Temporal–Spatial Scales of Observed and Simulated Precipitation in Central U.S. Climate

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ABSTRACT

Precipitation intensity spectra for a central U.S. region in a 10-yr regional climate simulation are compared to corresponding observed spectra for precipitation accumulation periods ranging from 6 h to 10 days. Model agreement with observations depends on the length of the precipitation accumulation period, with similar results for both warm and cold halves of the year. For 6- and 12-h accumulation periods, simulated and observed spectra show little overlap. For daily and longer accumulation periods, the spectra are similar for moderate precipitation rates, though the model produces too many low-intensity precipitation events and too few high-intensity precipitation events for all accumulation periods. The spatial correlation of simulated and observed precipitation events indicates that the model's 50-km grid spacing is too coarse to simulate well high-intensity events. Spatial correlations with and without very light precipitation indicate that coarse resolution is not a direct cause of excessive low-intensity events. The model shows less spread than observations in its pattern of spatial correlation versus distance, suggesting that resolved model circulation patterns producing 6-hourly precipitation are limited in the range of precipitation patterns they can produce compared to the real world. The correlations also indicate that replicating observed precipitation intensity distributions for 6-h accumulation periods requires grid spacing smaller than about 15 km, suggesting that models with grid spacing substantially larger than this will be unable to simulate the observed diurnal cycle of precipitation.

1. Introduction

Precipitation simulation for assessing the impacts of climate variability and anthropogenic climate change on natural and human systems demands not only accurate time averages but also accurate simulation of precipitation properties such as distributions in space, time, and intensity. The intensity of precipitation is highly relevant, for example, for assessing flooding potential, soil moisture replenishment, and water resource management. Numerical models therefore must be evaluated for how well they reproduce the intensity spectrum of precipitation. Here we examine this spectrum for a regional climate model (RCM). We focus on the U.S. northern plains, as this is a region that depends strongly on precipitation for agriculture while experiencing a wide spectrum of intensity, ranging from strong convective bursts to steady, light rainfall.

Errors in precipitation simulation are potentially sensitive to the temporal scales analyzed, as errors over

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periods of hours may cancel when averaged over longer periods, such as a day or more. Such cancellation can occur, for example, if a climate model's daily precipitation tends to occur as moderate precipitation over several hours while the actual precipitation has the same daily average total but occurs in shorter downpours. Models may smooth precipitation rates in time because their limited horizontal resolution prevents vertical motions and associated precipitation rates from being as strong as in the real atmosphere (Jones et al. 1995). We thus consider temporal scales of accuracy in simulated precipitation intensity for a regional climate simulation covering a 10-yr period.

The diurnal cycle produces an important temporal scale for precipitation in the U.S. northern plains. Precipitation in this region shows a prominent nocturnal maximum (Wallace and Hobbs 1977; Augustine and Caracena 1994) that presumably must be simulated well to capture the precipitation intensity spectrum, at least on subdiurnal timescales. The analysis here thus considers a range of temporal scales for precipitation, extending from accumulations over several hours to several days. In addition, the simulation examined here used a grid spacing of 52 km, which is within a range of grid spacings, 30–100 km, that are commonly used for regional climate simulation (e.g., Takle et al. 1999; Giorgi and Bi 2000; Pal et al. 2000; Rinke et al. 2000, among many others). Results from the present analysis that are linked to spatial resolution may thus have bearing on regional climate simulation by a broad range of models.

2. Simulation output and observational data

The focus of this study is the portion of the U.S. northern plains covered by Iowa and eastern Nebraska. This region has relatively little topographic variation and precipitation mechanisms that are fairly homogeneous in space, so that spatial variation due to local factors like topography is relatively weak. In the colder half of the year, precipitation is primarily from synoptic-scale midlatitude cyclones, whereas the warmer half has a mixture of convective and synoptic-scale precipitation events (e.g., Fritsch et al. 1986).

