Radar Data Assimilation in the Canadian High-Resolution Ensemble Kalman Filter System: Performance and Verification with Real Summer Cases

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ABSTRACT

An 80-member high-resolution ensemble Kalman filter (HREnKF) is implemented for assimilating radar observations with the Canadian Meteorological Center’s (CMC’s) Global Environmental Multiscale Limited-Area Model (GEM-LAM). This system covers the Montréal, Canada, region and assimilates radar data from the McGill Radar Observatory with 4-km data thinning. The GEM-LAM operates in fully nonhydrostatic mode with 58 hybrid vertical levels and 1-km horizontal grid spacing. As a first step toward full radar data assimilation, only radial velocities are directly assimilated in this study. The HREnKF is applied on three 2011 summer cases having different precipitation structures: squall-line structure, isolated small-scale structures, and widespread stratiform precipitation. The short-term (<2 h) accuracy of the HREnKF analyses and forecasts is examined.

In HREnKF, the ensemble spread is sufficient to cover the estimated error from innovations and lead to filter convergence. It results in part from a realistic initiation of HREnKF data assimilation cycle by using a Canadian regional EnKF system (itself coupled to a global EnKF) working at meso- and synoptic scales. The filter convergence is confirmed by the HREnKF background fields gradually approaching to radar observations as the assimilation cycling proceeds. At each analysis step, it is clearly shown that unobserved variables are significantly modified through HREnKF cross correlation of errors from the ensemble. Radar reflectivity observations are used to verify the improvements in analyses and short-term forecasts achievable by assimilating only radial velocities. Further developments of the analysis system are discussed.

1. Introduction

Since being introduced by Evensen (1994), the ensemble Kalman filter (EnKF) has been widely used for atmospheric data assimilation (e.g., Houtekamer and Mitchell 1998; Anderson and Anderson 1999; Anderson 2001; Bishop et al. 2001; Whitaker and Hamill 2002; Tippett et al. 2003; Anderson et al. 2009). The most problematic issues addressed by these studies involve calculation efficiency and insufficient ensemble spread that could lead to filter divergence. The EnKF scheme proposed by Houtekamer and Mitchell (1998, 2001) is able to reasonably increase ensemble spread by computing more than one Kalman gain, is relatively easy to implement, and parallels well. Hence, a global EnKF based on this scheme is in operational use at the Canadian Meteorological Center (CMC). The operational global EnKF provides the theoretical and practical basis for our high-resolution kilometric-scale EnKF (HREnKF), details of which will be elaborated in the next section.

After its success for large-scale data assimilation, the technique of EnKF was adopted for research purposes to assimilate radar data at the mesoscale and convective scale. Snyder and Zhang (2003) explored for the first time the possibility of using EnKF to assimilate radar observations. By assimilating simulated radial velocity into a perfect cloud-scale model, their study showed that accurate analysis can be produced after six radar-scans in 30 min. They also indicated that flow-dependent error covariances are important for reconstructing the unobserved fields. Furthermore, the study using simulated
radial velocity and reflectivity observations showed that reflectivity data in precipitation areas help to retrieve storm details, and no-reflectivity observations in non-precipitation areas are useful for suppressing false alarm storms (Tong and Xue 2005).

Compared to data assimilation of simulated observations in the context of a perfect forecast model, assimilating real radar data by EnKF is even more challenging because of the imperfect highly nonlinear model, and the limited knowledge of model and observation errors. Despite those problems, results from many studies demonstrated notable improvement in both analysis and forecast from assimilating real radar data (Aksoy et al. 2009, 2010; Dowell et al. 2004, 2011). In those studies, amplitude of innovations (i.e., observations minus background) in each cycle was consistently reduced during EnKF cycling. Short-term forecasts after EnKF cycling were improved in a few cases in terms of root-mean-square (rms) errors of reflectivity and radial velocity with respect to real observations.

Although some EnKF studies already dealt with real radar data, most of them focused on isolated convective systems happening within the model domain. The HREnKF in this article is carefully studied under varying weather conditions. Its impact on analyses and short-term forecasts is addressed, and the advantages and limitations of applying HREnKF for radar data assimilation are discussed. This study is an extension of Chung et al. (2013) and benefits from one more year of development work. Radar observations are provided here by McGill J. S. Marshall Radar Observatory. Experiments are performed in the context of the Global Environmental Multiscale Limited-Area Model (GEM-LAM) with 1-km horizontal grid spacing. For the moment, we focus on radial velocity assimilation strictly, leaving reflectivity data for the next stage of our program.

The remainder of the article is organized as follows. In the second section, the design of HREnKF is introduced including the GEM-LAM configurations, the preprocessing of observations, and the observation operator used. The third section shows the setup of HREnKF experiments, introducing three summer cases, and the evaluation methodologies. Results for these three summer cases are presented in the fourth section. Finally, this article concludes with a summary and discussion in the last section.

2. Description of HREnKF for radar data assimilation

a. The HREnKF scheme

The HREnKF inherits from the global EnKF scheme implemented operationally at CMC (Houtekamer and Mitchell 1998, 2001; Mitchell et al. 2002; Houtekamer et al. 2005; Mitchell and Houtekamer 2009). In the following discussion, the term “global EnKF” refers specifically to this Canadian operational global EnKF. The basic equations of HREnKF are similar to the equations in Evensen (1994) and Houtekamer and Mitchell (1998). Given a number of ensemble members equally divided into a few subgroups, the fundamental HREnKF algorithm can be described by the following set of equations:

\[ X_j^f = \mathcal{M}(X_j^a + \varepsilon_j), \]  
\[ K_i = \text{var}(X_j^f, HX_j^f)[\text{var}(HX_j^f, HX_j^f) + R]^{-1}, \]  
\[ X_j^a = X_j^f + K_i(O_j - HX_j^f), \]

