Constraining the Large-Scale Analysis of a Regional Rapid-Update-Cycle System for Short-Term Convective Precipitation Forecasting

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Abstract This study examines the impact of a large-scale constraint (LSC) on the large-scale analysis and precipitation forecast of convective weather systems in a regional rapid-update-cycle system. The LSC is imposed by assimilating Global Forecast System forecast fields as bogus observations with a scale selection scheme. The scale selection is achieved by skipping data points of Global Forecast System forecast fields in the horizontal and vertical directions. It is shown that the LSC is able to modify the large-scale component of the analysis fields while leaving the small-scale component mostly intact compared with a control experiment without the constraint. The effects of the LSC on precipitation forecast are verified and analyzed using nine convective cases in the Rocky Mountain Front Range and its east plains. The results show that the LSC is effective in improving the precipitation forecast of different cases. However, the cases with weak large-scale forcing show greater improvements than those with strong large-scale forcing. Further analyses on the dynamic and thermodynamic variables indicate that the use of the LSC is able to construct a favorable environment for the initiation and development of convection in the case of weak large-scale forcing, which leads to significant improvement of convective precipitation forecasting when radar observations are assimilated.

1. Introduction

Accurate prediction of high-impact convective weather systems remains a major challenge for the research and operation communities. The forecast skill of the traditional extrapolation-based nowcast methods (Wilson et al., 1998) decreases rapidly with increasing forecast length due to the transient nature of convective systems. With the increase of computing power and the availability of high-resolution observations in recent years, numerical weather predicting based nowcasting using “convection-permitting” limited area models (LAMs) has gained popularity (recent reviews by Sun et al., 2014, and Gustafsson et al., 2018). LAMs are traditionally initialized by downscaling other coarse-resolution global models or LAMs with a larger domain. This “cold start” initialization is generally unbalanced with respect to the LAM of interest. The first few hours of forecast, which is important for the prediction of convective weather, are unusable due to model spinup. Therefore, LAMs used for short-term convective weather prediction are commonly paired with a data assimilation (DA) system and run in a rapid-update-cycle (RUC) setup to improve the forecast skill of the first few hours. The use of RUC has been demonstrated to effectively reduce model spinup time and improve short-term prediction of convective weather systems (Benjamin et al., 2016; Sun et al., 2012).

Despite its effectiveness in improving the forecast of convective weather systems, distortion of the underlying large-scale environment can occur due to not only the treatment of lateral boundary conditions in LAMs but also the noise introduced by the RUC DA. There are situations when RUC could actually degrade the forecast compared to a cold start. As shown in Sun et al. (2012), the RUC experiments degraded the precipitation forecast of a convective storm during the International H2O Project (Weckwerth, 2004). The degradation was attributed to an erroneously forecasted convective system that distorted the environment for the real storm. The rapid update DA was unable to correct this environmental error because large-scale observations (such as those from the radiosondes) are sparse in space and time. In addition, RUC systems are usually optimized for the extraction of small-scale information from high-resolution observations due to the fact that DA systems have intrinsic difficulties in assimilating multiscale information simultaneously (Xie et al., 2011). Several studies (Li et al., 2015; Peng et al., 2010; Xie et al., 2011) introduced...
methods to retain the large-scale information during DA of high-resolution observations based on the principle of scale separation and optimization. Although the application of these methods (J. Gao et al., 2013; Ha & Lee, 2012; Tong et al., 2016) showed improved analysis fields and precipitation forecasts in real cases, their effect in improving large-scale analysis is still limited due to the sparseness of large-scale observations and the inherent shortcomings associated with lateral boundary conditions in LAMs.

Except for conventional observations, the analysis and forecast fields of operational global models (e.g., Global Forecast System [GFS]) can serve as an ideal source of large-scale information. Global models assimilate more large-scale observations (e.g., soundings and satellites) and are absent of lateral boundary errors, hence are better at representing large-scale flows (Guidard & Fischer, 2008). Several previous studies examined methods to better utilize the information from global models to improve the large-scale analysis and precipitation forecast in regional RUC systems. The partial cycle approach (Benjamin et al., 2016; Hsiao et al., 2012) was used to periodically reset the model state of a continuous cycled system to that of a global model. It is effective in eliminating accumulated error/bias in LAM DA and forecast, but at the expense of losing model-generated small-scale information. The blending method (Yang, 2005) was able to retain the LAM-generated small-scale information by means of scale separation and merging. The model states from both the LAM forecast and the global model forecast were each separated into two different scales, and the large-scale part of the global model was then combined with the small-scale part of the LAM. The blending method was shown to improve precipitation forecast (Hsiao et al., 2015; Wang et al., 2014). However, the rather brutal merging of fields from different models could introduce shock in the transition zone near the cutoff wavelength. Additional initialization processes (e.g., Lynch & Huang, 1992) or the nudging technique (Yue et al., 2018) had to be used to remedy the issue.

