Impact of Microphysics Scheme Complexity on the Propagation of Initial Perturbations

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ABSTRACT

The study of evolution characteristics of initial perturbations is an important subject in four-dimensional variational data assimilation (4DVAR) and mesoscale predictability research. This paper evaluates the impact of microphysical scheme complexity on the propagation of the perturbations in initial conditions for warm-season convections over the central United States. The Weather Research and Forecasting Model (WRF), in conjunction with four schemes of the Morrison microphysics parameterization with varying complexity, was used to simulate convective cases using grids nested to 5-km horizontal grid spacing. Results indicate that, on average, the four schemes show similar perturbation evolution in amplitude and spatial pattern during the first 2 h. After that, the simplified schemes introduce significant error in amplitude and spatial pattern. The simplest (liquid only) and most complex schemes show almost the same growth rate of initial perturbations with different amplitudes during 6-h forecast, suggesting that the simplest scheme does not reduce the nonlinearity in the most complex scheme. The evolution of vertical velocity and total condensates is more nonlinear than horizontal wind, temperature, and humidity, which suggest that the observations of cloud variables and vertical velocity should have a shorter time window (less than 1 h) compared to horizontal wind, temperature, and humidity observations. The simplified liquid-only microphysics scheme can be used as an acceptable substitute for the more complex one with a short time window (less than 1 h).

1. Introduction

The study of evolution characteristics of initial perturbation in a numerical model is important in four-dimensional variational data assimilation (4DVAR) and mesoscale predictability research. In a 4DVAR system, the adjoint of the tangent-linear version of a nonlinear model is employed to calculate the gradient of the cost function to initial perturbation. The tangent-linear model is also used to propagate the model prognostic variables when an incremental formulation is used (Courtier et al. 1994). Thus, the validity of the tangent-linear model plays a key role in the 4DVAR system. A simplified representation of physical parameterizations (e.g., Sun and Crook 1997; Honda et al. 2005; Huang et al. 2009; Kawabata et al. 2011; Wang et al. 2011) is usually employed to develop the tangent-linear and adjoint models. It is assumed that evolution of perturbations in the tangent-linear model with simple physics process has an acceptable accuracy during the data assimilation window.

Although 4DVAR systems with liquid-only microphysical schemes have been successfully used for the prediction of summertime deep convection (e.g., Sun and Crook 1997; Kawabata et al. 2011; Wang et al. 2011), the usefulness of the simple microphysical schemes needs thorough testing (Auligné et al. 2011). Liu and Moncrieff (2007) found that microphysical processes play an important role in the forecast of convective systems with model grid space under 10 km. It is reasonable to assume that more complex schemes have greater skills in simulating the true evolution of model states and initial perturbations. There are two sources of error when a tangent-linear model of a simplified microphysical scheme is used. The first is model error resulting from a simplified representation of the microphysics, and the second is error associated with its tangent-linear implementation. Differences in the evolution of initial perturbations using microphysics schemes of varying complexity need to be studied when simple microphysical schemes are employed in a 4DVAR system.
Investigation of the evolution of small perturbations is the prime subject of mesoscale predictability studies (e.g., Ehrendorfer et al. 1999; Zhang et al. 2003, 2006, 2007; Bei and Zhang 2007). Previous studies have shown that the rapid growth of small perturbations is critically dependent upon moist processes, which limit the predictability of mesoscale system (Tan et al. 2004; Zhang et al. 2007). A key question then is, what is the impact of microphysics complexity on predictability of convective and mesoscale systems?

This paper focuses on differences in the evolution of initial perturbations and features of the evolution of small perturbations with different amplitudes using microphysics schemes of varying complexity. The questions addressed are as follows: 1) How complex does a microphysics scheme need to be to propagate the perturbations for data assimilation within a short time window (e.g., a few hours) and to what extent is a simplified microphysical scheme an acceptable approximation to the complex scheme? 2) What are the differences in the evolution of small-amplitude perturbations in models using simplified and complex microphysics schemes? 3) What is the impact of microphysics complexity on predictability of summertime convections? To our knowledge, these questions have not been sufficiently addressed at convection-permitting scale. In the next section, we describe the experimental configuration. Results from the experiments are discussed in section 3. The final section provides a summary.