a. Simulation

Model output used here comes from a 10-yr period simulated by the regional climate model of Giorgi et al. (RegCM2; Giorgi et al. 1993a,b, 1996) using the same continental U.S. domain as experiment 1 of the Project to Intercompare Regional Climate Simulations (Takle et al. 1999). The grid spacing was 52 km on a Lambert conformal projection centered at (37.5°N, 100°W) with 14 layers in the vertical. The model used initial and lateral boundary conditions from a reanalysis (Kalnay et al. 1996) produced by the National Centers for Environmental Prediction (NCEP) and the National Center for Atmospheric Research (NCAR), supplemented by observations of surface temperatures in the Gulf of California and the North American Great Lakes. The simulation ran from October 1978 to December 1988 with the first three months discarded from analyses to reduce the influences of model spinup. Further details of the simulation appear in Pan et al. (2001).

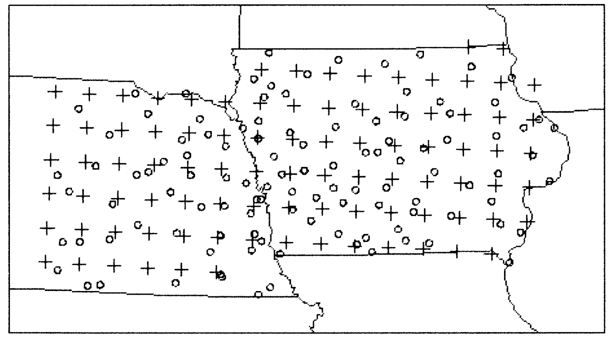

FIG. 1. Analysis domain, showing observing stations (circles) and model grid points (crosses) used in this study.

The model computed precipitation using the Grell (1993) convection parameterization and a simplified version (Giorgi and Shields 1999) of the Hsie et al. (1984) explicit moisture scheme. The Grell (1993) scheme is a version of Arakawa and Schubert (1974) convection that uses a single updraft and downdraft to represent cumulus cloud processes. The rate of large-scale convective destabilization determines the cloud's mass flux and, hence, convective precipitation rate. The simplified version of the Hsie et al. (1984) cloud microphysics computes stable precipitation using a prognostic cloud water equation with no explicit ice processes. Cloud water converts to rainwater by an autoconversion process and precipitates immediately. Simulated precipitation fell uniformly across a model grid box. We assigned precipitation rates to the grid-box center in our diagnoses, which used an analysis domain covered by 91 grid boxes across Iowa and eastern Nebraska (Fig. 1).

b. Observations

Observational data come from the National Climate Data Center archive of hourly precipitation observations contributed by primary, secondary, and cooperative stations (Hammer and Steurer 2000). Most precipitation sites used either a Fischer Porter or a Universal weighing-bucket rain gauge (Hammer and Steurer 2000). We assume that there are no significant differences in measurements between the two. Minimum values reported differed between stations, with some recording precipitation down to 0.01 in. and others only to 0.1 in. We treated recorded trace amounts as zero precipitation. We also used observations as given and made no adjustment for gauge undercatch, which can produce a negative bias in the observations of 3%–10% (e.g., Groisman and Legates 1994).

Stations used needed to report precipitation, including zero amounts, on at least 27 days of each month in the 10-yr study period, under the assumption that continuity of record implied greater operational reliability and thus an acceptable quality level in the data. Using this criterion, we selected 112 stations with approximately uniform distribution across Iowa and eastern Nebraska (Fig. 1). This number is about the same as the number of model gridpoints used for analysis, so the average station separation was roughly the same as the model's grid spacing. We note, of course, that station observations are point measurements whereas a model computes precipitation for a grid box surrounding a grid point. We assume that for a 10-yr record, the observing stations provide adequate sampling of the same region covered by the RCM grid boxes centered on the grid points.

3. Analysis procedures

We treated precipitation at all model grid points and observation sites as individual samples. We accumulated precipitation at each station and grid point into 6-hourly time series (0000–0600 UTC, 0600–1200 UTC, etc.). From these series we created corresponding 12-hourly, then daily, etc. time series, thus, first removing short and then successively longer timescales from the high-frequency end of the precipitation's temporal variability spectrum. For all time series, precipitation is reported in a common unit of centimeters per day, irrespective of accumulation interval, to ease comparison of results. We define a precipitation event as a nonzero precipitation record for one time interval at one location.