where \( i=1, 2, \ldots \), is a subgroup index; and \( j \) and \( j' \) represent the indices of ensemble members within and outside the subgroup \( i \), respectively. The matrix \( K_i \) is the Kalman gain used in subgroup \( i \), and calculated from all the ensemble members other than the ones in \( i \). Super-scripts \( a \) and \( f \) represent analysis and forecast (i.e., background) respectively; \( X \) is the model state vector; \( O_j \) represents perturbed observation vector (Whitaker and Hamill 2002); \( H \) stands for the observation operator; \( R \) is the observation error covariance matrix; \( \mathcal{M} \) is the nonlinear forecast model; and \( \varepsilon_j \) is a random perturbation added onto each analysis member to simulate model errors. The error covariance matrices in Eq. (2.2) are estimated from

\[ \text{var}(A_j, B_j) = \rho \frac{1}{N-1} \sum_{j=1}^{N} (A_j - \mu_x)(B_j - \mu_y)^T, \]

where \( A \) and \( B \) represent state vectors for different members in model space or in observation space [e.g., \( X_j^f \) or \( HX_j^f \) in Eq. (2.2)]; \( j \) is an ensemble member index; \( \rho \) represents the localization function, which will be explained later; and \( \rho < 1 \) means a Schur product with the localization function (Houtekamer and Mitchell 2001).

Brief descriptions of HREnKF features are given in following, while the details can be found in Houtekamer and Mitchell (2001) and Chung et al. (2013). Dividing ensemble members into several subgroups in HREnKF alleviates the problem of ensemble spread reduction caused by limited ensemble size (Mitchell and Houtekamer 2009). Otherwise, the filter could reject observations because of the underestimation of background uncertainties and result in filter divergence.
Three-dimensional localization works on top of the calculation of background error covariance matrices as shown in Eq. (2.4) in order to reduce noise effects in the estimation of covariances (Houtekamer and Mitchell 2001). The algorithm of both horizontal and vertical localizations follows Eq. (4.10) in Gaspari and Cohn (1999). According to some other studies in radar data assimilation (Dowell et al. 2004; Tong and Xue 2005; Aksoy et al. 2009), and the error correlation analysis in Chung et al. (2013), 10-km and 1 scale height (on the coordinate of natural logarithm of pressure) are realistic scale parameters in the above-mentioned localization equation for horizontal localization and vertical localization, respectively. The cutoff distances are twice as large as the above scale parameters.

Sequential processing allows HREnKF to assimilate observations sequentially in batches for reducing the calculation burden (Houtekamer and Mitchell 2001). The validation of such algorithms is subject to the condition that observation errors in different batches should be uncorrelated. In our study, data thinning will be done on radar observations in order to meet this requirement, details of which will be given in section 2c.

Another feature of HREnKF is the background check procedure, which eliminates observations that are far from the background fields (i.e., a short-term forecast). The criterion can be expressed by

\[(o - Hs) > 2\sqrt{\sigma_o^2 + \sigma_s^2}, \quad (2.5)\]

where \(o\) represents each single unperturbed observation; \(Hs\) is the ensemble mean forecast (i.e., background) mapped to the observation space for the corresponding observation; \(\sigma_o^2\) is the fixed observation error variance; and \(\sigma_s^2\) is the flow-dependent background error variance estimated from ensemble members in observation space. Observations satisfying the inequality in Eq. (2.5) are rejected by the background check. This procedure also prevents the model from being shocked by an occasional extreme update on a particular model state variable.

The above features and algorithms of HREnKF are shared with the global EnKF developed by Houtekamer and Mitchell (1998, 2001), besides which, HREnKF has its own specials. First, in addition to the control variables (temperature, specific humidity, and horizontal wind components) in the global EnKF (Houtekamer et al. 2005), HREnKF has vertical velocity \(W\) as an additional control variable, which contributes to the radial velocity [see Eq. (2.6)] and is crucial for small-scale convection. The microphysical variables are not updated directly in the analysis step, but are adjusted through model integration in the forecast step. Second, the time interval for analysis cycling is set as short as 5 min (as compared to 6 h for the global EnKF), which is the same as the output frequency of McGill radar observations. Last, 80 ensemble members are employed, but enough to produce reliable background error structures (Chung et al. 2013).

The HREnKF operates as shown in Fig. 1 and starts from 80 initial ensemble members. The approaches for providing those initial ensemble members will be given in section 3a. During the forecast step, random perturbations representing model errors are applied to ensemble members to prevent ensemble spread reduction [Eq. (2.1)]. Since model errors at the convective scale are not well understood, they are simply simulated here by homogenous and isotropic Gaussian distributed random fields (Chung et al. 2013). The perturbed variables include temperature, horizontal wind components, and specific humidity (standard deviations of perturbations are, respectively, 0.5°, 3 m s\(^{-1}\), and 0.1 on the natural logarithm of humidity). In our experiments, following the global EnKF, perturbations are applied everywhere on the model grid, although according to Snyder and Zhang (2003), localized perturbations may be useful for preventing the spurious convective cells. Given the 80 perturbed members as initial conditions, the high-resolution GEM-LAM is integrated for 5 min to yield 80 ensemble forecasts that are considered as 80 background fields ready for the analysis step. In the analysis step, 80 sets of observations are generated by perturbing real observations (Whitaker and Hamill 2002; Evensen 2003) according to their error structures modeled by Gaussian distribution and observation error standard deviation (see section 2c). They are then statistically combined with the background fields using the EnKF equations [Eqs. (2.2) and (2.3)] to produce an 80-member ensemble analysis, from which another ensemble forecast can be performed. The above process repeats until a final analysis is produced.

**FIG. 1.** Flowchart of HREnKF.
b. GEM-LAM configurations

The fully compressible GEM-LAM is used in our study. The model employs an implicit scheme in time and a semi-Lagrangian advection scheme. Detailed descriptions of the GEM model dynamics and physics formulations are available in Coté et al. (1998) and Mailhot et al. (1998), respectively. As shown in Fig. 2, a three-level nested domain is used in the model configuration to finally drive the 1-km model. The hourly forecasts from the global grid, which used the Sundqvist condensation scheme (Sundqvist 1978), were used as initial and lateral boundary conditions to launch a limited-area model in domain A with horizontal resolution of 15-km (hereinafter LAM-15 km). A second nested LAM forecast (domain B) starts 6 h later than LAM-15 km and runs at 2.5-km horizontal resolution (LAM-2.5 km). This domain (729 × 540 grid points) covers the southern part of the provinces of Ontario and Québec, Canada. The LAM at 1-km horizontal resolution (domain C, LAM-1 km) is launched 6 h later than LAM-2.5 km with an integration time step of 30 s. The LAM-1 km is centered over the Montréal region (300 × 300 grid points) to assimilate radar observations from the McGill J. S. Marshall Radar Observatory.

