USE OF NWP FOR NOWCASTING CONVECTIVE PRECIPITATION

Recent Progress and Challenges

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The demand for accurate nowcasts of convective precipitation has driven the development of high-resolution data assimilation and rapid cycling numerical weather prediction.

Since the early 1960s, techniques for nowcasting convective precipitation have been developed by extrapolating radar echoes. Wilson et al. (1998) provided a comprehensive review on the status of nowcasting that covered both fundamental and application aspects of the subject. Since that paper was published, a noticeable new development has been the increased application of NWP to the nowcasting problem. In this paper, we review the recent progress on the use of NWP for nowcasting convective precipitation and discuss some challenges, and hence opportunities, that are lying ahead. This review paper was inspired and benefited from the workshop on the use of numerical weather prediction (NWP) for nowcasting that was sponsored by the World Weather Research Programme (WWRP) of the World Meteorological Organization (WMO) and was held on 24–26 October 2011 at the National Center for Atmospheric Research (NCAR) in Boulder, Colorado. This workshop was a joint effort between the Working Group on Nowcasting Research (WGNR) and Working Group on Mesoscale Weather Forecasting Research (WGMWFR) under WWRP. (The invited participants, keynote speakers, workshop agenda, and presentations can be found at http://wmo-workshop-on-the-use-of-nwp-for-nowcasting.wikispaces.com.)

Nowcasting is taken here to be forecasting with local detail, by any method, over a period from the present to a few hours ahead, including a detailed description of the present weather. It is widely accepted that the nowcasting range refers to the 0–6 h of forecast, which is also referred to as "very short term." Traditionally, nowcasting was considered to provide a detailed initial state description with a forecast component derived through the extrapolation of these conditions in time. Nowcasting is now expanded to

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include the blending of extrapolation techniques, statistical techniques, heuristic[1] techniques, and numerical weather prediction. In recent years, the blending of traditional extrapolation-based techniques with high-resolution[2] NWP is gaining popularity in the nowcasting community. The increased need for NWP products in nowcasting applications poses great challenges to the NWP community because the nowcasting application of high-resolution NWP has different requirements from the longer-range NWP. To name a few, nowcasting requires accurate specification of the current weather condition with a resolution of a few kilometers; frequent accurate updates of the current weather and nowcasts are critical, particularly in the case of severe storms; and there is a much smaller tolerance for the timing and location errors of forecasted precipitation systems.

It is not a trivial task for the NWP community to improve the NWP to the extent that it meets the nowcasting requirements. Since Lilly (1990)'s history-making publication in which he challenged the meteorological community to consider the explicit prediction of thunderstorms at the county or city scales, tremendous efforts have been devoted to the improvement of NWP to tackle the problem. There are several great challenges. Among them are understanding how to assimilate observations at the convective scale, the need for running NWP with model resolutions less than a few kilometers to adequately resolve the dynamical processes relevant for predicting convection, accurately representing physical processes in NWP, dealing with the problems of model spinup and rapid error growth at the convective scale, and so on. Although considerable progress has been made in all these aspects in the past three decades, in this review we focus on the issues of the rapid update cycle and high-resolution convective-scale data assimilation because of their high relevance to the improved nowcasting of precipitation. Recently, progress has been made in the nowcasting of other weather elements such as visibility, wind gust, and so on (Isaac et al. 2014), but not discussed here.

HOW NWP IS USED IN NOWCASTING SYSTEMS. Broadly speaking, traditional nowcasting systems based on radar echoes can be classified into two types. The least complex form of nowcasting involves predicting storm evolution by extrapolating radar reflectivity echoes with or without the use of trends in echo size and intensity. Adding a bit more complexity is the so-called expert systems[3] that attempt to nowcast storm initiation and dissipation in addition to echo extrapolation. An example of systems of the first type is Thunderstorm Identification, Tracking, Analysis and Nowcasting (TITAN; Dixon and Wiener 1993). TITAN is an object-based tracking software that identifies areas of precipitation that are defined by a threshold. Other extrapolation techniques, such as the Corridor Integrated Weather System (CIWS; Evans and Ducot 2006), use spatial correlations between successive images to find storm motions. The skill of extrapolation-based techniques decreases rapidly with increasing forecast length. Attempts to improve the skill by trending storm growth rates did not improve this decrease in skill (Tsonis and Austin 1981). Recently, Radhakrishna et al. (2012) analyzed the scale dependence of the predictability of precipitation growth and decay and concluded that the growth and decay may be predictable up to about two hours for scales larger than 250 km.

