Fig. 6 (see the caption on Fig. 6 for details), while straight differences of the ENSO composites (based on the full fields) are shown in Fig. 7. The positive bias in Fig. 7 is as large as 30–40 additional wet days per season in CFS. One exception is in the Southwest and along the Gulf Coast during boreal summer, where the CFS has a negative bias in the number of wet days.

5. Wet and dry spells

Next we examine the number of wet and dry spells (i.e., periods of consecutive wet or dry days) in observations and in the CFS by season. For the comparison we use the last 59 yr of the CMIP1 simulation and 59 yr of observations (1948–2006) so that a direct comparison of the total numbers of wet and dry spells can be made (just divide by 59 to get the average number of wet or dry spells per season). The seasonal cycle of the total number of observed wet spells and the difference between observations and the CFS for the conterminous United States are shown in Fig. 8; in each case results are shown for wet spells of increasing duration.

During boreal fall and winter the Pacific Northwest experiences the largest number of observed wet spells of at least 5, 7, 10, and 15 consecutive wet days (Figs. 8a,d). The CFS has a positive bias in the number of wet spells in the Pacific Northwest and along the northern tier of states and a negative bias in the Southeast. For spells of 5 days or more the CFS exceeds the observa-
tions by more than a factor of 2 over much of the intermountain west and in the Great Lakes. The results suggest a systematic northward shift of the midlatitude (Pacific) jet stream and storm track and a tendency for the flow to be too zonal in CFS relative to observations during boreal fall and winter (not shown).

From the earlier comparison of the contributions of daily rainfall events to the total rainfall we know that the day 10 and day 100 CFS reforecasts tend to overestimate the number of cases for all categorical amounts during boreal winter except for amounts contributed by extreme events. This suggests that the number of wet spells in CFS during boreal fall and winter is influenced by the frequency of rainfall events of all intensities, not just the light rain events. In other words, the differences are not just due to the influences of the gridding procedure on the rainfall pattern.

During boreal spring and summer the CFS has a positive bias in the number of wet spells in the Pacific Northwest and Southeast and a negative bias in the number of wet spells in the Southwest (JAS only) and Great Lakes relative to observations (Figs. 8b,c). This suggests that the summer monsoon-induced precipitation is too weak in CFS with a southward shift of the midlatitude jet stream and an anomalously weak monsoon anticyclone in the west relative to observations. In addition, the number of wet spells along the Gulf Coast is too low in CFS relative to observations (especially JAS) suggesting that the strength and timing of diurnal convection may not be correctly simulated in the

FIG. 9. As in Fig. 8, but for total number of dry spells of at least 10-, 15-, 20-, and 30-days duration.
model. Overall, these analyses motivate additional synoptic studies aimed at improving the linkage between the daily precipitation patterns and related circulation features in the CFS. We note that when these analyses are repeated using various thresholds (e.g., 5 mm day$^{-1}$) we obtain similar results, namely that the CFS overestimates the number of events compared to observations.

The seasonal cycle of the total number of observed dry spells and the difference between observations and the CFS for the conterminous United States are shown in Fig. 9; in each case results are shown for dry spells of increasing duration. During boreal fall and winter the Great Plains and the Southwest experience the largest number of observed dry spells of at least 10, 15, 20, and 30 consecutive dry days (Figs. 9a,d). The CFS has a negative bias in the number of dry spells of all durations at most locations during boreal fall and winter, consistent with the earlier result that there is a positive bias in the number of wet spells in CFS. It is worth noting that there are very few dry spells longer than about 20 days in the CMIP runs (difference patterns are similar to observed patterns and of opposite sign).

During boreal spring the CFS has a negative bias in the number of dry spells of all durations at most locations except in the southwestern states (Fig. 9b). During boreal summer the CFS has a positive bias in the number of dry spells in the Southwest (consistent with weak monsoon-induced precipitation) and along the Gulf Coast (Fig. 9c).

The numbers of wet and dry spells of at least 5, 7, 10, 15, 20, and 25 days duration for the conterminous United States are shown in Fig. 9; in each case results are shown for spells of increasing duration. During boreal fall and winter the Great Plains and the Southwest experience the largest number of observed dry spells of at least 10, 15, 20, and 30 consecutive dry days (Figs. 9a,d). The CFS has a negative bias in the number of dry spells of all durations at most locations during boreal fall and winter, consistent with the earlier result that there is a positive bias in the number of wet spells in CFS. It is worth noting that there are very few dry spells longer than about 20 days in the CMIP runs (difference patterns are similar to observed patterns and of opposite sign).