The limited-area simulations are fully nonhydrostatic with 58 hybrid vertical levels and a lid at 10 hPa. The land surface scheme called the Interaction between Surface, Biosphere, and Atmosphere (ISBA; Noilhan and Planton 1989) is applied. The Kain–Fritsch moist convective parameterization scheme (Kain and Fritsch 1990) is employed in LAM-15 km; however, no convective parameterization is used in either LAM-2.5 km or LAM-1 km. As opposed to the multimodel option (different versions of physical parameterizations for different ensemble members) used in the global EnKF system, the HREnKF system currently keeps all the physical schemes fixed for model integration. The double-moment version of the Milbrandt and Yau (2005) microphysics scheme is used for the grid-scale processes. The model control variables include horizontal winds, temperature, specific humidity, vertical velocity, mixing ratio, and number concentration of six hydrometeor variables (cloud water, rain, snow, ice, graupel, and hail).

c. McGill radar observations

The radar observations assimilated by the HREnKF are provided from the S-band dual-polarized Doppler radar at the J. S. Marshall Radar Observatory operated by McGill University. The McGill radar collects data every 5 min at 24 angles (from 0.5° to 34.4°) in elevation and 360 angles (from 1° to 360°) in azimuth. The coverage of the radar is 240 km in radius.

Before radar data are brought to the HREnKF system, the J. S. Marshall Radar Observatory uses dual-polarization information such as the standard deviations of differential reflectivity (ZDR) and differential propagation phase (PhiDP) to identify the ground clutter (Cho et al. 2006). Mathematical algorithms are also used to remove data contaminations including blockage effect, Doppler ambiguity, and range folding (Doviak and Zrnic 1984). The measurement error of radial velocity is estimated to have a standard deviation of 1 m s⁻¹ (Keeler and Ellis 2000). This value is taken in HREnKF as observation error. To keep radar data quality, the plan position indicator (PPI) data are used for assimilation.

After quality control, data thinning is applied to ensure uncorrelated observation errors, which are required for two reasons. First, errors of raw radial velocity data are correlated between neighboring range gates and between neighboring beams (Xu et al. 2007; Keeler and Ellis 2000). On the other hand, their correlation structures are not fully known. Therefore, it is convenient to thin the data and ensure observation errors are uncorrelated after thinning. Second, the sequential assimilation process of HREnKF is only valid under the condition that the observation errors in different batches are independent. Because of the notable observation error correlation, especially in the radar far field (Fabry and Kilambi 2011), we assume that errors of two observations more than 4 km away from each other...
are not correlated. Thus, a 4-km data thinning is applied in three dimensions on the radar data in this study (Fig. 3). Moreover, thinning is performed at lower elevation angles first, and then at higher elevation angles, in order to keep more observations at lower elevations, since they are important for convection initiation. After data thinning, around 1/3 observations are kept from the raw data.

d. Observation operator for radial velocity

Radial velocities, the only type of observation directly assimilated in the current HREnKF, can be written as a function of three wind components as shown in Eq. (2.6):

\[
V_r = U \sin(\varphi) \cos(\theta) + V \cos(\varphi) \cos(\theta) + (W + V_t) \sin(\theta),
\]

(2.6)

where \(U\), \(V\), and \(W\) are the three wind components from model output; \(V_t\) is the terminal velocity; and \(\varphi\) and \(\theta\) are the azimuth and elevation angles, respectively. The terminal velocity can be calculated either from model output or from reflectivity observations. In our study, similar to other studies in the literature (e.g., Sun and Crook 1997; Chung et al. 2009; Wang et al. 2013), reflectivity observations are used to calculate \(V_t\). The relationship between \(V_t\) and reflectivity can be described by Eqs. (2.7) and (2.8):

\[
Z = 43.1 + 17.5 \log(M), \quad \text{and} \quad (2.7)
\]

\[
V_t = 5.94 M^{1/8} \exp \left( \frac{l}{2h} \right), \quad (2.8)
\]

where \(Z\) is the reflectivity, \(M\) is the precipitation concentration (g m\(^{-3}\)), \(l\) is the altitude (m), and \(h\) is a 10\(^3\) m scale height. Although reflectivity data are not assimilated directly by HREnKF, they are used in the observation operator for the calculation of radial velocity.

3. Experimental setup

a. Experiment design

The experiment procedure consists of 1-h HREnKF cycling and 1.5-h short-term ensemble forecasts, which are synchronous with a 2.5-h control run (Fig. 4). The HREnKF cycling process begins with 5-min model integration of the 80 initial ensemble members, then assimilates observations of radial velocity every 5 min for 12 cycles, and finally produces an ensemble of analysis. The short-term 80-member ensemble forecasts are initiated from the final analysis ensemble and lasts for 90 min. To investigate the impact of radial velocity assimilation by HREnKF on analysis and forecast, a control run is established during the same entire experimental period.

In the experiments to follow, two different approaches are intercompared to provide 80 initial ensemble members for HREnKF and lateral boundary conditions for the high-resolution GEM-LAM. In the first approach, following the preceding study (Chung et al. 2013), a deterministic forecast (as described in section 2b) provides the initial guess at the start point of HREnKF, on which Gaussian distributed random errors are added to yield 80 initial ensemble members. The statistical properties of initial perturbations are similar to model error perturbations described in section 2a, except for their standard deviation being multiplied by a factor of 2. The driving field of the deterministic forecast also provides the same lateral boundary conditions for all ensemble members in both HREnKF cycling process and short-term forecast. The control run corresponding to this approach is a model integration initiated from the initial guess. In the following text, this approach will be referred to as EXP1.

