Synoptic Control of Heavy-Rain-Producing Convective Training Episodes

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(Manuscript received 17 August 2013, in final form 20 February 2014)

ABSTRACT

This study examines the degree to which the downscale cascade of information from synoptic-scale motions constrains error growth in simulations of a particular type of heavy-rain-producing mesoscale convective system known as training lines. A total of 21 cases of training convection over a 7-yr period from 2000 to 2006 that produced extreme rainfall were dynamically downscaled from reanalysis data using a high-resolution convection-permitting configuration of the Weather Research and Forecasting Model. The NCEP/Department of Energy (DOE)-II and Interim ECMWF Re-Analysis (ERA-Interim), representing lower- and higher-resolution datasets, respectively, were used for this purpose. In most cases the model simulations were able to reproduce qualitative aspects of observed storm structure, including subjectively classified mesoscale convective system archetype and training characteristics, despite the absence of mesoscale features in the reanalysis datasets used to provide initial conditions and lateral boundary conditions to the simulations. Furthermore, models were capable of predicting that a heavy-precipitation event would occur in nearly every case. Increasing the horizontal resolution of the reanalysis dataset used for initial conditions and lateral boundary conditions did not result in measurable improvement in simulated precipitation placement skill relative to observations. A quantitative relationship between a measure of synoptic-scale uncertainty in the atmospheric state and error in the model forecast accumulated precipitation was established, with larger synoptic-scale uncertainty tending to be associated with larger model error. This result suggests that synoptic-scale uncertainty in numerical weather prediction model simulations partially controls error in the placement of heavy convective precipitation.

1. Introduction

Among the various manifestations of severe weather in the United States, extreme rainfall events and subsequent flash flooding result in more mean annual deaths than all other severe weather phenomena, excluding excessive heat outbreaks (National Oceanic and Atmospheric Administration 2012). A large percentage of extreme rainfall events result from particular organizations of deep convection in mesoscale convective systems (MCSs) that result in slow or repetitive storm motion over a particular geographic area (Moore et al. 2003; Schumacher and Johnson 2005, 2006). The sensitivity of particular hydrological basins to flash flooding varies considerably, and depends on a variety of nonmeteorological factors relating to local topography. Consequently, whether or not a heavy-rain-producing convective episode produces a flash flood is dependent on a combination of event placement and total rainfall production (i.e., the same precipitating system may cause a flash flood in a particularly susceptible hydrological basin, while having a negligible effect on another). This exemplifies the importance of understanding the predictability limits of the intensity and placement of extreme rainfall events.

Details regarding the triggering and placement of convection depend on complex interactions between many atmospheric processes ranging from meso-γ to synoptic scales (Wilson and Roberts 2006; Bluestein 2008). The current state of the atmospheric observational network, where upper-level observations are obtained with a spatial density of $O(100–1000)$ km and surface observations of $O(10–100)$ km, is ultimately insufficient to resolve many of the smaller-scale factors that influence
convection. It has been shown, however, that useful information regarding the dynamics of convective systems may be obtained from numerical weather prediction (NWP) models with far finer spatial grid resolutions than that of the observations used to construct analyses for initial model conditions (e.g., Kain et al. 2006). This is due to the fact that the presence and placement of many small-scale phenomena results from the downscale cascade of information from processes occurring on the synoptic scales (Lorenz 1969; Lilly 1990; Miguez-Macho and Paege 2000, 2001; Roebber et al. 2002, 2008; Weisman et al. 2008; Schumann and Roebber 2010).

Several previous authors have addressed the dynamics and morphology of heavy-rain-producing MCSs, along with the typical synoptic-scale environments in which they occur. Moore et al. (2003) assessed the climatology of these events in the U.S. Midwest, and found that the heaviest precipitation often occurred on the cold side of quasi-stationary synoptic-scale frontal boundaries where low-level isentropic up-glide and upper-level divergence is locally maximized. Schumacher and Johnson (2005) specifically categorized convective systems in which repetitive storm passage occurs over a local geographic area into two types: training line/adjoining stratiform (TL/AS) and backbuilding/quasi stationary (BB/QS). TL/AS events were found to typically occur adjacent to a quasi-stationary synoptic-scale frontal boundary or local outflow boundary where deep layer shear is roughly boundary parallel, while the dynamics of BB/QS events were more dependent on mesoscale convective processes. Further simulations of the convective archetypes considered in this paper (Schumacher and Johnson 2008; Schumacher 2009) have also identified substantial sensitivities to internal convective-scale phenomena, such as mesoscale convective vortices, stationary wave structures induced by latent heating, and the degree to which a surface cold pool is produced.

An obvious constraint on the predictability of these events is the degree to which NWP models can resolve the mesoscale processes that influence them. Since inadequate observations prohibit the representation of many mesoscale features in initial conditions (ICs) and lateral boundary conditions (LBCs), their accurate representation in NWP models is necessarily dependent on the quality of the synoptic analysis from which the model is initialized, and the degree to which their attributes are accurately rendered by the downscale cascade of information from synoptic scales. Therefore, intuition would suggest that potential predictability gains from improvements in synoptic-scale analyses (say, resulting from more observations) would depend on the degree to which the dynamics of a convective system depend on synoptic scales (i.e., synoptic sensitivity).