In addition to the above methods, DA-based methods were also introduced to include large-scale information from global models into regional RUC systems. The use of DA allows explicit consideration of the error statistics of global models and better integration of the large-scale information from the observations assimilated in a RUC system. Guidard and Fischer (2008) implemented a prototype system assimilating large-scale fields from Action de Recherche Petite Echelle et Grande Echelle (APREGE) into Aire Limitée Adaptation Dynamique développement InterNational (ALADIN). Dahlgren and Gustafsson (2012) assimilated the large-scale vorticity field of European Centre for Medium-Range Weather Forecasts (ECMWF) into the regional High Resolution Limited-Area Model (HILRAM). The key step in the DA-based methods is to apply scale separation on the full fields of global models such that only the large-scale part is assimilated. The above two studies were conducted using spectral models in which scale separation is straightforward. Vendrasco et al. (2016) assimilated GFS analysis fields in a case study to limit unreasonably large increments associated with radar DA in a grid point model. The study of Vendrasco et al. (2016) is promising because most RUC systems are based on grid point models.

This study presents a large-scale constraint (LSC) in a RUC system and examines its impact on the large-scale analysis and precipitation forecast of convective weather systems. The implementation is based on the large-scale analysis constraint introduced by Vendrasco et al. (2016) with three major differences. First, GFS forecast fields, instead of analysis fields as in Vendrasco et al. (2016), are assimilated. This change is important for future operational applications because of the latency of global model analysis. Second, a scale selection scheme is used when assimilating the GFS forecast fields. Thirdly, the LSC is only applied to the convective environment before radar data are assimilated with a two-step DA procedure. The performance of the LSC is evaluated with nine convective cases that occurred in the region of Rocky Mountain Front Range and its east plains. The multiple-case evaluation allows us to examine the scheme's performance under different scenarios of large-scale forcing. Another objective of the current study is to investigate whether the scale selection scheme of the LSC is able to modify the large-scale part of the analysis fields while leaving the small-scale part mostly intact. To further understand the role of the LSC under weak and strong large-scale forcing, we present detailed analysis for two representative cases.

The rest of this paper is organized as follows: Section 2 introduces the RUC system, experiment setup, and the metrics for forecast verification. Section 3 details the implementation of the LSC and its impacts on the analysis fields. Section 4 shows the impacts of the LSC on the precipitation forecast. Section 5 further examines the effects of the LSC on different types of precipitation systems. Conclusions and discussion are given in section 6.
2. Methodology

2.1. The RUC System

The experimental RUC system is composed of the Advanced Research version of the Weather Research and Forecasting Model (Skamarock et al., 2008) and its three-dimensional (3-D) variational DA system (WRFDA 3DVAR v3.9; Barker et al., 2004). All numerical experiments conducted in this study employed a one-way, two-domain nested grid as shown in Figure 1. The outer domain has 212 × 160 grids with a 15-km grid spacing, and the inner domain has 410 × 320 grids with a 3-km grid spacing in the horizontal direction. Both domains have 50 terrain-following levels in the vertical direction. Other model options include the Kain-Fritsch cumulus parameterization scheme (Kain & Fritsch, 1993) in the outer domain, the Thompson bulk microphysics scheme (Thompson et al., 2008), the Mellor-Yamada-Janjic PBL scheme (Janjic, 2002), the Noah land surface model (Ek et al., 2003), and the RRTMG radiation scheme (Iacono et al., 2008). Details of the above schemes and other available options can be found in the WRF technical report (Skamarock et al., 2008).

This version of WRFDA 3DVAR uses horizontal winds \(u, v\) as the momentum control variables, which allows closer fit to dense observations such as radar radial velocity (Sun et al., 2016). It is noted that WRFDA also provides other momentum control variable options, which may improve wind analysis in different conditions (F. Gao et al., 2015; Huang et al., 2013). Conventional observations obtained from GTS (Global Transmission System) as well as radar observations from the NEXRAD Weather Surveillance Radar-1988 Doppler are used in this study. The GTS observations include aircraft reports, meteorological aerodrome reports, surface synoptic observations, ship reports, and soundings. The radar data (see Figure 1 for their names and locations) include both radial velocity and reflectivity. A preprocessing and quality control procedure similar to that in Sun (2005) and Lim and Sun (2010) is employed to process radar observations and specify observation errors. The radar data are thinned to a grid with 3-km spacing in the horizontal direction by averaging all observations within the same grid. The background error statistics (BES) are calculated using two months of history forecasts over the same domain with the National Meteorological Center (NMC) method (Parrish & Derber, 1992).