It is now better documented in the literature (e.g., Nutter et al. 2004a,b; Saito et al. 2012; Caron 2013) that perturbing lateral boundary conditions in ensemble
forecast systems is important. Therefore, since a regional EnKF-15 km system (referred to as REnKF) is currently available in research mode at CMC, the second approach assigns each member of HREnKF different initial and lateral boundary conditions from the members of the REnKF. As shown in Fig. 5, the REnKF takes information from the operational global ensemble analysis and then assimilates conventional observations (same types as the global EnKF) every 6 h for two cycles. Presently, results coming from extensive validation tests of REnKF demonstrate that it scores as highly as the global EnKF against radiosonde observations after one month of cycling (results not shown). Similar to EXP1, the second approach consists of a downscaling procedure down to 1-km horizontal grid spacing. The model configurations in LAM-2.5 km and LAM-1 km are exactly the same as described in section 2b. In this approach, the 80-ensemble forecasts at 2.5-km grid spacing provide the lateral boundary conditions for each member at 1-km grid spacing. We emphasize the fact that REnKF, generally better captures mesoscale circulations as compared to global EnKF, and provides larger ensemble spread for both initial ensemble members and the ensemble lateral boundary conditions. Further details on this impact on ensemble spread will be given in section 4a. Note that the control run in this context takes the ensemble mean of the 80 analysis members of 15-km resolution REnKF and then use downscaling to 1-km grid spacing. This approach is given the name “EXP2” for simplicity in the following discussion.

In the case studies, only the first case exploits both EXP1 and EXP2, while the other two use only the second approach. The rationale for doing this will be elaborated in the next section along with the results of experiments.

b. Description of three cases

On 29 June 2011, a squall line appeared on McGill’s radar image and moved eastward (Figs. 6a,b). The HREnKF performs 12 data assimilation cycles from 0000 to 0100 UTC, and the following short-term ensemble forecast is from 0100 to 0230 UTC. The radial velocities in Fig. 6b show how observations look and where they appear with respect to the radar location (black dot). By comparing Figs. 6a and 6b, one may notice that the colored area of radial velocity image is slightly larger than that of reflectivity. This is due to the fact that reflectivities smaller than 7 dBZ are considered insignificant compared to the noise, and therefore are not colored in the figure. The radial velocities at the same locations, however, are significant. When radial velocity observations are provided, but reflectivities are unobserved or insignificant, terminal velocity cannot be obtained by Eqs. (2.7) and (2.8) and does not contribute to the observation operator. We emphasize that the reflectivity contains more information than the radial velocity does in Fig. 6, because the former contains both precipitation and nonprecipitation data, which is crucial for correcting position errors in data assimilation.

As discussed before, two different experiments, EXP1 and EXP2 are performed for this case, where the control runs are different. By comparing between observations (Fig. 6a) and the control runs for both experiments (Figs. 6c,d) at time 0000 UTC before the experiment starts, one can tell that the precipitation in EXP2 is more precisely located. This is a result of the ability of REnKF to track mesoscale circulations in EXP2, which reduces the error of the control run at the beginning of HREnKF. Because of the improvement brought by REnKF on better positioning the mesoscale flow in general, the next two cases will rely on REnKF for providing the initial ensemble and the driving ensemble fields. HREnKF will rather focus on improving the convective scales.

The second case happened on 12 June 2011 when severe storms struck the Montréal area in the afternoon, and delayed the “Grand Prix de Formule Un” car racing for more than 2 h. As seen in the radar image (Fig. 7a), many storms near the center of the domain were small scale, isolated, and strong. Those storms moved from southwest to northeast and lasted for many hours. On the southern portion of the domain, a well-organized stratiform weather system already existed and gradually
decayed. HREnKF is performed from 1600 to 1700 UTC. The short-term forecasts are from 1700 to 1830 UTC. The reflectivity output of the control run (Fig. 7b) shows clear location errors at the initial time, which challenges the HREnKF system.

In the third case, around 2100 UTC 23 June 2011, strong convections were observed to the south of the radar, and some light precipitation extends to the northeast of the domain (Fig. 8a). This mesoscale weather system developed and moved very slowly toward east-northeast. In this case study, HREnKF is performed from 2100 to 2200 UTC, and short-term forecasts are from 2200 to 2330 UTC. The reflectivity field of the control run (Fig. 8b) is similar to the observation in terms of the stratiform structure, but the location error is quite large.

c. Evaluation methodologies

The behavior of HREnKF and its impact on analysis and forecast are evaluated by several indicators. First, indicators in observation space are calculated during the cycling process of HREnKF in order to examine the ensemble spread and filter convergence. Second, the final analysis produced by HREnKF and the following short-term ensemble forecast are compared to the control run and the observations to demonstrate the improvement brought by HREnKF. We will call the 5-min forecast in cycling process “background” in the following discussion, because they serve as the background for the analysis step. The 1.5-h forecast is referred to as “short-term forecast.” In this way, we are able to literally differentiate the 5-min forecast in HREnKF and the 1.5-h forecast after HREnKF.

We now introduce observation-space diagnostic indicators for the HREnKF cycling process. By the end of each 5-min cycle, given the background and ensemble analysis calculated from Eqs. (2.1) and (2.3), respectively, the observation-space ensemble means of background and analysis can be obtained by projecting variables...
from model space to observation space and averaging over all members. Then, two indicators are computed: root-mean-square (rms) error of ensemble mean background with respect to observations (hereinafter referred to as “background rms”), and rms error of ensemble mean analysis with respect to observations (hereinafter referred to as “analysis rms”). The computation of rms error is given by

$$\text{rms} = \sqrt{\frac{1}{M} \sum_{m=1}^{M} (o_m - HX_m)^2}, \quad (3.1)$$

where $M$ is the number of observations used for the current analysis step, $o_m$ is the $m$th observation, $HX_m$ is the model state in observation space for the $m$th observation, and its average is taken over all the ensemble members. When $X = X^a$, representing the analysis state vector, Eq. (3.1) calculates the analysis rms.

Based on the information of ensemble members and ensemble mean of background, the ensemble spread of background can be calculated as well. To be comparable to the background rms, the ensemble spread is computed also in observation space as

$$\text{spread} = \sqrt{\frac{1}{M} \sum_{m=1}^{M} \left[\frac{1}{N-1} \sum_{n=1}^{N} (HX_{n,m} - HX_m)^2\right]}, \quad (3.2)$$

where $M$ is the number of observations used for the current analysis step, $N$ is the number of ensemble members, and $HX_{n,m}$ is the ensemble background of member $n$ in observation space for the $m$th observation. Sufficient ensemble spread is a necessary condition of

![Fig. 7](image1.png)

**Fig. 7.** The case at 1600 UTC 12 Jun 2011. (a) Reflectivity observations at the fourth elevation angle (0.9°). (b) Model output of reflectivity for the control run, interpolated to the fourth elevation angle. The black dots near the centers of figures denote radar location.