Deep convection, however, is capable of quickly and substantially modifying the adjacent synoptic-scale environment through heat and moisture transports. In many cases this nonlinear property amplifies local analysis errors at a much faster rate in numerical simulations than errors averaged over large scales (Zhang et al. 2003). This complicates the predictability issue associated with convection in NWP models, where skill in the prediction of the placement of mesoscale convective features may be uncorrelated with the predictive skill of synoptic-scale fields, despite the dynamical dependence of these mesoscale features on synoptic-scale dynamics.

The goal of this study is to examine aspects of the variability in simulations of heavy-rain-producing MCSs, assuming that synoptic-scale conditions in the ICs and LBCs are analyzed as accurately as possible. A series of simulations of observed heavy-rain-producing MCS cases were conducted using the Advanced Research version of the Weather Research and Forecasting Model, version 3.3.1 (WRF-ARW; Skamarock et al. 2008). We then assessed model performance in terms of the accuracy of reproduction of observed qualitative aspects of storm structure, the spatial variability in predicted placement of heavy precipitation, and the degree to which this variability is explained by a reasonable degree of analysis uncertainty on the synoptic scale (i.e., uncertainty in the placement of synoptic-scale features). The results provide insight into the degree to which these systems are regulated by synoptic-scale dynamics, as well as the limitations to their practical predictability in the context of operational weather forecasting.

The organization of this paper is as follows. Section 2 describes the methodology for case selection and the experiment design. Section 3 describes the verification procedures, while results from experiments and sensitivity tests are analyzed in section 4. In section 5, we briefly analyze two cases where obvious differences in the modeled placement of synoptic-scale features (or the lack thereof) contributed to variability in the modeled precipitation placement. The results of these experiments are discussed in the context of previous studies and operational weather forecasting in section 6.

2. Experiment setup
   a. Case selection

Heavy-rainfall cases were identified from 7 years of daily gridded precipitation data from the (NOAA) Climate Prediction Center Daily U.S. Unified Precipitation [NOAA/Office of Atmospheric Research/Earth System Research Laboratory/Physical Sciences Division
This analysis was constructed from rain gauge observations in the continental United States, interpolated onto a 0.25° × 0.25° grid. We selected rainfall events producing over 150 mm of precipitation in a 24-h period at one or more grid points in the central and eastern United States (Fig. 1).

We then categorized heavy-rainfall events through visual examination of Weather Surveillance Radar–1988 Doppler (WSR-88D) composite reflectivity, which was obtained from the National Center for Atmospheric Research (NCAR) Case Selection Archive (http://www.mmm.ucar.edu/imagearchive/). We specifically focused on cases where heavy rain was produced by MCSs, which were defined as rainfall regions containing reflectivity greater than 45 dBZ that spanned a region over 100 km in any direction (Orlanski 1975; Parker and Johnson 2000). The 45-dBZ threshold has been commonly used in the literature to identify convective precipitation based on radar reflectivity. Cases where convection was associated with a tropical cyclone or its remnants were subjectively identified and omitted from the analysis.

Training episodes were considered to be MCS cases when heavy rain was produced by repeated and continuous storm cell (echoes greater than 45 dBZ) passage over a fixed location for a time period exceeding 6 h. The final set of 22 cases included MCSs that exhibited visual characteristics of the aforementioned Schumacher and Johnson (2005) archetypes, as well as several additional archetypes from Parker and Johnson (2000).

The most commonly observed storm structures were consistent with the TL/AS, and to a lesser extent the BB/QS archetypes of Schumacher and Johnson (2005). Example reflectivity images of two TL/AS cases and two BB/QS cases are shown in Figs. 2 and 3, respectively. Note that the TL/AS systems (Fig. 2) exhibit a much larger spatial extent, as well as a better-defined linear convective region than BB/QS cases (Fig. 3). Most of the remaining non-TL/AS or BB/QS systems fit the classic Parker and Johnson (2000) archetypes (see that study for more information on these MCS archetypes), where convective systems are categorized based on the orientation of stratiform (usually less than 40 dBZ) precipitation relative to convective precipitation (usually greater than 40 dBZ) in a convective system. The following terminology was used to indicate convective systems that fit the archetype descriptions of these authors: trailing stratiform (TS), parallel stratiform (PS), or leading stratiform (LS).
b. Model setup

The WRF-ARW was used to conduct numerical experiments in this study. This nonhydrostatic primitive equation model has been used in both research and operational forecasting to simulate phenomena on a wide variety of spatial and temporal scales. The dynamical and microphysical parameterization...
The schemes that were used for the simulations are listed in Table 1.

Following the methodology of Roebber et al. (2008), we implemented a nested model structure, with a fixed 2790 × 2790 km² (15-km grid spacing) outer domain (Fig. 1) and a 765 × 765 km² (3-km grid spacing) inner domain centered on the regions where heavy rainfall was produced. The western edge of the outer domain

Fig. 3. As in Fig. 2, but for two BB/QS events. Note the event that occurred on 7 May 2000 is examined in much greater detail in a case study by Schumacher and Johnson (2005).
was truncated to the east of the Rocky Mountains in order to avoid complications associated with flow interactions with complex terrain. Sensitivity to the inner domain size and location was tested for a subset of the 21 cases and was subjectively determined to not appreciably affect the simulations. Since the rainfall cases that were considered in this paper varied in geographic location, the inner domain was moved from case to case so that the center of this domain remained fixed over the region of heaviest rainfall (case locations are shown in Fig. 1; dots indicate the region where heaviest rainfall accumulation was observed), with the periphery of the inner domain kept at least 75 km from the periphery of the outer domain.