From these time series, we constructed histograms of precipitation intensity, lumping together precipitation events from all grid points or all observation sites. Shorter accumulation intervals could have much larger precipitation rates than longer intervals, so bin widths for the histograms were larger for time series with a shorter accumulation interval. All bin widths easily satisfied minimum width criteria suggested by Wilks (1995) for avoiding excessively fine and potentially noisy gradations in precipitation intensity. Time series with shorter accumulation intervals also would have potentially many more precipitation events than daily or longer time series, so to aid comparisons between different accumulation intervals, all histograms were normalized by dividing the event count for each bin by the total number of precipitation events in all samples contributing to the histogram. For the output stratifications presented here, the number of precipitation events ranged from 12 000 to over 150 000.

We also constructed spatial correlations of precipitation events to infer their spatial scales. We computed the correlation of precipitation at one station (designated the anchor station) with precipitation at each of the other stations. Each station became the anchor station in turn, ultimately yielding a function of correlation versus station separation distance. We computed correlations using only intervals with precipitation occurring at the anchor station, though not necessarily at the other station. We followed the same procedure for the model output, treating each grid point as a ''station.'' However, model output can include much smaller precipitation amounts in 6-h periods than observations, for which precipitation must exceed 0.01 in. (or for some stations, 0.1 in.) in an hour to be recorded. Therefore, the correlation computation used precipitation events at model anchor points for which at least 1.25 mm fell in 6 h (an average rate of slightly less than 0.01 in. h^{-1}). We computed the statistical significance of the correlations using standard techniques (e.g., Gutowski et al. 1997). The degrees of freedom differed between simulated and observed time series, depending on factors such as the number of precipitation events and the estimated autocorrelation time in a time series. Table 1 gives the minimum correlations that are significantly different from zero at the 95% confidence level for each accumulation period.

TABLE 1. Correlations that are significantly different from zero for at least the 95% confidence level, stratified by data source and accumulation period.

	6 h	1 day	10 day
Observations	0.11	0.14	0.21
Model	0.04	0.06	0.18

In order to compare simulated versus observed functions of correlation versus distance, we segregated correlations according to distance from the anchor point in 50-km intervals, (e.g., 0–50, 50–100 km, etc.). The interval 0–50 km contained no model correlation because of the model's grid spacing (except of course the autocorrelation at distance 0 km). Within each interval we extracted the median correlation and assigned it to the central distance of the interval. The resulting median correlation versus distance curve was representative of the pattern given by the entire set of points. For some cases, we also extracted the corresponding 25th and 75th percentiles of the correlation distributions, again assigning the values to the central distance of the interval. Curves of the 25th and 75th percentiles indicated the spread in values at each distance.

To segregate seasonal factors, we stratified our records into warm season (April–September) and cold season (October–March) periods to distinguish the influences of seasonal precipitation mechanisms on the model's degree of agreement with the observations.

4. Results

a. Precipitation intensity histograms

Observed and simulated histograms for cold season 6-hourly precipitation (Fig. 2a) display typical simu-