![Fig. 8](image2.png)

**Fig. 8.** As in Fig. 7, but for the case at 2100 UTC 23 Jun 2011.
successful operation of EnKF. The ensemble spread is usually generated at the beginning of EnKF and should be maintained during the cycling process. For example, Dowell and Wicker (2009) discussed the use of additive noise for producing and maintaining ensemble spread for storm-scale ensemble data assimilation. In our HREnKF, the ensemble spread is maintained by dividing ensemble members into subgroups (Houtekamer and Mitchell 1998). Two different approaches of obtaining initial ensemble members (see section 3a) will also be examined. Another possible method of keeping sufficient ensemble spread is inflation (e.g., Anderson 2007). In the results section of this article, we will show that ensemble spread is supposed to meet the requirement that \((\text{spread}^2 + \text{observation error variance})\) is greater than or comparable to \(\text{background rms}^2\). 

Another diagnostic indicator for the HREnKF cycling process is proposed here to test the convergence between background and truth implying filter convergence. In our real data study, since the truth is unknown, observations that are closely related to the truth are considered as references to judge the convergence. For the purpose of measuring the difference between background and observations, “observation-pass-ratio” is defined as the ratio of the number of observations that pass the background check to the total observation number available for each cycling step. As explained in section 2a, the background check aims at excluding the observations greatly differing from the background [Eq. (2.5)]. Accordingly, a larger observation-pass-ratio implies model states being closer to observations, since a larger proportion of observations are able to pass the background check. A gradually growing observation-pass-ratio suggests filter convergence. Note that a larger observation-pass-ratio does not necessarily suggest that more data are assimilated because the absolute number of assimilated observations depends also on the total observation number before background check.

Besides the above indicators exploring the performance of HREnKF, two other scores are used for verifying the accuracy of final analysis and short-term ensemble forecast, given observations as reference. The first score is the “bias” defined as the spatial average of the differences between ensemble and ensemble forecast or analysis (zero-time lead forecast) at each radar elevation angle for each ensemble member. A score closer to zero implies better quality of the analysis or the forecast. The score is given by

\[
\text{bias}_{ln} = \frac{1}{M'} \sum_{m=1}^{M'} (\text{om}_m - \text{HX}_{n,m}^f),
\]

where \(l\) means the \(l\)th elevation angle, \(n\) denotes the \(n\)th member, and \(M'\) is the number of observations at the \(l\)th elevation angle. The second score is the “rms” of ensemble forecast with respect to observations at each elevation angle for each member. If the forecast is closer to the observation, the rms is expected to be smaller. The rms is calculated by

\[
\text{rms}_{ln} = \sqrt{\frac{1}{M'} \sum_{m=1}^{M'} (\text{om}_m - \text{HX}_{n,m}^f)^2},
\]

where \(\text{rms}_{ln}\) is the forecast rms at the \(l\)th elevation angle for ensemble member \(n\). It is important to realize that this score is different from Eq. (3.1), which calculates the rms of the ensemble mean. Given the bias and rms for 80 ensemble members, the ensemble mean and ensemble standard deviation of the bias and rms are calculated from the scores of each member.

For the control run, similar scores can be calculated from Eqs. (3.3) and (3.4), where \(X^f\) means the model state vector of the control run that has only one member.

4. Results

a. Results of the case on 29 June 2011

The results of two experiments for the first case study will be shown in this section. The first experiment (hereinafter CASE1_EXP1) and the second experiment (hereinafter CASE1_EXP2) take the schemes of EXP1 and EXP2, respectively, as defined in section 3a.

The first results we present are the indicators of rms errors and ensemble spread over the HREnKF cycling period, which can be used to examine the sufficiency of ensemble spread. The ensemble spread and rms errors are presented in \(V_r\) observation space, including only the observations that pass the background check. In CASE1_EXP1 (Fig. 9a), the ensemble spread is smaller than the background rms for all cycles, thus puts the HREnKF in danger of underestimation of the background uncertainty. This problem is due to the fact that the initial ensemble spread of CASE1_EXP1 is decided by the set of random perturbations applied in the beginning of HREnKF, whose variances are not large enough. Nevertheless, we do not want to amplify the initial perturbations because it could perturb the model dynamical and physical balance too severely. Therefore, the relatively small amplitude of random perturbations results in the insufficiency of ensemble spread. Another important reason for the small ensemble spread in CASE1_EXP1 is its fixed lateral boundary conditions, which gradually influence the inner domain through the model integration and reduce the ensemble spread near the boundaries. Similar discussions about rms errors and ensemble spread can also be found in Aksoy et al. (2009, 2010) and Dowell et al.
Our results focus on the improvement of sufficiency of ensemble spread brought by implementation of the regional EnKF.

Unlike in CASE1_EXP1, the initial ensemble members in CASE1_EXP2 are derived from the REnKF, which guarantees large ensemble spread (Fig. 9c) as well as realistic balanced model fields. Moreover, since each member has its own lateral boundary conditions, the ensemble spread near the boundary does not shrink as in CASE1_EXP1. Quantitatively speaking, the ensemble spread for CASE1_EXP2 is around $2.5 \text{ m s}^{-1}$ (Fig. 9c), while the ensemble spread for CASE1_EXP1 is no more than $2 \text{ m s}^{-1}$ (Fig. 9a). Correspondingly, the total spread squared (ensemble spread squared + observation error variance) is $(2.5^2 + 1^2)$ for CASE1_EXP2 and $(2^2 + 1^2)$ for CASE1_EXP1. Given the background rms staying around $2.3-2.5 \text{ m s}^{-1}$ for both CASE1_EXP1 and CASE1_EXP2, by applying the criterion for deciding the ensemble spread sufficiency as described in section 3c, one can tell that the ensemble spread is sufficient in CASE1_EXP2 but insufficient in CASE1_EXP1.