Simulations were run for 48 h with both domains initialized at the same time. The integration timeframe of the simulation was chosen to allow for approximately 12 h of “spinup time” between the simulation onset, and the initiation of the convection that was responsible for the heavy-rain production (since simulated convective initiation times were not always in sync with observations, there was some variation in the simulated time of the heaviest rainfall). A cumulus parameterization was implemented in the outer domain; however, the inner domain was sufficiently small to capture the gross characteristics and impacts of convective systems absent such parameterization (e.g., Weisman et al. 1997). It must be noted that substantially finer resolution would be required for explicit resolution of convective plumes (Bryan et al. 2003); however, the inner-domain grid resolution implemented here is consistent with that of operational high-resolution forecast models.

c. Initial and lateral boundary conditions

Since the spatial distribution of global atmospheric observations is highly irregular, data assimilation schemes must be relied upon when constructing a gridded analysis. Consequently, there is an inherent degree of uncertainty present in gridded analyses owing to the inevitable shortcomings of the numerical schemes that are utilized to “fill in the gaps,” especially in data-sparse regions. This intuitively results in error growth within numerical weather prediction models that are initialized from these analyses. In a synoptic-scale sense, this analysis error has been shown to translate to forecast error that grows linearly with time over the relatively short time scales (12–24 h) considered in this paper (e.g., Roebber et al. 2008; Swanson and Roebber 2008). Since we were trying to represent synoptic-scale conditions as accurately as possible, we constrained large-scale drift from the reanalysis in the outer domain by analysis nudging, so that “errors” entering the inner domain will remain proportional to uncertainties in the large-scale analysis (confirmed postsimulation by comparing outer domain solutions to reanalysis data). The nudging interval was 6 h and was applied above the boundary layer to the horizontal components of the wind, temperature, and specific humidity on the outer domain (Table 1).

We represented a realistic minimal degree of synoptic-scale uncertainty (consistent with representing synoptic-scale fields as “accurately as possible”) by performing two simulations for each case, with ICs, LBCs, and analysis nudging provided by the National Centers for Environmental Prediction/Department of Energy (NCEP/DOE) II reanalysis (2.5° grid, 18 pressure levels; Kanamitsu et al. 2002) for one simulation and the Interim European Centre for Medium-Range Weather Forecasts (ECMWF) ReAnalysis (ERA-Interim) (0.7° grid, 38 pressure levels; Dee et al. 2011) for the other. The analysis difference (AD) between the two reanalysis datasets thus represented a quantitative proxy for the analysis uncertainty of the hypothetical synoptic-scale atmospheric state driving
the simulations. Roebber et al. (2008) and Swanson and Roebber (2008) show that AD tends to be correlated with local and downstream forecast skill when comparing simulations to observations, suggesting that it captures at least a portion of the “true” analysis uncertainty. For the purposes of this study, however, we will assume that AD is an exact measure of analysis uncertainty, and the analysis will subsequently compare the magnitude of AD with drift in convective precipitation placement between the two sets of simulations (one set driven by NCEP/DOE-II and one by ECMWF ERA-Interim).

Differences in the placement of the convective systems considered in this paper between pairs of model simulations of a particular event resulted from differences in where the simulations place synoptic-scale features or their handling of the character of such features (which is constrained by AD, due to nudging), as well as from convectively driven upscale error growth (Zhang et al. 2006). If the former source of error were dominant, one would expect a correlation to be evident between AD on the synoptic-scale and precipitation placement errors, and thus conclude that training systems are strongly constrained by the synoptic scale. On the other hand, if the latter source were dominant, one may conclude that the scale of position errors evident in the simulations results predominantly from model-to-model differences in the handling of internal storm dynamics and/or small-scale stochastic processes (such as the position of individual convective cell initiation and happenstance inflow–outflow interactions). The former scenario is more promising from a predictability standpoint, since reasonable improvements in observational frequency can lead to substantial reduction in the uncertainty of a synoptic analysis (Swanson and Roebber 2008). This is apparent when comparing relatively low reanalysis uncertainty over the continental United States (where observations are frequent) to the relatively high uncertainty over the Pacific Ocean where observations are sparse [see Swanson and Roebber (2008)].

While we later discuss the implications of the results in the context of high-resolution numerical weather prediction models, it must be noted that since future meteorological observations are not available for construction of analysis products in a real-time operational setting, these models obtain LBCs from other numerical model forecasts (which in most cases are configured with coarser resolutions over larger regional domains). Growth of IC error in the coarse-resolution model solutions used to provide LBCs to operational high-resolution simulations is therefore unconstrained—this contrasts with hindcast experiments, where observational analyses are available throughout simulations, and LBC errors are constrained by errors in these analysis products. The variability in simulated precipitation placement of the convective rainfall between simulation pairs of events discussed herein thus highlights the practical upper bound for the accuracy of predicted placement of such events in operational NWP, given the current accuracy of analysis techniques.

3. Verification procedures

Simulated reflectivity fields from numerical simulations were visually analyzed for evidence of storm morphologies. We classified simulated storms in the same subjective manner as was described in section 2, in order to discern whether the model qualitatively reproduced the observed storm archetype and behavior.