The setup of experiment features a two-RUC configuration as shown in Figure 2. The first cycle is initialized by the GFS forecast and updates every 3 hr (hereafter referred to as \(3\)-hourly cycle) with WRF forecast as background. At each update cycle, only GTS observations are assimilated with the BES obtained by the
The second cycle is initialized by the forecast of the 3-hourly cycle and updates every hour with a partial cycle strategy (hereafter referred to as hourly cycle). Only radar data are assimilated with a reduced length scale and increased variance scale from the computed BES. The LSC is only applied to the 3-hourly cycle at each update cycle on the inner domain. The use of two RUCs allows large-scale and small-scale information being treated separately and optimally, which is consistent with the principle of multistep DA in recent studies (Ha & Lee, 2012; Tong et al., 2016).

2.2. Experimental Setup and Verification

Nine convective cases (Figure 3) occurred in the Rocky Mountain Front Range and its east plains during short-term explicit prediction (STEP) Hydromet Experiment (https://www.ral.ucar.edu/project/step_hydromet) in 2015 are used to examine the effect of the LSC. STEP is a National Center for Atmospheric Research cross-laboratory effort aimed at improving short-term quantitative precipitation forecast and flash flood prediction. In each case, a 3-hourly cycle is first initialized at 12 UTC (6 a.m. MDT) on the previous day and continuously cycles till 06 UTC (12 a.m. MDT). The 3-hr forecasts of the 3-hourly cycle initialized at 18, 21, and 00 UTC are used to initialize three hourly cycles at 21, 00, and 03 UTC, respectively. Finally, three 12-hr forecasts are conducted at 00, 03, and 06 UTC after three continuous hourly cycles assimilating radar observations. The total number of forecasts for verification is 27 (3 × 9). The forecast hours cover the time with most convective activities in this region when cooled and dry air moves from the Rocky Mountains into the great plain creating an unstable environment of large lapse rate.

Eleven experiments (Table 1) were conducted for all of the nine convective cases. A cold start (COLD) experiment initialized directly by the GFS forecast and a control 3DVAR experiment (CTRL) without the LSC are included as benchmarks. The next four experiments, named with the similar pattern ḤnSm, are the same as CTRL but with the LSC applied. They are generally referred to as the LSC experiments. Their names mean that every n grid point of GFS forecasts is assimilated in the horizontal direction above the m lowest model levels. More detail of the LSC experiments will be discussed in the next section. The CTRL and LSC experiments were all conducted with the 3-hourly cycle as indicated by the upper row (in the red dotted box) in Figure 2. The experiments with the suffix ”_R” are those with radar DA via the partial hourly cycle initialized with the 3-hourly analysis from the 3-hourly cycle experiments (in the green dotted box in Figure 2).

The ultimate goal of this study is to improve short-term precipitation forecast. Therefore, the performance of different experiments is evaluated by the skill of precipitation forecast in addition to some diagnoses on the dynamical variables of the 3DVAR analysis fields. The skill of precipitation forecast is measured by the fractional skill score (FSS; Roberts & Lean, 2008), which is defined as

\[
FSS = 1 - \frac{\frac{1}{N} \sum_{k=1}^{N} [P_m(k) - P_o(k)]^2}{\frac{1}{N} \sum_{k=1}^{N} [P_m^2(k) + P_o^2(k)]}.
\]  

where \(P_m(k)\) and \(P_o(k)\) are the forecast and observed fractional coverage of precipitation at the kth grid point that exceeds a given threshold and \(N\) is the total number of grid points in the verification domain. The thresholds used in the study were 1 and 5 mm and had a radius of 10 km. Higher FSSs mean better skill,
and FSS equals to 1 when the forecast is perfect. Since FSS is sensitive to bias (Mittermaier & Roberts, 2010), the bias score is calculated as

\[ \text{bias} = \frac{a + b}{a + c}, \]  

(2)

where \(a\), \(b\), and \(c\) stands for the hitting, false alarm, and missing points, respectively. Bias is greater (less) than 1 when the spatial precipitation coverage is overforecasted (underforecasted).

### 3. Implementation of the LSC and Its Impacts on 3DVAR Analysis

#### 3.1. Implementation of the LSC

The approach of assimilating GFS fields is similar to that described in Vendrasco et al. (2016). A new term \(J_k\) is added to the cost function of the WRFDA 3DVAR system in the 3-hourly cycle:

![Table 1](image)