The second set of results we now discuss are the observation-pass-ratios that indicate the convergence of background to observations during HREnKF cycling process. The observation-pass-ratio for CASE1_EXP2 increases from about 74% to almost 80% after the fourth cycle (Fig. 9d), while the ratio for CASE1_EXP1 generally remains around 57% after the third cycle (Fig. 9b). This infers first that the background gradually converges to observations during the cycling process in CASE1_EXP2, and second, the HREnKF in CASE1_EXP2 incorporates a larger proportion of observations than CASE1_EXP1 because of its larger ensemble spread (Fig. 9c). Although the increasing observation-pass-ratio after the fourth cycle in CASE1_EXP2 suggests filter convergence, it drops from 80%–74% in the first three cycles. This is because the observation-pass-ratio decreases when the ensemble mean deviates from observations, or ensemble spread.

![Fig. 9. Results of cycling process for the case on 29 Jun 2011. Each cycle takes 5 min. (a),(b) CASE1_EXP1 and (c),(d) CASE1_EXP2. (a),(c) Ensemble spread in observation space ($V_r$) (dashed line), background rms of $V_r$ (12 upper points on the solid line), and analysis rms of $V_r$ (12 lower points on the solid line) during the cycling process. (b),(d) Observation-pass-ratio.](http://journals.ametsoc.org/mwr/article-pdf/142/6/2118/4293242/mwr-d-13-00291_1.pdf)
The ensemble spread is large at the beginning (before any assimilation proceeds), and therefore allows many observations to pass the background check. After the first assimilation step, however, all ensemble members are constrained by observations, and the resulting smaller ensemble spread leads to the reduction of observation-pass-ratio. For the following cycles, although the ensemble spread reduces (see Fig. 9c), the ensemble mean becomes closer to the observations. Consequently, fewer observations are rejected and the observation-pass-ratio increases.

After showing diagnostic indicators exhibiting the quality of the HREnKF cycling process, we now verify the impact of radial wind assimilation on analysis and short-term forecast by comparing them to the control run. Note that control runs for CASE1_EXP1 and CASE1_EXP2 are different (see section 3a).

The third results we show are scores of bias, rms, their ensemble mean, and the ensemble standard deviation computed at analysis time 0100 UTC on different radar elevation angles (Figs. 10a and 11a), which are similar to results presented by Aksoy et al. (2010). Although “radar beam elevation index” is used as y axis in the figures, it is still able to generally describe different altitudes in the atmosphere. While both bias and rms describe the accuracy of analysis and forecast, rms is a more direct measure of errors. As shown in Eq. (3.4), rms does not allow errors to cancel each other as the bias does in Eq. (3.3). On the other hand, bias is helpful to detect whether errors happen in small scale or are caused by the large-scale flow. When the radial velocity of analysis has significant errors, small bias is still possible when the inaccuracy is caused by large-scale flow. This is because large-scale errors (the entire wind field is overestimated/underestimated to the same direction at large scale) have opposite signs on opposite sides of the radar.

Figures 10a and 11a show the improvement of the analysis over the control run for both experiments, with observations used as reference. Note that all evaluations against radar data are done without data thinning. The total number of data used for verifications as a function of elevation angles appears on the right-hand side of each panel. For CASE1_EXP1 at analysis time 0100 UTC (Fig. 10a), the red curves being closer to the zero lines than the blue curves indicates that the analysis has smaller bias and rms than the control run on almost all elevation angles. Similar results can also be observed in Fig. 11a for CASE1_EXP2. In addition, the entire error bars representing ensemble standard deviations in Figs. 10a and 11a are mostly closer to the zero line than the blue curve, which demonstrates that the improvement is not limited to the ensemble mean, but for most ensemble members.

The fourth results for this case study include the scores of bias and rms in short-term forecasts. The curves in Figs. 10b, 10c, and 10d show that the bias and rms scores of short-term forecast gradually approach the scores of the control run over the forecast period in CASE1_EXP1. At time 0230 UTC, 90 min after initiation of the ensemble forecast, the rms curves of forecast and control run are almost identical especially in the lower elevations, but the bias of forecast is still generally smaller than control run. This means the impact of HREnKF still exists in forecast after 90-min model integration. Different from CASE1_EXP1, the accuracy of analysis in observation space in CASE1_EXP2 does not guarantee a precise forecast. The scores for CASE1_EXP2 illustrate that at time 0130 UTC, just 30 min after the start of the short-term forecast it is already difficult to tell whether the forecast or the control run is better, especially when the error bars are taken into consideration. In other words, the impact of assimilating radial velocities in CASE1_EXP2 does not last as long as in CASE1_EXP1.

Given the above results of short-term forecast, one can tell that the HREnKF has much more influence on the forecast in CASE1_EXP1 than in CASE1_EXP2. This can be explained by the role of REnKF, which is to provide more precise mesoscale initial ensemble members for CASE1_EXP2. Since the REnKF works on larger scales and assimilates conventional observations, it is able to correct large-scale flows, and directly update more model variables other than only wind components. Consequently, the improved large-scale circulation, which strongly affects the prediction in this case study, removes many errors at the beginning of HREnKF in CASE1_EXP2. The evidence can be found in Fig. 6 as the control run at the initial time in EXP2 has much less errors than in EXP1. After the HREnKF cycling process starts in CASE1_EXP2, errors are further corrected by radial velocity assimilation. However, most corrections happen at small scales because large-scale errors are already reduced by the use of REnKF. Therefore when large-scale errors dominate the short-term forecast, the impact of HREnKF quickly diminishes in CASE1_EXP2 (Fig. 11). The effect of REnKF can be verified by comparing the blue curves of control runs in Figs. 10 and 11. For example, at 0130 UTC, the rms of control run in CASE1_EXP1 (Fig. 10b) is around 6 m s$^{-1}$, while the control run in CASE1_EXP2 (Fig. 11b) has smaller rms values around 5 m s$^{-1}$. Hence, the relatively limited and short-lived impact of HREnKF on short-term forecast in CASE1_EXP2 is more likely attributable to the accuracy of its control run, rather than a defect of HREnKF.