2. Experiment configuration

a. The Morrison microphysics

The Advanced Research Weather Research and Forecasting Model (ARW-WRF; Skamarock et al. 2008) with the Morrison bulk microphysics parameterization (Morrison et al. 2005, 2009) is used to conduct numerical simulations. Four different schemes with increasing complexity have been developed from the Morrison parameterization. These four schemes differ in the number of prognostic variables (hydrometeor species and moments) and associated microphysical processes. Here, different schemes of a single microphysics parameterization were tested, rather than different parameterizations. This allows us to isolate sensitivity to the level of complexity while retaining the same formulations for relevant processes. The first scheme is a simple one-moment (i.e., predicting mass mixing ratios only) liquid-only scheme. It only includes two prognostic hydrometeor variables: cloud water and rain mass mixing ratios. The second scheme has four species (cloud water, rain, cloud ice, and snow) and is one moment for all species but cloud ice, which has two prognosed moments (i.e., both mass and number mixing ratio). The third scheme is more sophisticated, with five species (cloud water, rain, cloud ice, snow, and graupel), two moments for cloud ice and rain, and one moment for all other species. The fourth scheme is similar to the default Morrison scheme in WRF and includes five species (as in the third scheme, except for hail instead of graupel).1 The WRF with the first scheme is called $M^1$, with the second scheme is called $M^2$, and so on. The model $M^4$ with the most complex will be regarded herein as the reference.

b. Cases and model configurations

The cases chosen here are weather systems during 2–10 June 2008 over the central United States, which are strongly influenced by deep convection. Six hourly WRF forecasts are initiated at 0000 UTC each day. There are nine forecasts in total. A two-way interactive, three-domain nested grid is employed. The initial conditions of the first and second domains are the analyses produced by the ensemble Data Assimilation and Research Testbed (DART) system, which was first described in the literature as an ensemble adjustment Kalman filter (Anderson 2001). The DART system was run in 3-hourly continuing cycling mode during June 2008 with 30 ensemble members at both 45- and 15-km resolutions. The DART analyses also provide the boundary condition for the first domain, but the boundary conditions of the second (third) domains are provided by the first- (second-) domain forecast. Initial conditions of the third domain at 5-km horizontal grid spacing are interpolated from the second domain at 15-km grid spacing by the WRF. The third domain (Fig. 1) is placed to cover most of the deep convection during the simulation period. The model physics options, including the Rapid Radiative Transfer Model longwave radiation (Mlawer et al. 1997), Dudhia shortwave radiation (Dudhia and Moncrieff 1989), and Yonsei University PBL schemes (Hong et al. 2006), are the same for all three domains. The Kain–Fritsch cumulus parameterization (Kain 2004) is applied to the outer two lower-resolution nested domains but not the third domain. The model domains and simulated surface precipitation averaged over the nine 6-h forecasts initiated from ensemble mean with the WRF $M^4$ in the third domain are shown in Fig. 1.

c. Comparison method

The spread of two vectors is measured by the root-mean-square of their difference vector $\delta X$ (RMSD).

1 Note the Morrison parameterization in WRF includes a switch to represent the rimed ice species as either hail or graupel. In the default model this switch is set to graupel. However, here we set the switch to hail in this version as it has been shown to improve simulations of midlatitude deep convection (Bryan and Morrison 2012).
where $\delta x_i (1 \leq i \leq n)$ are elements of $\delta X$. The similarity of two perturbation vectors of $\delta X$ and $\delta Y$ is measured by the correlation coefficient (CORR),

$$\text{CORR} = \frac{\sum_{i=1}^{n} (\delta x_i - \bar{\delta X})(\delta y_i - \bar{\delta Y})}{\sqrt{\sum_{i=1}^{n} (\delta x_i - \bar{\delta X})^2 \sum_{i=1}^{n} (\delta y_i - \bar{\delta Y})^2}},$$

where $\delta Y$ is a vector with element $\delta y_i; 1 \leq i \leq n$; and $\bar{\delta X}$ and $\bar{\delta Y}$ correspond to the mean of vector $\delta X$ and $\delta Y$, respectively.

Here, we consider hydrometeors in terms of the total condensate,

$$Q_{tc} = Q_{cw} + Q_{ic} + Q_{rn} + Q_{sn} + Q_{gr},$$

where $Q_{cw}$ is cloud water mixing ratio, $Q_{ic}$ is ice mixing ratio, $Q_{rn}$ is rainwater mixing ratio, $Q_{sn}$ is snow mixing ratio, and $Q_{gr}$ is graupel. The two metrics defined will be used for winds $u$, $v$, and $w$; potential temperature $T$; water vapor mixing ratio $Q_v$; and total cloud condensate $Q_{tc}$.

3. Results

a. The validity of simplified scheme

A set of experiments (set A in Table 1) with increasing complexity of the microphysics scheme is carried out. These experiments are conducted to address the following question: What are the differences in evolution of initial perturbations using microphysics schemes of varying complexity, and can simple microphysics schemes provide an acceptable approximation for perturbation evolution to the complex scheme? Model error can be evaluated by the differences between forecasts produced by $M^1$ (or $M^2$ or $M^3$) and $M^4$ with the same initial conditions.