<table>
<thead>
<tr>
<th>Name</th>
<th>Initial field</th>
<th>Cycle frequency</th>
<th>Cycle length</th>
<th>LSC</th>
<th>Observation</th>
</tr>
</thead>
<tbody>
<tr>
<td>COLD</td>
<td>GFS</td>
<td>/</td>
<td>/</td>
<td>/</td>
<td>/</td>
</tr>
<tr>
<td>CTRL</td>
<td>GFS</td>
<td>3</td>
<td>18</td>
<td>/</td>
<td>GTS</td>
</tr>
<tr>
<td>HSS4</td>
<td>GFS</td>
<td>3</td>
<td>18</td>
<td>y</td>
<td>GTS</td>
</tr>
<tr>
<td>HSS1</td>
<td>GFS</td>
<td>3</td>
<td>18</td>
<td>y</td>
<td>GTS</td>
</tr>
<tr>
<td>H1S4</td>
<td>GFS</td>
<td>3</td>
<td>18</td>
<td>y</td>
<td>GTS</td>
</tr>
<tr>
<td>H10S4</td>
<td>GFS</td>
<td>3</td>
<td>18</td>
<td>y</td>
<td>GTS</td>
</tr>
<tr>
<td>CTRL_R</td>
<td>CTRL</td>
<td>1</td>
<td>3</td>
<td>/</td>
<td>Radar</td>
</tr>
<tr>
<td>HSS4_R</td>
<td>HSS4</td>
<td>1</td>
<td>3</td>
<td>/</td>
<td>Radar</td>
</tr>
<tr>
<td>HSS1_R</td>
<td>HSS1</td>
<td>1</td>
<td>3</td>
<td>/</td>
<td>Radar</td>
</tr>
<tr>
<td>H1S4_R</td>
<td>H1S4</td>
<td>1</td>
<td>3</td>
<td>/</td>
<td>Radar</td>
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<tr>
<td>H10S4_R</td>
<td>H10S4</td>
<td>1</td>
<td>3</td>
<td>/</td>
<td>Radar</td>
</tr>
</tbody>
</table>

Note. GFS = Global Forecast System; LSC = large-scale constraint. The LSC experiments have the same naming convention \(HnSm\), which means that every \(n\) grid point is assimilated in the horizontal direction above the \(m\) lowest model levels.

![Figure 3](image)

Figure 3. The precipitation distribution of the nine cases at the mature stage of their lifecycle.
\[ J = J_b + J_o + J_k, \]  

where \( J_b \) and \( J_o \) are the background and observation terms. \( J_k \) represents the LSC that is expressed by

\[ J_k = \frac{1}{2} (y^b - H(x_b) - Hx)^T V^{-1} (y^b - H(x_b) - Hx), \]

where \( y^b \) represents the vector of the horizontal wind \( u \) and \( v \), temperature, and specific humidity fields from the GFS forecast (0.25°); \( x \) contains the control variables of WRFDA; \( x_b \) is the background field; \( H \) represents an operator that interpolates a variable from the grid space to the location of \( y^b \); \( H \) is the linear form of \( H \); and \( V \) is the error covariance matrix of the GFS forecast. The forecast fields, instead of the analysis fields, are assimilated because the former does not have a latency issue as the latter in real-time applications. The GFS forecast fields of each case initialized at 06 UTC on the previous day are first processed into the same regular grids as the outer domain via the WRF preprocessing system and then assimilated as bogus observations in the inner domain during the 3-hourly cycle. So the horizontal grid spacing of the bogus observation is 15 km. It should be noted that the formulation of (4) assumes no correlation between the GFS and the WRF forecasts (as well as the GFS forecast and the GTS observation; Guidard & Fischer, 2008). We further assume that \( V \) is diagonal with no cross correlation between the assimilated GFS forecast fields. The error for wind, temperature, and water vapor mixing ratio is 2.5 m/s, 2 °C, and 3 g/kg, respectively. These values are determined by the diagnostics of the GFS from the Environmental Modeling Center’s web page (http://www.emc.ncep.noaa.gov/GFS). It is noted that neglecting the correlations could introduce some error in the analysis. However, previous studies (Hsiao et al., 2015; Vendrasco et al., 2016) have shown that the benefit of these bogus data may far exceed the error caused by neglecting the correlation error.

The scale selection of the LSC is achieved by a data-thinning scheme. The GFS forecast fields on the WRF preprocessing system-processed regular grids are assimilated at a specified interval in the horizontal direction, that is, the grid spacing of GFS forecasts actually being assimilated is increasing with more skipped points. The grid spacing of a two-dimensional field and the wavelength it can represent is connected by the Nyquist-Shannon sampling theorem, which states that a discrete grid can only accurately represent wavelengths greater than twice its grid spacing (Pielke, 2002). Compared with previous studies using spectral models, the scale selection achieved by the LSC is implicit for two reasons. First, the data-thinning scheme cannot filter out all small-scale information on the points where convection does happen. Second, the unresolved small-scale information may alias into other scales. However, as will be shown in the following sections, the scale selection scheme introduced in this study is effective in modifying the large-scale component of the analysis field while minimizing the impact on the small scale. Four experiments with different thinning parameters are performed (see Table 1) to understand the effect of the scheme on different scales of the analysis fields and the precipitation forecast. As mentioned before, their names (HnSm) mean that every \( n \) grid point is assimilated in the horizontal direction above the \( m \) lowest model levels. The bottom levels of the atmosphere are strongly affected by the topography, surface, and turbulence, which are able to produce significant small-scale variations. These variations are important to the initialization and development of convection. Since skipping data points in the horizontal direction will not filter out all small-scale information, the skipping of the lowest \( m \) levels can minimize the possible impact of GFS forecasts on the small-scale features in the LAM and result in more effective assimilation of surface observations.