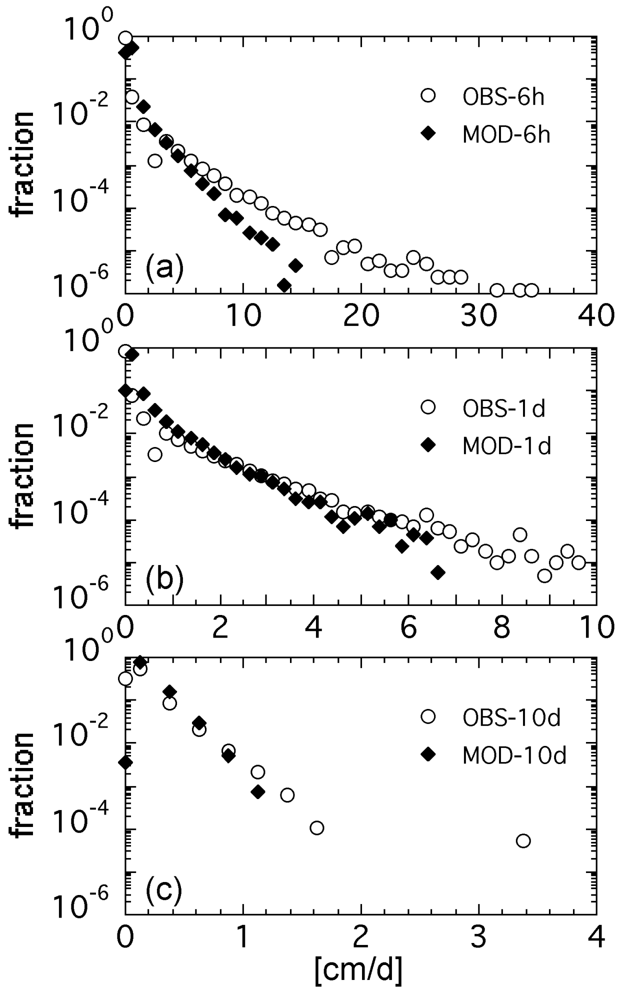

FIG. 2. Cold season precipitation histograms for (a) 6-h, (b) 1-day, and (c) 10-day accumulation intervals. Note different *x*-axis scales on each panel.

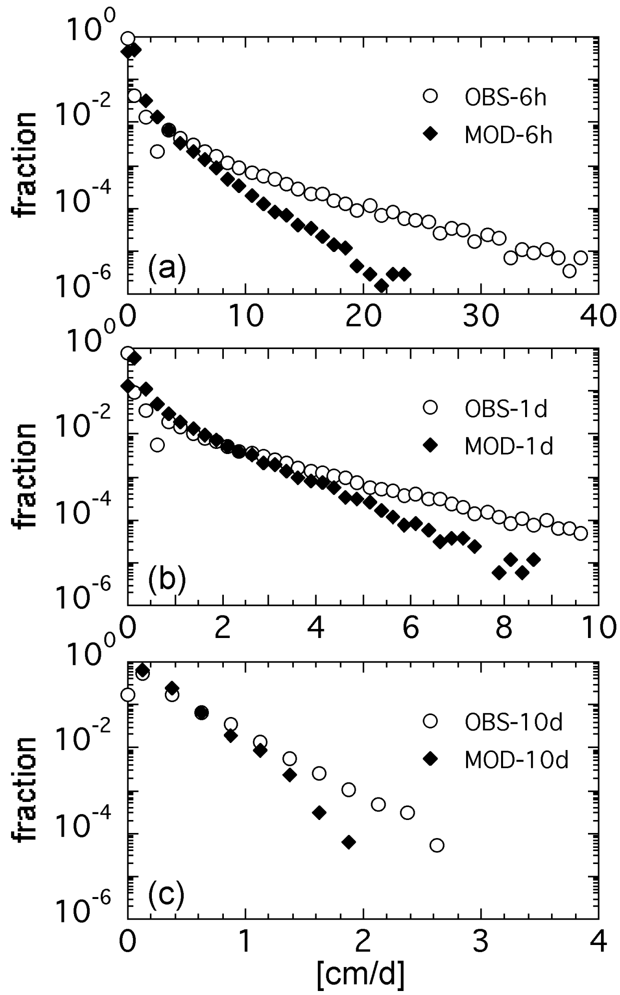

FIG. 3. As in Fig. 2 but for the warm season.

lation behavior for extreme intensities (cf. Mearns et al. 1995; Chen et al. 1996; Giorgi and Marinucci 1996), with the simulation producing too few high-intensity events and too many ''drizzle'' events compared to observations (note that the *y* axis is logarithmic). A multivariate randomized block permutation (MRBP) analysis (Tucker et al. 1989; Mielke 1991) indicates that the probability of the two histograms in Fig. 2a being drawn from the same distribution and thus being statistically indistinguishable is much less than 1%. Between these two extremes, counts for simulated precipitation decrease more rapidly with increasing intensity than do observational counts. The model has substantially fewer events for all categories with rates exceeding 6 cm day^{-1}, and only a small portion of its spectrum of intensities has counts that are approximately the same as observed.