Quantitative verification of modeled convective precipitation, on the other hand, presents complications that are not encountered when analyzing model skill for other fields. Convection is a highly localized, intermittent phenomenon, where large time intervals and regions may not experience forecast or observed precipitation. This contrasts with other metrics that are often used in model verification, such as geopotential height and pressure fields where the quantity of interest is present continuously in space and time. A more thorough discussion of issues pertaining to verification of precipitation areas can be found in Davis et al. (2006a,b). Those authors presented a comprehensive methodology for verifying simulations of convection, where precipitation areas are treated as objects, and the statistics of subsequent object distributions are compared between forecasts and observations. The following procedure is a brief overview of the methodology described in the Davis papers, which has been modified here to facilitate the specifics of this study.

The data used to verify the numerical simulations were available on differing grid locations and resolutions and at differing grid spacing than the inner model domain [model: 3-km Euclidian grid; observed accumulated precipitation: 4-km Euclidian grid, from the stage-IV precipitation (http://www.emc.ncep.noaa.gov/mmb/ylin/pepanl/references.html; Lin and Mitchell 2005); radar data: less than 1-km latitude–longitude]. It was therefore necessary to interpolate all data onto a common grid for comparison. We chose a 7-km grid with roughly the same external dimensions as the inner WRF-ARW domain. This common grid resolution was a compromise allowing some retention of the fine details of precipitating systems (such as variability within rainfall accumulation regions caused by individual convective cells within a MCS), while being sufficiently coarse to avoid inconveniently large computational requirements. A sample 48-h accumulated precipitation field from a model simulation is shown in the top-left panel of Fig. 4.
These data were then smoothed so that small individual elements that are part of a larger organized structure were aggregated (Fig. 4, top right). For each grid point within the common grid, we computed the average of surrounding grid points weighted by a spherical bivariate-Gaussian function with a standard deviation of 7 km (equal to that of the common grid spacing).

Rainfall totals below a masking threshold of 150 mm (this threshold was applied in all cases, including observations) were omitted from these data to determine object boundaries (Fig. 4, bottom left). Convective objects were defined as spatial “islands” within these data, completely surrounded by omitted data. Each object within a field at a given output time was then assigned a numerical identifier to facilitate object matching.

The purpose of matching objects between model simulations (Fig. 4, bottom right), or between a model simulation and observations was to determine which forecast rainfall area, if any, was the most suitable “counterpart” for an observed rainfall area (or rainfall areas produced by another forecast). Note that in most cases, the duration of the modeled heavy-rainfall-producing convective system was far less than 24 h, thereby rendering the 24-h precipitation total temporally centered about the system’s lifetime nearly equivalent to the 48-h precipitation total. For the purpose of distance error calculations here after, and to avoid the highly subjective procedure of “centering” a 24-h precipitation accumulation window over the duration of the heavy-rainfall-producing convective system, objects were exclusively identified in the 48-h total model precipitation accumulation fields (this includes model output and observations valid over the model simulation timeframe).

We used a relatively simple procedure to determine the distance between rainfall objects produced by two
different model simulations, or between simulated and observed rainfall areas where objects in a model simulation were matched to their nearest neighbor in another model simulation or observations. For instance, consider a situation where a model simulation produces \( n \) rainfall objects, and \( m \) are observed. Object centroid locations were first obtained by computing the rainfall weighted mean of the locations of all the grid points contained within an object. The distances between the \( i \)th object centroid in a model forecast and \( m \) object centroids in observations were then computed, where the subscript \( F \) denotes the model forecast. Likewise, the same procedure was conducted for distances \( dD_{O,j} \) between the \( j \)th object centroid in observations (denoted by the subscript \( O \)) and \( n \) object centroids in the model forecast. The \( i \)th object in the model forecast and \( j \)th object in observations were matched if \( \min(dD_{F,i}) = dD_{F,ij} = D_{O,j} = \min(dD_{O,j}) \).

The restriction that each object be the closest to the other out of all the other available matches involving the two objects prohibited the involvement of more than two objects in a match (i.e., an object was only allowed to be matched to one other object). The overall distance error for a particular case was defined as the average distance between matched object pairs in two model simulations, or a model simulation and observations, with comparatively smaller (larger) overall distance error indicating more (less) skillful predicted placement of precipitation. It must be noted that while the overall distance error for a particular case indicates the magnitude of position error between two simulations, or a simulation and observations, it does not convey information pertaining to over- or underproduction of rainfall. Other quantitative verification metrics, such as differences in area-integrated precipitation totals between simulation pairs, as well as differences in precipitation-object areas did not yield noteworthy results in terms of their connection to large-scale uncertainty, and are not described in further detail in this analysis.

4. Analysis of results

Results from subjective analysis of simulated composite reflectivity produced by the simulations are summarized in Table 2. We specifically determined which MCS archetype(s) (if any) were produced by the model, whether the simulated archetype(s) were in agreement with those observed in WSR-88D reflectivity, and whether training behavior (as defined in section 2) occurred within the simulation. We have also indicated whether or not the model produced 48-h accumulated precipitation in the inner domain above the 150-mm threshold.