The design of the LSC aims to minimize the “transition zone” problem commonly found in the attempt of merging information from different models. In the blending methods, the large-scale and small-scale information come from completely different sources. While in the LSC, the GFS forecasts are only used to constrain the large-scale part of the regional analysis fields. The majority of large-scale information is still from the regional model itself. Furthermore, the consideration of error statistics of the bogus data and the use of other large-scale observations, like the conventional observations, also limit the impact of GFS forecasts. In general, adding the LSC to the cost function of WRFDA allows a simultaneous “optimal” fitting to both observations and the large-scale information better represented by the global model.

### 3.2. Impacts of LSC on 3DVAR Analysis

The impacts of the LSC on the analysis were evaluated by comparing the deviations of the 3DVAR analysis fields from the corresponding GFS forecast fields. Figure 4 shows the horizontally averaged root-mean-
square difference (RMSD) of the horizontal winds, temperature, and specific humidity fields between the GFS forecast fields and the analysis fields of the 3-hourly cycle experiments. Compared with CTRL, the LSC experiments show smaller RMSDs as expected, and the RMSDs decrease with less data thinning (smaller \( H \)). The difference between H5S4 and H5S1 indicates that leaving out the bottom four levels results in notable differences on the temperature and humidity fields but only at the low levels. It is also noted that there is a near-surface peak in the horizontal winds and temperature, which could be the result of assimilating dense surface data observations.

Figure 4 indicates that the LSC is able to modify the 3DVAR analysis fields of the 3-hourly cycle so that the analysis fields do not deviate too far away from the corresponding GFS fields. As discussed in section 1, it is critical that the modification should mainly occur in the large-scale part. In order to investigate the impacts of the LSC on different scales of the analysis fields, the full analysis fields of the 3-hourly cycle experiments and the corresponding GFS fields are separated into two distinct scales with a cutoff wavelength of 400 km. The scales above 400 km are first obtained by applying a sixth-order implicit tangent filter (Raymond & Garder, 1991), and the scales below 400 km are then obtained by subtracting the large-scale part from the analysis field. The choice of 400 km as the cutoff wavelength is consistent with our previous definition of “large scale” in the sense that a typical convective system has horizontal scales less than 400 km, and similar cutoff wavelengths have been used in previous studies (Dahlgren & Gustafsson, 2012; Guidard & Fischer, 2008).

Figure 5 shows the percentages of RMSD (PRMSD) of the LSC experiments divided by that of CTRL for the two scales. The smaller the PRMSD is, the more impact the LSC produces. Similar to the RMSDs of the full

Figure 4. The horizontally averaged root-mean-square differences of WRF 3DVAR analysis fields from their corresponding Global Forecast System forecasts at different model levels in the 3-hourly cycle experiments.

Figure 5. The percentages of root-mean-square differences (from Global Forecast System forecasts) of the large-scale constraint experiments divided by that of the CTRL experiment in the large-scale (≥400 km, the upper row) and the small-scale (<400 km, the bottom row) parts.
fields in Figure 4, both the large-scale (the upper row) and small-scale (the bottom row) PRMSDs decrease with smaller $H$. However, the large-scale PRMSDs are much smaller than those of the small scale for the same $H$, which confirms that the modification by the LSC mainly occurs in the large-scale part of the analysis fields. This result indicates that proper selection of skipped points in the LSC can achieve the objective of constraining the large scale while maintaining the small scale largely intact. Applying the LSC at every horizontal grid point as in H1S4 results in significant modification of the fields toward those of the GFS not only in the large scale but also in the small scale, which can lead to degraded precipitation forecast, as will be shown in the next section. The difference between H5S4 and H5S1 is again only evident at the lower levels in the large-scale part for the temperature and specific humidity fields.

### 4. Effects of LSC on Precipitation Forecast

The effect of the LSC on short-term precipitation forecast is shown in Figure 6 by the averaged FSSs and bias scores for each experiment. The Multi-Radar Multi-Sensor (MRMS; Zhang et al., 2016) data are used as the true value of precipitation. Comparing CTRL and COLD at 1 mm shows that the use of RUC can only improve the FSS before 6 hr but degrade it after that. The decrease of FSS is likely associated with the degradation of the large-scale pattern by the regional RUC. The high-resolution RUC can better resolve atmospheric convection than GFS, but it is also prone to small-scale errors, which, in addition to errors associated with lateral boundary conditions, can cause detrimental effects to the large-scale environment. The positive impact of the LSC on precipitation forecast is evident in Figure 6 by the improved FSS skills of the LSC experiments. All LSC experiments significantly improve the FSS compared with CTRL over the 12-hr forecast, and some experiments (e.g., H5S4) even outperform (or at least match) the COLD experiment in the latter 6 hr. The improved FSS, especially in the latter 6 hr, indicates that the LSC is effective in introducing positive information from the GFS forecast fields and lead to better precipitation forecasts. The results at 5 mm are generally similar to those at 1 mm except that the improvements over CTRL become less significant. The bias scores of CTRL and the LSC experiments are close and all tend to underforecast the precipitation. The similar bias scores indicate that the improved FSS is not caused by biased forecasts.