When cold season precipitation is accumulated into daily intervals (Fig. 2b), the precipitation rates overall are less intense than the 6-hourly rates. Very strong precipitation rates usually are not sustained for an entire day, and accumulating daily values will smooth shorter bursts of precipitation. The simulation inadequacies at the intensity extremes remain; however, the simulation's daily intensity spectrum has a much larger portion (1.25–6 cm day^{-1}) that roughly matches the observations. Thus, for moderate intensities on daily timescales, the model agrees quite well with observations. The same behavior holds for 3-, 5-, and 10-day (Fig. 2c) accumulation intervals, whereas 12-h intervals produce model–observation histogram differences intermediate to the 6-hourly and daily histograms.

Warm season, 6-hourly simulated rainfall (Fig. 3a) also has too little high-intensity precipitation and too much light precipitation. Simulated daily precipitation intensity (Fig. 3b) agrees much better with observations in the middle part of the spectrum, though not as well as in the cold season (Fig. 2b). The simulated 3-, 5-, and 10-day (Fig. 3c) accumulation intervals also have intensity distributions that agree better with observations than the 6-hourly distribution.

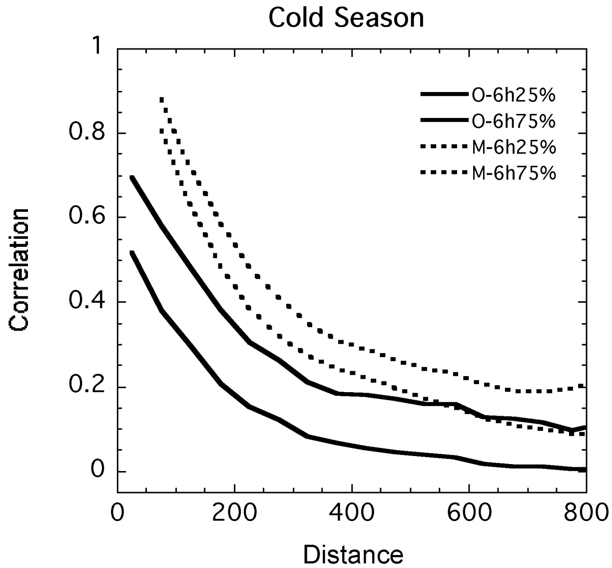

FIG. 4. The 25th and 75th percentiles of the precipitation correlations vs distance for the cold season precipitation accumulated in 6-h periods.

In comparison to the cold season, warm season precipitation has a larger portion that is convective. Simulated convective precipitation is, of course, produced by a parameterization in this simulation rather than by the explicitly resolved circulation. Parameterized precipitation rates are a challenge for simulations, so reduced agreement in the warm season is not surprising. Also, the warm season's observed intensity distributions for each accumulation period are shifted slightly toward greater intensity and thus shifted toward an end of the intensity spectrum where the model produces less rainfall than is observed. However, even in the range 1.25–6 cm day^{-1} for daily accumulation, the model's warm season intensity distribution does not match the observations as well as for the cold season.