The initial perturbation $\delta X$ is defined as the difference between the first ensemble member and the ensemble mean of the DART analysis. The control experiment V4 is initialized from the first ensemble member of the analysis and the ensemble mean. The perturbation evolution from this experiment is regarded as the reference. Similar to V4, other experiments, V1, V2, and V3, use $M^1$, $M^2$, and $M^3$, respectively.

The evolution of RMSD is shown in Fig. 2. The RMSD is averaged among the nine forecasts at the same forecast time. For $u$, $v$, $w$, $T$, and $Q_{tc}$, the RMSD begins to spread after 2-h forecast. For total condensate $Q_{tc}$, the RMSD begins to spread after 1-h forecast. It is of interest to compare relative importance of initial error compared to model error introduced by simple schemes. It is found that growth of forecast errors caused by model error is comparable to that of initial error during 6-h simulations (figures not shown).

<table>
<thead>
<tr>
<th>Expt name</th>
<th>Descriptions</th>
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<tbody>
<tr>
<td>Set A</td>
<td></td>
</tr>
<tr>
<td>V1</td>
<td>$M^1(X_{0}^u + \delta X_{0}) - M^1(X_{0}^u)$</td>
</tr>
<tr>
<td>V2</td>
<td>$M^2(X_{0}^u + \delta X_{0}) - M^2(X_{0}^u)$</td>
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<tr>
<td>V3</td>
<td>$M^3(X_{0}^u + \delta X_{0}) - M^3(X_{0}^u)$</td>
</tr>
<tr>
<td>V4</td>
<td>$M^4(X_{0}^u + \delta X_{0}) - M^4(X_{0}^u)$</td>
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<tr>
<td>Set B</td>
<td></td>
</tr>
<tr>
<td>E-0</td>
<td>$M(X_{0}^s + 6\delta X_{0}) - M(X_{0}^s), s = 1.0, M^1$ or $M^4$</td>
</tr>
<tr>
<td>E-1</td>
<td>$M(X_{0}^s + 6\delta X_{0}) - M(X_{0}^s), s = 0.1, M^1$ or $M^4$</td>
</tr>
<tr>
<td>E-2</td>
<td>$M(X_{0}^s + 6\delta X_{0}) - M(X_{0}^s), s = 0.01, M^1$ or $M^4$</td>
</tr>
<tr>
<td>E-4</td>
<td>$M(X_{0}^s + 6\delta X_{0}) - M(X_{0}^s), s = 0.0001, M^1$ or $M^4$</td>
</tr>
</tbody>
</table>
FIG. 2. Time evolution of averaged RMSD of experiments V1, V2, V3, and V4 for variables (a) $u$, (b) $v$, (c) $w$, (d) $T$, (e) $Q_{v}$, and (f) $Q_{Tc}$. 
The evolution of the patterns is compared by the correlation coefficient described in section 2c. All correlations are computed with respect to the reference experiment V4. These correlations are averaged among the nine forecasts at the same forecast time and are shown in Fig. 3. Correlations of the \( u, v, T, \) and \( Q_c \) smoothly decrease with forecast lead time but remain fairly high (larger than 0.8) over the duration of the 6-h forecasts. However, correlations decrease more quickly for the fields of \( w \) and \( Q_{tc} \).

The above results indicate that the four schemes of the Morrison microphysics parameterization show similar perturbation evolution in amplitude and pattern during the first 2 h of forecast. After that, the simplified schemes introduce significant error in amplitude and spatial pattern (according to RMSD and CORR). These results indicate that the liquid-only scheme is an acceptable approximation to the complex scheme during the first 1–2 h.

b. The evolution of perturbations

To estimate the linearity of the propagation of perturbations, another set of experiments was carried out (set B in Table 1). Only the simplest and most complex schemes of Morrison microphysics parameterization are retained. The initial perturbations (difference from first ensemble and ensemble mean of the DART analyses) are rescaled by a factor \( s \) with values of 1.0, 0.1, 0.01, and 0.0001 to obtain the four perturbed initial conditions.

These experiments address the following questions: What are the differences in the perturbations with different amplitude propagated by the model \( M^1 \) and \( M^4 \)? What are the features of small perturbation evolution? Figures 4 and 5 show the evolution of RMSD and CORR averaged over the nine forecasts, respectively. It is seen that the evolution of initial perturbations with different amplitudes in the model \( M^1 \) is almost the same as that in the model \( M^4 \) in terms of growth rate and pattern correlation.

An interesting feature in Fig. 4 is that smaller perturbations are associated with relatively faster growth rates using both the liquid-only and most complex schemes. This feature of smaller perturbations associated with faster growth is consistent with previous studies on mesoscale predictability (Zhang et al. 2003; Tan et al. 2004; Zhang et al. 2006, 2007). In addition, our results indicate that the representation of microphysics has little impact on the growth of initial perturbations during 6-h forecasts.