Figure 6. The fractional skill score (FSS; a and b) and bias (c and d) of the 3-hourly cycle experiments averaged over all cases at the 1- and 5-mm thresholds.
The different FSSs among the LSC experiments suggest the importance of the scale selection scheme. As shown in Figure 6a, H10S4 outperforms H1S4 before 7 hr but conversely after that. The better skill of H1S4 after 7 hr can be attributed to its closeness to the GFS fields in the large scale, and the worse skill before 7 hr is likely associated with the excessive modification of the small-scale part (Figure 5). Although global models are believed superior over LAM models in representing large-scale patterns, their representation of the small-scale features is generally worse than LAMs because of model resolutions and the use of local dense observations. The modification on the small-scale part should be avoided as done in the blending (Yang, 2005) and previous DA-based methods (Dahlgren & Gustafsson, 2012; Guidard & Fischer, 2008). The adverse effects on the precipitation forecast from modifying the small-scale part is more significant at 5 mm, in which H1S4 even underperforms CTRL before 6 hr. The experiments H5S1 and H5S4 have overall higher FSS skills at 1mm, confirming that the preservation of the RUC-generated small-scale features (PRMSD is above 90% in Figure 5) is important for precipitation forecasting. As the horizontal resolution of the bogus observation is further increased as in H10S4, the FSS skill degrades at 1 mm because of the insufficient large-scale correction. The slight increase of FSS skill at 5 mm by H10S4 is reasonable because the more intense convective precipitation is associated with even smaller-scale features and hence the near zero adjustment of the small scale (PRMSD near 100% in Figure 5) benefits the forecast of convective rainfall.

Since the ultimate goal of the LSC is to improve the analysis of convective environment such that the precipitation forecast after radar DA can be improved, a set of radar DA experiments (those with "_R" in Table 1) with the partial hourly cycle was conducted with their corresponding 3-hourly cycle experiments as the first guess. Figure 7 shows the impacts of the radar DA in the hourly cycle experiments by the averaged FSSs and bias scores of all cases. All experiments show higher FSSs at least for the first 10 hr after the radar DA, and the LSC experiments again show notable improvement over CTRL after 3 hr. The bias scores are also similar between the RUC experiments. However, instead of underforecasting as in Figure 6, the experiments tend to overforecast when radar data are assimilated. The further improvement of the FSS after the radar DA in the LSC experiments indicates that the large-scale information introduced by the LSC and the small-scale information introduced by the radar DA work synergistically. Among the LSC experiments, H5S4_R shows the best overall skill especially in the first 8 hr. Both the results with or without radar DA indicate that the
parameter $H = 5$ is the optimal configuration in this study. As shown in Figure 5, the experiment with $H = 5$ is able to effectively modify the large-scale part of the analysis fields while leaving the small-scale part mostly intact. It is noted that the radar DA also adversely lowered the FSSs of the last 2 hr compared with COLD, which is probably attributed to the adverse impact on the dynamic balance of the initial field by frequent DA during the RUC. The degradation of FSS signifies the importance of using the two RUCs setup to prevent this error from accumulating. We expect this issue to be resolved by introducing a method to select different skipping points at different vertical levels in the future.

5. Effects of LSC on Different Precipitation Systems

The verification in the previous section shows that the LSC is able to improve the precipitation forecast in a general sense. However, it is worth noting that the impact of the LSC varies in different cases. According to the relative improvement of FSS, the nine cases used in this study can be generally divided into two groups. The six cases in the first group (the first two rows in Figure 3) with more widespread precipitation are dominated by strong large-scale forcing based on the U.S. daily weather map (http://www.wpc.ncep.noaa.gov/dailywxmap/index.html). In contrast, the three cases in the second group (the bottom row in Figure 3) with localized precipitation have weak large-scale forcing. The difference of the large-scale forcing between the two groups can be understood by the spectral variance of each case. A discrete cosine transform (Denis et al., 2002) is applied to the GFS geopotential field at 00 UTC of each case to only keep the variances with wavelengths $\geq 400$ km. As shown in Figure 8, the three cases (22 July, 5 August, and 12 August) in the second group show smaller percentages of total variance than the six cases in the first group.

Figure 8. The percentages of total variance of the Global Forecast System geopotential field at 00 UTC of each case with wavelengths $\geq 400$ km.