b. Spatial correlation

Spatial correlations of precipitation provide insight into the histogram improvement that occurs when accumulating precipitation over periods of 1 or more days. Figure 4 shows the 25th and 75th percentile curves of correlation versus distance for observed and simulated 6-hourly, cold season precipitation. The correlation for the observed precipitation decreases rapidly with distance, with both percentiles plotted falling below 0.7 (50% of the explained variance) in less than 75 km. Most observed correlations are statistically insignificant beyond 600 km. The correlation 25th percentile and 75th percentile curves for simulated precipitation do not fall below 0.7 until the separation distance is about 125 km, and they remain significantly different from zero out to 800 km. The model's grid spacing of 52 km implies that the model will not contain circulation patterns with scales less than about 100 km (two grid points). The resolved circulation governs the precipitation distribution, so the model's slower decrease in correlation with distance compared to observations is consistent with its inability to resolve scales of atmospheric motion under 100 km. The observed correlation versus distance implies that the 6-hourly precipitation for this region has prominent scales of behavior that are smaller than 50 km, which the model cannot resolve. The observed precipitation also yields greater spread in the correlation curves than does the simulated precipitation. Part of this difference may be due to observational error, but the result suggests that resolved model circulation patterns producing 6-hourly precipitation on these spatial scales are more limited in the range of precipitation patterns they can produce compared to the real world.

Similar behavior occurs for warm season precipitation (not shown), except that correlations for both the model and observations tend to be roughly 0.2 units smaller and decrease more rapidly with distance for separations less than 200 km. This behavior is consistent with the warm season having a larger fraction of its precipitation as convection, which can occur on smaller scales than stratiform precipitation in both the model and observations.

These results indicate limitations in the model's ability to resolve precipitation-producing circulations at scales that are important in the atmosphere. If simulated precipitation events of any magnitude (including drizzle) are included in the anchor-point events, the model's correlation curves decrease somewhat less rapidly with distance compared to the model curves in Fig. 4. More intense events thus appear to be associated with shorter spatial scales, whereas drizzle includes longer scales. Short spatial scales not resolved by the model may have vertical motions stronger than those at the scales the model does resolve (Jones et al. 1995). Thus, it is not surprising that the model produces too few 6-hourly events over the higher-intensity portion of the spectrum. Coarse spatial resolution does not appear to cause overabundant light precipitation.

For longer accumulation periods, the spatial correlation of observed precipitation decreases more slowly with distance (Fig. 5), as might be expected for example when a storm system moves through the region, producing daily precipitation over a wider area than a 6-hourly distribution. Whatever the reason, the correlations for 1- and 10-day accumulations of observed precipitation decrease more slowly with distance than does the correlation for 6-hourly observed precipitation, implying potential for the model to resolve precipitation patterns on longer timescales. Warm season correlations also tend to be smaller, with most observed correlations becoming statistically insignificant beyond 400 km for all accumulation periods. However, these factors by themselves do not appear to explain the merging of histograms for moderate precipitation rates in Figs. 2 and 3, because the model's correlations for 1- and 10-

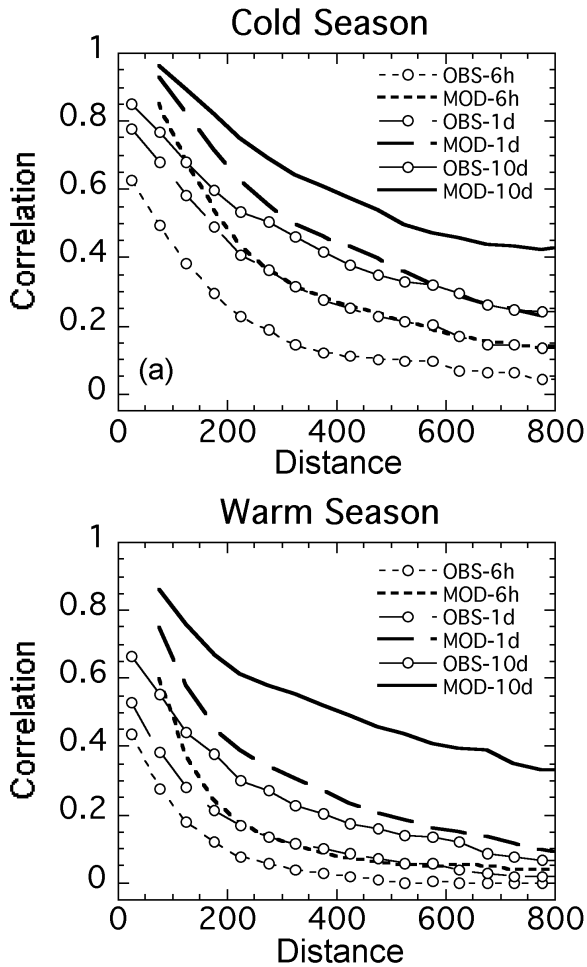

FIG. 5. Spatial correlation of precipitation vs distance during the precipitation events accumulated in 6-h, 1-day, and 10-day periods, for the (a) cold season and (b) warm season.