The last results discuss the ensemble standard deviation of bias and rms in Figs. 10 and 11. By comparing the
The difference between results of CASE1_EXP1 and CASE1_EXP2 suggests that applying REnKF before HREnKF has many benefits, such as providing the sufficient ensemble spread, and correcting larger-scale circulation. Accordingly, the following two case studies will follow only the experimental procedure of CASE1_EXP2.

b. Results of the case on 12 June 2011

This case study is hereinafter named CASE2. Note that CASE2 allows REnKF to provide the initial ensemble members, and ensemble boundary conditions.
for the 1-km model used in HREnKF. The ensemble spread and rms errors of analysis and background during the cycling process are shown in Fig. 12a, where no severe ensemble spread insufficiency appears. The observation-pass-ratios plotted in Fig. 12b prove that larger proportion of observations pass the background check as more cycles are involved, indicating that background fields tend to gradually converge to observations.

Figure 13 shows the one-step increments (analysis minus forecast) of the $V$ component of the wind and humidity in the third cycling step at 1615 UTC. As directly involved in the observation operator [Eq. (2.6)], the $V$ component is partly observed by the radar, and thus can be directly updated by assimilating radial velocities. The maximum change of the $V$ component can reach more than 2.1 m s$^{-1}$ (Fig. 13a). On the other hand, the humidity field does not appear in the observation operator equation, and therefore requires cross correlation between errors of humidity and observed variables (e.g., $U, V$ components) to be updated (Snyder and Zhang 2003). The increment of humidity is up to 0.5 g kg$^{-1}$ at some locations in Fig. 13b (e.g., to the southwest of the radar), a value big enough to trigger convection under certain conditions (evidence of this in a parameterized convection context is given in Fillion and Bélair 2004).

In addition, although the unobserved variables can be updated by HREnKF, we still need to verify that the
entire model state approaches the truth. Despite the truth being unknown, reflectivity observations provided by the same radar used in the assimilation system can reasonably be considered as a reference for examining the impact of radial velocity assimilation on precipitation. As an example, shown in Fig. 14 are snapshots of reflectivity fields of the eighth analysis member and the control run together with the reflectivity observations at 1700 UTC when all cycles are completed. We choose to show single ensemble members instead of ensemble mean because the ensemble mean could smooth the field and wipe out small-scale information. Figure 14d shows at each pixel, the percentage of ensemble members producing precipitation stronger than 30 dBZ with respect to the total 80 ensemble members. For example, 20% in Fig. 14d indicates 16 out of 80 members produce precipitation stronger than 30 dBZ. In general, given reflectivity observations as reference, Figs. 14c and 14d exhibit relatively more accurate storm locations near the center ("west–east distance" between 150 and 200 km, and "south–north distance" between 100 and 150 km) and in the north of the domain (south–north distance greater than 150 km), compared to the control run (Fig. 14b). It infers that the HREnKF is able to correct the storm location error to some extent. However, some precipitation in the southeastern area is observed by the radar, but is missed by both the analysis members and the control run. Additionally, some spurious storms, around which radial velocity observations are unavailable, are difficult to be eliminated. Assimilating reflectivity data, especially the non-precipitation observations will be helpful for removing false alarms in a future development of our HREnKF system.

FIG. 12. Results of cycling process for CASE2 on 12 Jun 2011. Each cycle takes 5 min. (a) Ensemble spread in observation space ($V_r$) (dashed line), background rms of $V_r$ (12 upper points on the solid line), and analysis rms of $V_r$ (12 lower points on the solid line) during the cycling process. (b) Observation-pass-ratio.

FIG. 13. The analysis increments (difference between ensemble mean background and ensemble mean analysis) of the $V$ component of wind and specific humidity close to the surface (around 800 hPa), for the third cycle at 1615 UTC for CASE2 on 12 Jun 2011. The black dots near the centers of figures denote radar location.
To have a deeper view, the convective available potential energy (CAPE) fields for the control run and the eighth member of ensemble analysis are investigated (Fig. 15). CAPE describes the convective instability present in model and we stress that its computation involves unobserved variables. Near the center of the domain and to the east of the radar (west–east distance around 220 km, and south–north distance around 150 km), the CAPE values in the eighth analysis are much greater than in the control run, which demonstrates that the assimilation of radial velocity greatly increases the instability. In the west of domain, the CAPE values for the eighth analysis are smaller than the control run. Although no data are available in this region (see Fig. 14a), the CAPE are probably reduced by the perturbations or by assimilating the nearby observations, which gradually modify the environment through the 12 assimilation cycles. In the southeast part of the domain, both analysis and control run give small CAPE values, even though plenty of observations are available over that region. One plausible reason explaining this fact is that the cross correlation between wind components and other variables is too weak, and the background is too far from the reality.

Last, the effect of HREnKF on analysis and short-term forecast is shown by scores of radial wind bias and rms in Fig. 16. At 1700 UTC, the values of rms for analyses are generally much smaller than those for the control run (right panel of Fig. 16a), and such patterns last until 1830 UTC for 90 min (right panels of Figs. 16b, 16c, and 16d) during short-term forecasts. These forecast results are consistent with many other studies about EnKF systems working with simulated radar data (Tong and Xue 2005) and real radar data (Aksoy et al. 2009, 2010; Dowell et al. 2011). Although the REnKF is applied on both CASE2 and CASE1_EXP2, the superiority of short-term forecasts over the control run is more evident in CASE2 than in CASE1_EXP2.
As opposed to the squall-line precipitation structure in CASE1_EXP2, convections in CASE2 are localized at small scale, and are less influenced by large-scale flow. Consequently, most of the correction made on small-scale errors is done by HREnKF itself rather than from the REnKF. In brief, HREnKF plays a more important role in CASE2 than in CASE1_EXP2 due to the precipitation happening at small scales in CASE2.

c. Results of the case on 23 June 2011

This case study is referred to as CASE3 in the following discussion. The analysis performance indicators for CASE3 shown in Fig. 17 exhibit large ensemble spread and increasing observation-pass-ratio, which are similar to the previous two cases, except for the growing ensemble spread during the cycling process (Fig. 17a). In fact, while the ensemble spread slightly increases, does the observation-pass-ratio. It is difficult to determine whether the rise of observation-pass-ratio is caused by the convergence between background and observations as discussed in section 4a, or by the slightly growing ensemble spread that gradually allows larger portion of observations to pass the background check. We noted, however, that for CASE1_EXP2, the ensemble spread decreases when observation-pass-ratio increases (Figs. 9c,d), which suggests that the better agreement between background and observations is the only reason for the rising of observation-pass-ratio. Therefore, CASE1_EXP2 is more convincing than CASE3 in terms of convergence of model states to observations. On the other hand, although the ensemble spread rises slightly here, the analysis rms shows a tendency of decrease in CASE3 (Fig. 17a), implying that the ensemble mean analysis contains smaller errors with respect to observations as more cycles are conducted.