Figure 9. The fractional skill scores (FSSs) of the hourly cycle experiments averaged over the six cases with widespread precipitation (the upper row) and the three cases with localized precipitation (the bottom row) at the 1- and 5-mm thresholds.
above the tenth model level, which indicates relatively weak large-scale forcing in the second group. Figure 9 shows the averaged FSSs of the first and second groups. The LSC experiments show slightly higher FSSs than those of CTRL at 1 mm and are comparable at 5 mm in the first group. However, significant improvements are achieved by the LSC experiments in the second group. The improvement is more evident at 5 mm.

The result that the LSC shows greater improvements in the cases with weak large-scale forcing is understandable. In fact, the useful information introduced by the LSC is the difference between the WRF forecast and the GFS forecast that is relevant to the weather system of interest. When the large-scale forcing is strong, it is easier for both LAM and global model to capture its evolution. Therefore, the application of LSC may not contribute additional information to the 3DVAR analysis. However, weak large-scale forcing is more difficult to predict accurately because it is more likely to be affected by the errors in the boundary conditions as well as other errors (Xiao et al., 2017). Moreover, the development of weakly forced convective system can be sensitive to small difference in the large-scale environment. To better illustrate the precipitation characteristics of the two groups and how the LSC modifies the analysis fields and consequently improves the forecasts, two representative cases are selected from the two groups for further analysis. Since H5S4_R generally shows the best forecast skill as shown in the last section, its forecasts are used to represent the effect of the LSC.

5.1. A Weak Large-Scale Forcing Case (22 July 2015)

Figure 10 shows the precipitation forecast at the 2, 4, 6, 8, and 10 hr from the COLD, CTRL_R, and H5S4_R experiments initialized at 03 UTC 22 July 2015 together with the corresponding Multi-Radar Multi-Sensor (MRMS) as the true value.

![Figure 10](image-url)
The COLD experiment entirely missed C1 and only showed weak precipitation near C2 after 6 hr. CTRL_R and H5S4_R are able to predict the occurrence of the two target systems. However, the location and structure of the forecasted precipitation are different. The two target systems are disorganized in CTRL_R with large areas of false precipitation in the north of New Mexico at 2 hr. H5S4_R shows better location forecast of the target systems and less false precipitation. At 6 hr, the forecasted locations of C1 and C2 are off to the south and north in CTRL_R, respectively. The location and intensity of C1 and C2 are better predicted in H5S4_R. At 10 hr, C1 appears to be dissipated and located further off to the south in CTRL_R. H5S4_R only shows small location error to the south, and the pattern and intensity of the precipitation are much closer to the observation.

To better understand how the LSC leads to better precipitation forecasts, the analysis fields at 00 UTC from CTRL and H5S4 are compared in more detail. Figure 11 shows the large-scale part (wavelength greater than 400 km) of the horizontal wind fields of GFS, CTRL, and H5S4 at the fourth model level and the difference of wind and divergence fields between H5S4 and CTRL. H5S4 shows a large-scale pattern somewhere in between GFS and CTRL. The difference of divergence field shows a few banded regions. It is noted that the two convective systems near the eastern border of Colorado and the southeast corner of the model domain (see Figure 10) correspond to the regions of large-scale convergence. The low-level convergence is critical for the development of convection (Doswell et al., 1996) by lifting particles to the level of free convection.

Figure 12 shows the large-scale part of the temperature fields of GFS, CTRL, and H5S4 at the fourth model level and the difference between H5S4 and CTRL. The inner domain shows positive difference except for small regions on the west and north borders. The regions near the two convective systems have temperature differences >0.5°. The increase of lower level temperature is associated with increased convective available potential energy in the boundary layer (not shown), which provided potential energy for the development of convection (Weisman & Klemp, 1982). The destabilization is believed to be the reason for the more intense precipitation near the Oklahoma panhandle predicted by H5S4_R.

Figure 13 shows the large-scale part of the specific humidity fields of GFS, CTRL, and H5S4 at the fourth model level and the difference between H5S4 and CTRL. The region (the eastern border of Colorado) where
the storm C1 is initiated (Figure 10) shows positive difference up to 2 g/kg. The availability of moisture is essential for the development of precipitation (Doswell et al., 1996). Weckwerth (2000) have shown that the difference of 2 g/kg in the humidity field could determine whether the convection can be initialized. It is noted that the region of positive humidity difference corresponds well with the convergence field shown in Figure 11 and the positive temperature difference in Figure 12. These three factors create a favorable environment, which is conducive for the development of convection.