Model simulations were able to show that extreme rainfall was possible in the inner domain in most cases, with 86% of ERA-Interim-driven and 91% of NCEP/DOE-II-driven simulations producing rainfall accumulations greater than 150 mm, respectively. It must be noted that a model bias toward overproduction of rainfall totals above this threshold cannot be excluded as an influencing factor on this result (e.g., Roebber and Eise 2001). Interestingly, superior horizontal resolution of the atmospheric features within the ERA-Interim ICs, LBCs, and nudging did not have an appreciable impact on whether the model was capable of predicting that heavy rainfall above the 150-mm threshold would occur, with differences in success rates between the two reanalysis-driven datasets well within the expected sampling variability of these data (i.e., the 86% and 91% values were not statistically different). Model simulations also were equally successful at predicting that training behavior would occur at some point within the inner domain, with a success rate of 86% for ERA-Interim-driven simulations and 82% for NCEP/DOE-II-driven simulations respectively (again, this difference was not statistically significant). Finally, the correct convective morphology was evident in simulated reflectivity 68% of the time for ERA-Interim-driven simulations and 64% for NCEP/DOE-II-driven simulations, again with no apparent dependence on the spatial resolution of the reanalysis product used to drive the model simulation (the percentage difference was again statistically insignificant). It must be noted that the subjective verification only addresses probability of detection, and not false alarms. A comprehensive assessment of false alarms in the context of the convective systems that we have considered in this study is an ambitious undertaking, and beyond the scope of this study.

Distance errors for simulations against observations, and distances between model-simulated rainfall areas are summarized in Fig. 5 (we will hereafter refer to differences between different model forecasts as errors for simplicity). Distance errors between model simulations (rightmost bar) are smaller than the mean errors between individual model forecasts and observations (left two bars), indicating that model forecasts generally verified better between themselves than individually against observations. This bias was statistically significant to a very high level of confidence (greater than 97.6%) as determined by a bootstrapping procedure (described in greater detail below). It is unclear whether this bias stemmed
Table 2. Results from qualitative verification of WRF-ARW simulations for the database of heavy-rainfall cases. Event dates and observed convective archetypes are listed in the left four columns. The remaining two sections are attributes of model simulations deduced from simulated reflectivity and accumulated precipitation fields: whether or not training occurred (as defined in the text), whether or not the observed archetype occurred, and whether or not rainfall over 15 cm was produced. Percentages of correctly portrayed model behavior are listed in the bottom row.

<table>
<thead>
<tr>
<th>Year</th>
<th>Month</th>
<th>Day</th>
<th>Observed archetype</th>
<th>ERA-Interim ICs and LBCs</th>
<th>NCEP/DOE-II ICs and LBCs</th>
<th>Year</th>
<th>Month</th>
<th>Day</th>
<th>Observed archetype</th>
<th>ERA-Interim ICs and LBCs</th>
<th>NCEP/DOE-II ICs and LBCs</th>
</tr>
</thead>
<tbody>
<tr>
<td>2003</td>
<td>May</td>
<td>6</td>
<td>TL/AS</td>
<td>TL/AS</td>
<td>Yes</td>
<td>2003</td>
<td>May</td>
<td>8</td>
<td>BB/QS</td>
<td>BB/QS</td>
<td>Yes</td>
</tr>
<tr>
<td>2003</td>
<td>May</td>
<td>18</td>
<td>TS</td>
<td>BB/QS</td>
<td>Yes</td>
<td>2003</td>
<td>Jun</td>
<td>23</td>
<td>BB/QS</td>
<td>BB/QS</td>
<td>Yes</td>
</tr>
<tr>
<td>2004</td>
<td>Feb</td>
<td>6</td>
<td>TS</td>
<td>TL/AS</td>
<td>Yes</td>
<td>2004</td>
<td>Sep</td>
<td>15</td>
<td>TL/AS</td>
<td>TL/AS</td>
<td>Yes</td>
</tr>
<tr>
<td>2004</td>
<td>Nov</td>
<td>21</td>
<td>BB/QS</td>
<td>BB/QS</td>
<td>Yes</td>
<td>2005</td>
<td>Apr</td>
<td>1</td>
<td>TL/AS</td>
<td>TL/AS</td>
<td>Yes</td>
</tr>
<tr>
<td>2006</td>
<td>Sep</td>
<td>23</td>
<td>TL/AS</td>
<td>TL/AS</td>
<td>No</td>
<td>2006</td>
<td>Oct</td>
<td>7</td>
<td>PS</td>
<td>TL/AS</td>
<td>No</td>
</tr>
</tbody>
</table>

Overall performance: 86% 68% 86% 82% 64% 91%

From the construction of the reanalysis datasets, from the model configuration, or from nonlinear interactions between the two aforementioned error sources. Additional experiments, for example varying model physics, would need to be conducted to pursue this issue but is beyond the scope of the present study. Once again, spatial resolution differences did not appreciably affect model performance in this context. Figure 6, which summarizes the scope of the present study. Once again, spatial resolution differences did not appreciably affect model performance in this context. Figure 6, which summarizes the distance errors for each individual case, illustrates the considerable variability in precipitation placement errors, with values ranging from $O(10)$ to nearly $O(1000)$ km.

While there are many ways to compute analysis differences, one of the more comprehensive measures is difference total energy (DTE; Zhang et al. 2003), which captures the combined differences between kinematic and thermodynamic fields. We computed DTE between the NCEP- and ECWMF-driven outer domain solutions, where

$$DTE(t) = \frac{1}{2} \sum_{i,j,k} \left( u_{ijk}^2 + v_{ijk}^2 + \frac{C}{R} T_{ijk}^2 \right)$$

and is summed over all $x$, $y$, and $\sigma$ ($\sigma$ being the vertical coordinate in WRF) grid points at a given output time, and primed quantities denote differences between the two reanalysis datasets.