The verification scores of bias in Fig. 18a show that at time 2200 UTC, the improvement of analysis over the control run is insignificant. The control run is even better in terms of bias, probably because it happens to be very accurate at that time. After the forecast starts, however, the control run scores begins to deviate from the zero line at the lowest eight elevation angles, while the bias values of ensemble forecast remain smaller (Fig. 18b). This situation holds until 2330 UTC. This tells that even though the impact of HREnKF on analysis is not clear in observation space, the forecast is still under its influence because the entire model state is improved and able to produce more accurate prediction.

The verification scores of rms in Fig. 18 indicate that the analyses are better than control run below elevation angle 11 at 2200 UTC. Similarly, the superiority of forecasts can be seen below angle 7 at 2230 UTC, and is also evident below angle 5 at 2300 UTC. At 2330 UTC, the end of ensemble forecast, the impact of HREnKF on forecast vanishes. Therefore, for this stratiform precipitation case, the improvement on forecasts lasts longer at lower elevation angles than at higher elevation angles.

5. Summary and discussion

This study introduces a high-resolution ensemble Kalman filter (HREnKF) system designed in particular for convective-scale radar data assimilation. The key features of HREnKF include a set of 80 ensemble members divided into four subgroups, three-dimensional error correlation localization, sequential assimilation, and background check of observations. The observations assimilated by the HREnKF in current experiments are radial velocities from the McGill Radar Observatory and...
cover the Montréal region. Radial velocity observations are incorporated by HREnKF every 5 min for 12 cycles during the 1-h assimilation process, by the end of which, final analyses are produced and a 1.5-h 80-member ensemble forecast is launched.

Three summer cases in 2011 are studied including the first case with squall-line precipitation structure on 29 June 2011, the second one with isolated strong small-scale storms on 12 June 2011, and the third case of widely distributed stratiform on 23 June 2011. Studies of all three cases involve the Canadian regional EnKF (REnKF) for generating the initial ensemble members and ensemble lateral boundary conditions for HREnKF. In addition, another experiment is done for the first case study, where a deterministic forecast provides initial guess and fixed lateral boundary conditions for the experiment.

The indicators of ensemble spread, analysis rms, and background rms exhibited sufficient ensemble spread during the cycling process in all three cases, as long as REnKF are implemented to provide ensemble initial and lateral boundary conditions. In contrast, if a deterministic forecast is used as an initial guess for HREnKF and if lateral boundary conditions are the same for all ensemble members (as in the first experiment of the first case), this results in insufficient ensemble spread and underestimation of forecast uncertainty.

**FIG. 16.** As in Fig. 10, but for experiment CASE2 on 12 Jun 2011.
We also systematically measured the difference between background and observations by the **observation-pass-ratio** defined as the ratio of the number of observations passing the background check to the total observation number. As the cycling procedure proceeds, the portion of observations kept by the background check gradually increases for all three cases. Given that the ensemble spread reduces (the first case) or not significantly increases (the second and the third cases), one can conclude that the model state in HREnKF gradually converges to the observations during the cycling process.

Besides the observed wind components, unobserved variables are also updated by the HREnKF through the error cross correlation between observed and unobserved variables. For example, the results of the second case study showed notable increment of the humidity field in one cycle although humidity is not observed by the radar. Moreover, images of reflectivity and CAPE for the second case show that the model convective instability is consistent with radar observations. In the areas devoid of observations, although the spurious storms are different to be directed removed, the surrounding data are able to modify the environment to some extent.

After the cycling process completes, the analysis and the short-term forecast are still under the influence of radial velocity assimilation. The first case showed that for the weather system controlled by large-scale flows, error corrections by the REnKF has more effect than HREnKF. The second case demonstrated that when localized convection happens, the HREnKF accounts for most of the corrections and is able to improve the location of the storms in the resulting analyses. In addition, the ensemble forecast is much better than the control run with respect to radial velocity observations, and lasts up to 90 min after forecast initiation. The third case showed that for this wide spread and stationary stratiform case, the improvement lasts longer at lower elevation angles than at higher elevation angles.

Some limitations exist in our current experiments. First, although HREnKF improves short-term forecasts, the improvement unfortunately does not survive for more than 90 min. This can be explained by the growing errors of ensemble forecasts due to the use of an imperfect model and the invasion of inaccurate lateral boundary conditions. Second, observations of radial velocity only provide information of one wind component, and therefore have difficulty in efficiently improving 3D wind field and unobserved variables. The update of unobserved fields relies on the cross correlation between errors of observed and unobserved variables, which could occasionally be too weak to accomplish all necessary corrections. For example, results of the second case show that the assimilation of radial velocity in the southeast of the domain is unable to generate CAPE values large enough to trigger convections. Third, the homogenous model error applied at every cycle and the fixed localization algorithm are not most favorable for the HREnKF. In fact, model error is not homogenous but difficult to estimate. The localization algorithm should be made consistent with the spatial correlation distance of background errors, which is shorter in precipitation area and longer otherwise.

For a consistent incremental development of our HREnKF analysis system, we deliberately limited our study to the assimilation of radial velocity data. As a further step toward full exploitation of available radar observations, reflectivity data will be considered in addition to radial velocities in the near future. Actually, including reflectivity data will probably contribute much more to the analysis and forecast in terms of correction of storm location and intensity, since it directly relates to the microphysical variables. Hence, the
The next step of HREnKF implementation is to assimilate in addition reflectivity observations and examine its impacts.

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