5.2. A Strong Large-Scale Forcing Case (27 July)

The characteristics of precipitation on 27 July 2015 (Figure 14) are distinct from that on July 22. This is a typical prefrontal precipitation system driven by a cold front, which shows a well-organized precipitation band in the northeast and southwest direction. The precipitation gradually weakens and dissipates during the 12-hr forecast. Due to the strong large-scale forcing, the COLD experiment is able to reproduce the middle
portion of the precipitation system before 6 hr and becomes even more skillful when the system weakens after 6 hr. This is different from the 22 July case in which the COLD experiment entirely missed the target system.

The precipitation forecasts of CTRL_R and H5S4_R are similar and more skillful than that of COLD. Both experiments are able to predict the pattern and evolution of the precipitation band with notable overprediction in the first 6 hr. At 2 hr, H5S4_R slightly reduced the overprediction of CTRL_R. At 6 hr, the forecasted precipitation becomes weaker in both experiments, which is consistent with the MRMS data. CTRL_R still shows more overprediction than H5S4_R. At 10 hr, the target system totally dissipated. There is some weak precipitation remaining in CTRL_R and H5S4_R.

Similar to the analysis on the 22 July case, the analysis fields of CTRL and H5S4 at 00 UTC 27 July 2015 are studied in more detail. Figure 15 shows the large-scale part of the horizontal wind fields of GFS, CTRL, and H5S4 at the fourth model level and their difference of wind and divergence fields. The difference of divergence field also shows a few banded regions, and the magnitude of the difference is greater than that in the 22 July case (Figure 11). The increased divergence in the rain band region in H5S4 may have contributed to the reduction of the precipitation overprediction occurred in CTRL.

Figure 16 shows the large-scale part of the temperature fields of GFS, CTRL, and H5S4 at the fourth model level and the difference between H5S4 and CTRL. The inner domain shows positive difference except for small regions on the west and east borders. The shape and orientation of the positive difference corresponds well with that of the target precipitation system. Compared with the temperature distributions in Figures 16a and 16b, the positive difference is attributed to the higher temperature in the precipitation region of H5S4. Unlike the weak forcing case of 22 July where the higher temperature in H5S4 helped the convective initiation, the higher temperature for this strong forcing case is likely a result of the precipitation through the reduced evaporative cooling of less overprediction accumulated with cycles in H5S4.

Figure 17 shows the large-scale part of the specific humidity field of GFS, CTRL, and H5S4 at the fourth model level and the large-scale difference between H5S4 and CTRL. The inner domain generally shows negative difference except for the lower east border and the border between Colorado and Kansas. It is therefore likely that the widespread regions with reduced specific humidity (negative difference) is responsible for less overprediction in H5S4_R, especially in southeast Colorado.
6. Conclusion and Discussion

This study introduces a LSC in a regional RUC system to improve the large-scale pattern and precipitation forecast of short-live convective systems. The LSC is achieved by assimilating GFS forecast fields as bogus observations and features a scale selection scheme in the grid point space. Two parameters are used to skip data points in the horizontal and vertical direction after the GFS forecast fields being preprocessed into regular grids. Analyses show that the impacts of the LSC on different scales of the analysis fields are closely related to the number of grid points skipped in the horizontal direction. It is possible to tune the parameter so that only the large-scale part is significantly modified. The scale selection ability of the LSC is augmented by the use of two related RUCs with different cycle length and frequency in the regional RUC system. Verification based on nine convective cases shows that the LSC is able to reduce the difference between the GFS forecast fields and the LAM analysis fields and improve the precipitation forecasts.

Despite that the use of the LSC improves the precipitation forecast in a general sense, the degrees of improvement are different on cases with different precipitation characteristics. The cases with widespread precipitation show marginal improvement while those with localized precipitation show more significant improvement. Two representative cases with localized and widespread precipitation are analyzed in more details to understand how the LSC modifies the large-scale dynamic and thermodynamic fields and consequently affects the precipitation forecast. The first case has two small and localized storms. The analysis of the large-scale difference fields shows convergent, destabilized, and moistened regions at the lower level near the target convective systems. These favorable conditions collaboratively promoted the later development of the convection and lead to better precipitation forecast. The second case shows a typical frontal system with a widespread precipitation band. All analyzed experiments are able to reproduce the evolution of the system with different accuracy. The large-scale difference of the divergence and specific humidity fields may have contributed to the slightly less overprediction in H5S4_R.

The LSC shown in this study is simple and effective in improving the large-scale pattern and the precipitation forecast of short-live convective systems. However, there are still some issues that require further investigation. First, skipping the same number of points at different levels is not able to reflect the variation of scales of weather systems in the vertical direction. Second, since the GFS forecast fields are assimilated as bogus observations, the scale impacted by the LSC is also related to the BES of a particular model setup. The optimal parameters presented in this study may not be valid in other systems. Finally, only a few convective cases in the Central Plains of United States are tested, how the proposed method performs in different climate backgrounds still awaits further investigation. Despite these limitations, this study demonstrates a practical and effective framework to improve the representation of large-scale information in a regional RUC system and the precipitation forecast of short-live convective systems.

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