Since the purpose of the DTE metric here was to act as a proxy for analysis uncertainty on the synoptic scale (excluding hypothetically unresolved features on mesoscales), two-dimensional low-pass Fourier filtering was applied to the raw fields $u$, $v$, and $T$ for both datasets. This produced the low-pass-filtered fields $u_e$, $v_e$, and $T_e$; thus, separating the signatures of processes occurring on mesoscales from those occurring on synoptic scales. First, the two-dimensional discrete Fourier transforms of each field were computed as

$$F(n,m) = \sum_{j=0}^{N-1} \sum_{k=0}^{M-1} f(x_j, y_k) e^{-2\pi i [(x_j/X) + (y_k/Y)]},$$

where $F$ is the transformation of any arbitrary field $f$; $n$ and $m$ are zonal and meridional wavenumbers, respectively; $x_j$ and $y_k$ are $x$ and $y$ gridpoint locations, respectively (with $x_0 = y_0 = 0$); $N$ and $M$ are the number of grid points in the $x$ and $y$ directions, respectively; and $X$ and $Y$ are the $x$ and $y$ dimensions of the outer model domain, respectively. To obtain a Fourier-filtered...
representation of \( f \) in physical space, the discrete inverse Fourier transform of \( F \) was computed, with \( F \) augmented by a coefficient matrix \( C \):

\[
\hat{f}(x_j, y_k) = \frac{1}{NM} \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} C(n, m) F(n, m) e^{2\pi i [(x_j/n)/X] + [(y_k/m)/Y]},
\]

where \( f_l \) is the low-pass-filtered version of \( f \), and the high-pass-filtered field \( f_p = f - f_l \). Note that \( C \) is typically structured so that short wavelengths (high wave-numbers) are removed or weighted to a lesser extent than longer wavelengths (low wave-numbers). A typical configuration for \( C \) is a circular filter (“circular” refers to the shape of \( C \) in Fourier space):

\[
C(n, m) = \begin{cases} 
1 & \min(n, m) \leq r \\
0 & \min(n, m) > r 
\end{cases},
\]

where \( r \) is a user-selected parameter. An example of the application of (4) to a temperature field on the outer model domain of our experiment setup is shown in Fig. 7. Note that the resulting high-pass-filtered field exhibits unphysical distortion around the periphery of the domain owing to the exclusion of wave modes with high aspect ratios (i.e., long and skinny) in (4) (bottom panels of Fig. 7). An alternative configuration for \( C \), where

\[
C(n, m) = \left\{ \begin{array}{ll}
1 & \min(n, m) \leq r \\
0 & \min(n, m) > r
\end{array} \right.,
\]

alleviated such edge distortion (top panels of Fig. 7), yielded a better subjective separation between synoptic-scale and mesoscale features, and was therefore utilized for the purposes of scale separation in this study. Note that (5) forms a cross shape in Fourier space centered at \( n, m = 0 \), and we thus refer to it as a “cross filter.” In our subsequent analysis, synoptic DTE was computed using the differences between low-pass cross-filtered fields with \( r = 1 \), and mesoscale DTE using the differences between the perturbation fields. Note that \( r = 1 \) corresponds to an exclusion of wave modes with a wavelength of less than 2790 km (the width of our outer domain) in both the zonal and meridional directions.

Connection between DTE and distance errors

Values for the aforementioned analysis uncertainty quantities over the first 24 h of the simulation were correlated with errors between 48-h accumulated precipitation placement (note that this is the error value at the last model simulation hour) in the two high-resolution model solution solutions (the approximate time when convection associated with the TL/AS system initiated
The resulting correlation coefficients are plotted in Fig. 8 (note, cases where the model failed to produce over 150 mm of precipitation accumulation were omitted from these computations). A scatterplot of such distance errors and synoptic DTE values is also included in Fig. 8 to further illustrate the statistical relationship between the two quantities.

We tested the sensitivity of these correlations to sampling with a bootstrapping procedure, where \( N \) random integers from a uniform distribution ranging from 1 to \( N \) (where \( N \) is the sample size) were generated 1000 times and used as indices to sample subsets from these data. The correlations between pairs in these subsets were subsequently computed, and the range between the 95th percentile highest correlation and the 5th percentile lowest correlation from these subsamples was considered in the statistical analysis. If this range is entirely same signed, then there is a low likelihood (5% or lower) that a correlation value is statistically zero.

This percentile range of correlations is represented in Fig. 9 by brackets extending in the positive and negative direction from the actual correlation values, which are indicated by stars. Correlation values between DTE and errors between precipitation objects in model simulations were positive for all times considered. Furthermore, correlation magnitudes were relatively high for synoptic DTE between 5 and 20 h in the 0.5–0.6 range (Fig. 8, middle panel), with the lower confidence bound well separated from zero. Note that this positive relationship between the two quantities is also evident in the scatterplot (Fig. 8, bottom panel). This indicates that when differences between outer domain synoptic-scale states were smaller (larger), there tended to be more (less) agreement in the placement of heavy precipitation between high-resolution solutions. The correlation between synoptic DTE and distance error was notably smaller at the simulation initialization time than for later times. This may be owing to necessary “spin up” resulting from downsampling coarse reanalysis data onto a relatively fine model grid.

The overall correlation results indicate that up to one-third of the variance in distance error was accounted for by synoptic DTE. Certainly, there are many factors that contribute to distance error. For example, physics uncertainty is a likely source, and perhaps accounting for the interaction between synoptic uncertainty and physics uncertainty, as well as these sources independently, would go much farther in explaining the magnitude of the distance errors for these events. These are useful future research directions.