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United States in the observations and in the CFS CMIP1 simulation are given in Table 3. These results are obtained by computing the number of wet (dry) spells at each grid point and then by computing the area average for the conterminous United States. Results are shown by season based on 59 yr in the observations (1948–2006) and the last 59 yr of the CFS CMIP1 simulation. The area mean results are consistent with the discussions of the spatial maps above for wet and dry spells.

6. Discussion: Statistical adjustment of CFS operational forecasts

In this study we examined the statistics of daily precipitation within seasonal climate over the conterminous United States using gridded station data and output from the NCEP Climate Forecast System (CFS). Differences in the occurrence of daily precipitation between the observations and a set of CFS reforecasts were examined as a function of forecast lead time for 1982–2005. Differences in the daily precipitation statistics by ENSO phase and in the frequencies of wet and dry spells were also identified using a longer period of gridded station data (1948–2006) and a pair of 100-yr CFS coupled simulations. The comparisons exposed the regional and seasonal dependence of the bias in the CFS reforecasts over the conterminous United States.

Knowledge of the distributions of daily precipitation frequency and intensity in the observations and in the CFS reforecasts can be used to develop tools for the statistical adjustment of operational CFS precipitation

Fig. 9. (Continued)
forecasts. In particular, one can correct forecast errors by using the reforecasts and their corresponding verifications to calibrate the ensemble-based probabilistic forecasts. While the day-to-day weather cannot be predicted at leads of 2–4 weeks, shifts in time averages (e.g., the average weather over the period of a week or two) may still be predicted skillfully, and it may be possible to predict an increased or decreased likelihood of extreme events (e.g., risk of flash floods, flash droughts, prolonged severe cold-air outbreaks, heat waves, and high fire danger). At these leads, because noise is large and signal is small, expressing forecasts probabilistically is a practical necessity. Such an approach would be immediately useful for the statistical calibration of forecast tools currently used in CPC forecast operations to prepare the 6–10 day and 8–14 day outlooks and hazards assessments for the United States, Africa, and the global tropics.

In a series of recent publications the effectiveness of this approach has been demonstrated for both weather predictions (e.g., Hamill et al. 2006) and short-term climate forecasts (days 6–10 and week two; e.g., Hamill et al. 2004). Hamill et al. (2004) employed a multidecadal ensemble reforecast dataset to statistically calibrate operational forecasts. Their approach allowed them to separate the predictable signal from the noise due to chaotic error growth and model drift. Their model-based technique worked well because at 1–2 weeks the predictive skill was still somewhat influenced by the initial state of the atmosphere. At longer leads, for example, from ~2 weeks to 2 months, the anomalous boundary conditions that might have an influence on

![Fig. 9. (Continued)](image-url)
predictable modes of atmospheric climate variability must be considered. For example, a shift of the atmospheric state away from its long-term average climatology can be predicted from the state of sea surface temperature anomaly patterns such as the El Niño-Southern Oscillation (ENSO) or other recurring patterns of sea surface temperature variation. The relationship of the current boundary condition to future shifts from the unconditional climatology may be linear in character, and the fully nonlinear numerical weather prediction models may have very large systematic errors. In these situations, statistical models such as the linear inverse model (Winkler et al. 2001; Newman et al. 2003) are useful for diagnosing sources of forecast skill, and they may provide forecasts competitive with those from general circulation models (GCMs). Future work should focus on determining the specific boundary forcings and internal dynamics that contribute to predictability in each season.

Existing reforecast datasets from CFS can be used to determine what the requirements are for a reforecast dataset that optimizes the skill of forecast products in the appropriate time ranges. Such a suite of operational products can be augmented with new more customized forecast products suitable to a larger variety of end users. Since there are currently no skillful climate forecast products at these time ranges, such an effort would contribute directly to the National Weather Service strategic goal of providing “a seamless suite of weather and climate forecasts” spanning weather and intraseasonal and interannual time scales (Leetmaa 2003).

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