The dependence of error growth rate on the initial amplitude indicates that the mechanisms for perturbation growth are nonlinear. Nonlinear behavior is further indicated by lower correlations (Fig. 5) as the initial perturbation size is decreased. Figure 5 also shows the degree of nonlinearities differs among the prognostic variables. Correlations of \( u, v, T, \) and \( Q_c \) are larger than those of \( w \) and \( Q_{tc} \), indicating greater nonlinearity (and hence shorter predictability) of \( w \) and \( Q_{tc} \) compared to \( u, v, T, \) and \( Q_c \). This feature was also pointed out by the previous research (Fabry and Sun 2010). Our results suggest that cloud variables should have a short time window (less than one hour) compared to horizontal wind, temperature, and humidity.

The shorter predictability of \( w \) and \( Q_{tc} \) may limit the performance of an ensemble Kalman filter. Zhang et al. (2006) found that the ensemble Kalman filter was less efficient in correcting error in the vertical velocity and problematic in hydrometeor variables. Frequent observations at smaller scales may improve vertical velocity and hydrometeor variable analyses. However, the rapid nonlinear growth of \( w \) and \( Q_{tc} \) indicates that, given more spectral power at short spatial scales, they will likely to lose the predictability information sooner quickly even if observed more frequently.

Figures 4 and 5 reveal that the simple microphysics scheme does not reduce the nonlinearity compared to the most complex scheme. Thus, even when simple microphysics is employed, it is suggested that a short time window (less than 1 h) be used for 4DVAR to reduce the model error and nonlinearity and thus improve the validity of tangent-linear model.

4. Summary

This study evaluates the impact of microphysical scheme complexity on the propagation of small perturbations in initial conditions for warm-season deep convection over the central United States. Results indicate that, on average, the models with the four schemes of the Morrison microphysics parameterization show similar consistent error evolution in amplitude and pattern during the first 2 h. Thus, the simple liquid-only scheme is an acceptable approximation to the complex one in the first 1–2 h. Initial smaller-amplitude perturbations have relatively faster growth rates using either the liquid-only or complex scheme used, suggesting that the summer mesoscale systems investigated have limited intrinsic predictability. This dependence of error growth rate on the amplitude indicates that the mechanisms for perturbation growth are nonlinear. The simplest scheme does not reduce the nonlinearity in the most complex scheme. On the other hand, the growth of forecast errors caused by model error introduced by the simple schemes is comparable to that of initial error during 6-h simulations. Thus, the model error has a noticeable impact on practical predictability.

Our results indicate that the representation of microphysics has little impact on the growths of initial
Fig. 3. Time evolution of averaged correlations between experiments V1, V2, V3, and V4 for variables (a) $u$, (b) $v$, (c) $w$, (d) $T$, (e) $Q$, and (f) $Q_{tc}$. 
FIG. 4. Time evolution of averaged RMSD of experiments E-0, E-1, E-2, and E-4 for variables (a) $u$, (b) $v$, (c) $w$, (d) $T$, (e) $Q_{\infty}$, and (f) $Q_{tc}$. RMSD from model $M'$ ($M''$) is plotted by the solid (dashed) curve.
FIG. 5. Time evolution of averaged CORR between experiments E-0, E-1, E-2, and E-4 for variables (a) $u$, (b) $v$, (c) $w$, (d) $T$, (e) $Q_v$, and (f) $Q_{tc}$.
perturbations over short periods. We propose that convective-scale dynamics and latent heating associated with cloud water condensation in convective updrafts, which is treated identically in all of the schemes using the saturation adjustment technique and is indeed treated similarly in all microphysics schemes, dominate the convective-scale perturbation growth and its subsequent upscaling. Thus, differences in hydrometeor phase partitioning and production and evaporation of precipitation between the schemes have little impact on perturbation growth relative to cloud condensation.

Results also showed that the perturbation evolution of horizontal wind, temperature, and humidity is less nonlinear than those of vertical velocity and total condensate.

Our results suggest that, even when the simple microphysics scheme is used, cloud variable observations should have a short time window (less than one hour) compared to horizontal wind, temperature, and humidity observations. Frequent observations at smaller scales may improve vertical velocity and hydrometeor variable analyses. However, the rapid nonlinear growth of $w$ and $Q_c$ indicates that they will likely lose predictability information quickly even if they are observed more frequently.

The simplest liquid-only scheme may be an acceptable substitute to the complex scheme in a 4DVAR system with a short assimilation time window less than 1 h. This result supports previous findings that a 4DVAR system with a liquid-only scheme can produce reasonable analyses that improve summertime convective forecasts.

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