These caveats aside, the results, along with that from the subjective analysis, suggest that the MCS mode, along with the placement of training MCS, exhibit significant dynamical dependence on the downsampling cascade of information (i.e., the upscale growth of individual convective elements into the heavy-rain-producing convective systems that are considered here is in some sense emergent from the synoptic-scale environment, rather than the result of fortuitous interactions between convective-scale storm elements).

Mesoscale DTE correlations with distance errors (Fig. 8, top panel) were similar to the analogous quantities for synoptic DTE; however, correlation values exhibited far greater sensitivity to sampling, with lower bounds extending below zero for all hours considered prior to 12 h (by which time part of these mesoscale differences were likely associated with the convection from which distance errors where computed). Mesoscale DTE was also well correlated with synoptic DTE, which suggests that much of the mesoscale information in the domain solutions is highly dependent on the downsampling cascade of information from synoptic scales. Therefore, it is questionable whether correlations obtained from the mesoscale DTE metric reveals anything beyond the relationship that was observed between synoptic DTE and distance errors.

Notably, both DTE metrics were nearly uncorrelated with distance errors between individual model forecast and observed rainfall. Though the comparison of
analysis differences to divergence between model forecasts has suitably illustrated that the downscale cascade of information from synoptic scales clearly influences the evolution of the phenomena that we have investigated (assuming that model dynamics on synoptic scales reasonably capture “reality”), it is possible that differences between the reanalysis datasets and truth are in fact larger than and sometimes uncorrelated with differences between reanalysis datasets. This speculation may be further supported by the tendency of model forecasts to agree better with each other than with observations (discussed earlier in this section), a behavior that might result from the initial states of the model forecasts also being closer to one another than to truth. We may additionally be encountering the limitations of the model (i.e., the numerical formulations and parameterizations), such that nonlinear amplification of IC/LBC errors by these shortcomings dilutes the predictability signal associated with the synoptic scale.

5. Case examples

The synoptic-scale environments associated with two cases were examined in greater detail in order to gain physical insight as to the influence of model solution uncertainties on convective precipitation placement. We specifically analyzed one case where precipitation placement differences were large in conjunction with high synoptic DTE, and one case where precipitation placement differences and synoptic DTE were comparatively
small. Note that the influence of large-scale uncertainty on simulated convective behavior is complex, and a comprehensive analysis of such a causal relationship is well beyond the scope of this study. Thus, the analysis included here forth constitutes the identification of obvious synoptic-scale differences in the region of heavy convective rainfall, and speculation as to their effect on the behavior of simulated convection. Since this study has focused on differences between modeled solutions of the events considered, rather than differences between the model solutions and observed characteristics of the convective systems, our analysis here for both cases will focus on differences between the ERA-Interim- and NCEP/DOE-II-driven model solutions.

A BB/QS-type MCS produced a localized region of heavy rainfall over northern Alabama during the early morning hours of 5 May 2003. This system developed within a broad region of moist conditionally unstable southerly flow from the Gulf of Mexico, and was far removed from synoptic-scale kinematic and thermodynamic gradients (i.e., synoptic-scale forcing for ascent). The temporal mean DTE (computed as described in section 3) between simulation hours 6 and 12 was 966 762 J (the second highest among our cases), and the mean precipitation placement error (computed as described in section 3) was 454 km (the highest among our cases). The overall low-level synoptic regime was characterized by an anticyclone off the southeast U.S. coast, and southerly-to-southwesterly flow out of the Gulf of Mexico into the region of heavy rainfall around the periphery of the anticyclone (Fig. 9). One notable difference in the outer-domain portrayals of the aforementioned features was a stronger southerly flow in the NCEP/DOE-II-driven simulation (and thus stronger moisture flux) through the northern Gulf and southeastern United States. This difference was presumably attributable to differences in the model portrayed strength of the aforementioned anticyclone (where DTE is locally maximized).

The ERA-Interim-driven simulation (weaker southerly flow and moisture flux) produced a robust BB/QS over northern Alabama, while the NCEP/DOE-II (stronger southerly flow and moisture flux) produced both earlier convective initiation and persistent convection much farther northeast of the region where heavy precipitation was observed, along with more widespread (than ERA-Interim) and less-organized convection through the region where the ERA-Interim produced the BB/QS convective system (Fig. 10). A possible influence of the increased southerly flow in the NCEP/DOE-II simulation over ERA-Interim in this case was to both promote convection farther to the northeast in the NCEP/DOE-II simulation (due to stronger moisture transport to this region) and to promote the more widespread convective initiation within the region of observed heavy rainfall (again due to greater moisture flux into this region). The latter difference in the NCEP/DOE-II simulation may have had a deleterious influence on the BB/QS MCS over Alabama (some semblance of which was still captured in this simulation, see Fig. 10) due to early alleviation of instability and a comparative lack of a convective focal point.
In the second case, a regionally broad TL/AS-type MCS produced a southwest–northeast-oriented swatch of heavy precipitation over northern Iowa and southern Minnesota during the night of 14 September 2004. The MCS developed to the north of a quasi-stationary warm front oriented parallel to the convective system, and ahead (northeast) of a well-developed low-level cyclone and upper-level progressive trough. The temporal mean DTE between simulation hours 6 and 12 was 441 865 J (among the lowest values from our cases), and the mean precipitation placement error was 24 km (also among the lowest values from our cases). Figure 11 depicts outer domain low-level flow solutions prior to this event, as well as moisture flux differences between the two model solutions. Note that there is better qualitative agreement between wind direction and speed near the event location relative to the 5 May 2003 case. Note also that local DTE and moisture flux difference maxima are less pronounced than in the 5 May 2003 case, and significantly removed from the region where heavy rainfall occurred (especially by 1200 UTC 14 September 2004). The simulated radar evolutions (Fig. 12) exhibit remarkable qualitative similarities in the positioning and structure of the convective system (in contrast with the pair of radar evolutions for 8 May 2003; Fig. 10). While the wind and moisture fields shown do not encompass all
of the atmospheric features that likely influenced the evolution of this system (stronger kinematic and thermodynamic gradients, and thus synoptic-scale forcing, were present here than in the 5 May 2003 case), fields in addition to those depicted in Fig. 10 also exhibited qualitative agreement in terms of their placement and strength.