day accumulations decrease even more slowly with distance and show no clear sign of converging with corresponding observational correlation functions as the accumulation time increases.

5. Discussion and conclusions

An examination of precipitation intensity histograms for simulated and observed precipitation in the U.S. northern plains shows that the model replicates a broad spectrum of the intensity distribution when precipitation is accumulated over periods of one to several days. For subdaily accumulation periods, the model produces too few events in all intensity categories except for the smallest (light precipitation). Part of this behavior appears to be due to insufficient resolution for simulating the most intense events occurring in 6-h periods, because observations show shorter spatial scales (Fig. 4) than the model can resolve.

The results suggest that there is a range of precipitation accumulation periods for which the model has skill. This range depends on the spatial scales resolved by the model, with finer grid spacing potentially reproducing more faithfully the more intense precipitation events that occur over shorter periods. For the model we used with 52-km grid spacing, realistically simulated accumulation periods appear to be no shorter than 1 day. This means that the model cannot be expected to resolve well subdaily precipitation variability, such as the nocturnal precipitation maximum observed for the northern plains.

The observed correlation of precipitation versus distance for 6-h accumulation periods suggests that a model needs to resolve precipitation behavior with spatial scales of approximately 50 km and less, implying that grid spacing smaller than about 15 km is needed to adequately replicate precipitation intensity distributions on 6-h accumulation periods. This scale approaches the size of mesoscale convective systems, for example, which are important precipitation sources, especially in summer (Fritsch et al. 1986). Note that this behavior occurs even though the model does reproduce an important diurnally varying moisture source, the nocturnal low-level jet of the U.S. Great Plains (Stensrud 1996). Simulations by Giorgi and Marinucci (1996) for Europe using grid spacings of 50, 100, and 200 km show that increasing spatial resolution indeed can give increasing frequency of high-intensity precipitation events. How much their results can be extrapolated to smaller grid spacing or translated to the central U.S. region remains unknown.

Our correlation analysis also suggests that excessive low-intensity precipitation is associated with larger spatial scales, so that decreasing grid spacing may not yield much, if any, improvement. Indeed, examination of the precipitation intensity spectra in Giorgi and Marinucci (1996) also shows in some cases an increasing frequency of lowest-intensity precipitation as the grid spacing decreases. Model deficiencies in low-intensity precipitation may be more important than those in high-intensity precipitation for overall water budget simulation. For example, for daily, cold season precipitation in the simulation examined here (Fig. 2b), nearly all of the difference between the observed and simulated total precipitation comes from events smaller than 0.75 cm day^{-1}, whereas the high-intensity events contribute little to the overall model-observation differences because they contributed little to the total precipitation. Furthermore, for each accumulation period in Figs. 2 and 3, the sum of the events in the no-precipitation and lightest precipitation categories is approximately the same; excessive light rain frequency reduces the number of simulated dry periods.

A further hypothesis that cannot be tested with the current model is that the model may be producing appropriate precipitation forcing on scales of several hundred kilometers, but has insufficient resolution to replicate the response on scales of tens of kilometers or less. It thus may produce precipitation in response to the forcing, but only on the larger scales and thus only on timescales consistent with those scales. Simulated convection, for example, may be viewed as a response to resolved large-scale forcing. The presence of convective forcing in the resolved flow may prompt convection, but with less intensity due to the spatial scales resolved, which will smooth the forcing distribution. The convection will still occur but with less intensity, so that the convective instability takes longer for the model to eliminate.

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