6. Summary and discussion

This research investigates the influence of synoptic-scale flow patterns on training MCSs that result in extreme local rainfall totals. A total of 21 cases were identified from gridded precipitation analyses and composite radar reflectivity for examination. Two simulations were produced for each case using the WRF-ARW with ICs and LBCs from the NCEP/DOE-II and ECMWF ERA-Interim reanalysis datasets, respectively. Despite the absence of mesoscale features in NCEP/ECMWF reanalysis ICs/LBCs, these simulations were able to reproduce qualitative aspects of storm behavior in most cases, including training behavior and local accumulation of extreme rainfall. This suggests that the upscale evolution of convection into training MCS archetypes is typically intrinsic to a particular synoptic-scale environment, rather than a result of fortuitous interactions between storm-scale processes. We further supported this conclusion by establishing a statistically significant quantitative relationship in which larger synoptic-scale uncertainty tended to be associated with larger model error in forecast location of accumulated precipitation. The synoptic-scale environments associated with two cases—one with high analysis uncertainty and large precipitation placement errors, and one with low analysis uncertainty and small precipitation placement errors—were then qualitatively analyzed. We identified potential mechanisms for influence of obvious differences in synoptic-scale environments and convective behavior, and thus differences in convective precipitation placement.

![Fig. 10. Representative simulated radar reflectivity images from the (top) NCEP/DOE-II and (bottom) ERA-Interim inner-domain (3 km) model solutions of the 8 May 2003 heavy convective precipitation event. Valid times for each column of panels are listed at the bottom of the figure.](image-url)
The results presented here have several implications in the context of numerical weather prediction. First, numerical weather prediction models initialized with a reasonable degree of analysis uncertainty can be expected to produce minimum heavy-rain-producing MCS placement errors of $O(150–200)$ km over a 1–2-day timeframe. Note, however, that these experiments do not account for unconstrained synoptic-scale drift that might occur in forecast settings, and thus these should be considered as best-case estimates. Regardless, these errors are large relative to the spatial scale of individual hydrological basins, suggesting that accurate deterministic prediction of the placement of such convective rainfall (and subsequent flash floods) is well beyond the current capabilities of NWP models. This further motivates ensemble-based probabilistic approaches.

Despite these large spatial errors in a quantitative sense, there remains some qualitative value, since a forecaster may be able to discern that a heavy-rain-producing MCS archetype is possible within a particular geographic region (i.e., the simulations reproduce training behavior in the approximate location where it will occur). This supports the conclusions of previous work (e.g., Kain et al. 2006) that highlight the utility of subjective analysis of high-resolution model output in operational forecast settings.

Modest improvements to the upper-level sounding network may substantially improve analyses of the larger-scale atmospheric state (e.g., Swanson and Roebber 2008). Such modest observational improvements [e.g., the addition of $O(10)$ new observation sites], however, might have little impact on the resolution of mesoscale features represented by the perturbed mesoscale fields considered in this paper. Therefore, the connection established in this study between placement errors of heavy-rain-producing MCSs and uncertainty in the analyzed synoptic-scale atmospheric state is promising in the sense that modest analysis improvements may lead to better-predicted placement of such phenomena.

These results echo those of Miguez-Macho and Paegle (2000, 2001), who found that the dominant mechanism for local error growth from global model simulations...
was the downscale cascade of errors from the larger scales and also those of Roebber et al. (2008), who presented similar results in the context of landfalling Pacific Northwest rainstorms.

Further elaborations on this work are needed. For example, the verification approach used here does not comprehensively capture every aspect of precipitation placement error. Other verification metrics, such as differences in total precipitation production and the area of heavy-precipitation production, could be considered. An obvious supplemental investigation would be to examine whether there are systematic model “misplacements” of certain synoptic-scale features that contribute to the divergence in precipitation placement between simulations. One approach to studying this might involve an individual case study using a large number of ensemble members, driven by more sophisticated ensemble perturbation methods, including model physics perturbations, and stochastic physics perturbations. Additional ongoing work by the first author seeks to investigate the MCS archetypes considered here from a quasi-idealized modeling perspective, and to ascertain the potential effects of varying physical and microphysical parameterization schemes on the simulated behavior of such systems.

Acknowledgments. This work composed a portion of the master’s thesis of John M. Peters. We thank Clark Evans, Brock Burghardt, Russ Schumacher, Sergey Kravtsov, and the anonymous reviewers for their helpful comments and feedback.

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