Since it has been shown repeatedly that NWP models generally produce superior quantitative precipitation forecasts (QPFs) than nowcasting systems beyond a few forecast hours, it is logical to blend radar echo extrapolation with a numerical model to generate a seamless 0–6-h forecast. Nowcasting and Initialization for Modeling Using Regional Observation Data System (NIMROD; Golding 1998) was likely the first system that blended radar echo extrapolation with a numerical model. For the first hour nowcast, the extrapolation of the observed precipitation field was given full weight, and it was gradually relaxed with increasing lead time to where the model eventually received full weight. Figure 1 shows an example of forecast skill[4] versus forecast length for extrapolation (black line), NWP (blue line), corrected NWP (green line), and extrapolation blended with corrected NWP (red line). It should be noted that Fig. 1 (and other skill score figures in this paper) does not include confidence intervals.

[1] Heuristic is defined as forecast rules based on experiment, numerical simulation, theory, and forecast rules of thumb.

[2] Throughout this paper, the term "high resolution" is used to mean horizontal grid spacing less than 4 km.

[3] In nowcasting, an expert system is a computer system that emulates the decision making of a human expert. Predictors are knowledge based and obtained from conceptual forecast models, forecaster experience, statistics, and research studies.

[4] Different skill scores are used in Figs. 1, 2, 4, 5, and 6, and these skill scores are computed with different domain sizes and at different regions and times. They are not intended for comparison between each other; rather, each figure is only meaningful within its own context.

Although not ideal, they suffice to serve the main purpose of this review article. Improvement in the use of appropriate metrics of forecast skill for convective precipitation prediction is one of the areas that deserve attention in the future, and some discussions will be given in the last section. Figure 1 is based on skill scores for July 2012 for the eastern two-thirds of the United States obtained from the aviation forecast system called Consolidated Storm Prediction for Aviation (CoSPA; Pinto et al. 2010). Extrapolation is based on the CIWS algorithm, while the 3-km High-Resolution Rapid Refresh (HRRR) model supplies the model forecast data. The corrected NWP is the HRRR model after intensity and position errors have been corrected through comparison with extrapolation. Blended forecasts evaluated in Fig. 1 were generated by blending the CIWS extrapolation forecasts with the corrected HRRR model forecast data. Figure 1 shows that after five hours the model skill, while low, exceeds that of extrapolation. The corrected model forecast skill exceeds that of extrapolation at a forecast lead of four hours. Key to this level of model skill is the fact that latent heat estimated from radar reflectivity data is used to provide the model improved initial conditions wherever storms are present. The blending of the corrected model forecasts with extrapolation forecasts allows for a smooth transition from the extrapolation to model forecasts. Similar figures have been shown for numerous years starting with Browning (1980), Doswell (1986), and Austin et al. (1987). A recent paper by Sokol and Zacharov (2012) described a new blending method that assimilates the extrapolated radar reflectivity using a nudging technique. The primary two points from Fig. 1 are the rapid decrease in extrapolation skill with increasing forecast length and the low skill afforded by all techniques for lead times greater than three hours. The decrease in skill by extrapolation is related to the size and organization of the precipitation [Wilson (1966) and reproduced in Wilson et al. (1998)].

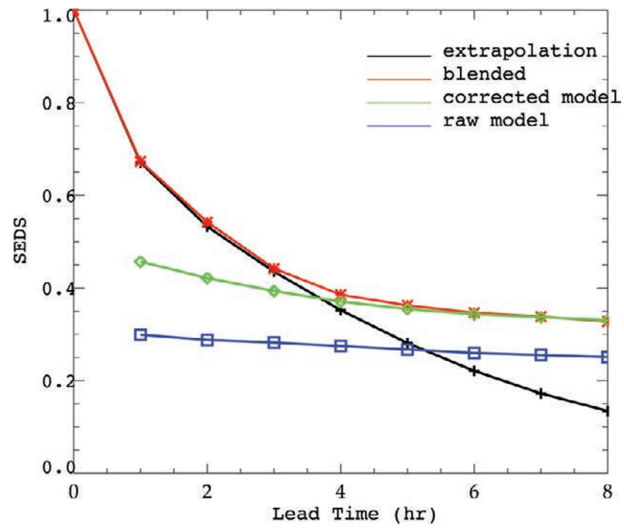

Fig. 1. Forecast skill of vertical integrated liquid (VIL) with the threshold of 1.5 km m^{-2} (corresponding to ~25 dB*Z*) as measured by symmetric extreme dependency score (SEDS; Hogan et al. 2009). The blue, green, black, and red curves show the skills of HRRR, corrected HRRR, CIWS, and the blending of the latter two, respectively, over the month of July 2012 for a partial U.S. domain east of 105°W longitude.

Improved nowcasts beyond a few tens of minutes require predicting storm initiation, growth, and decay. Expert systems have only shown improved skill during the first hour over extrapolation by predicting storm initiation, growth, and decay when the location of boundary layer convergence lines are included (Roberts et al. 2012). Current observational networks primarily designed for synoptic forecasting generally cannot provide the environmental conditions with the temporal and spatial resolution required by nowcasting. As an alternative, analyses from NWP models are often used to supply atmospheric stability conditions and the location of large-scale convergence zones important for convective initiation. The detection of mesoscale boundary layer convergence lines is essential to determining the specific location of convective initiation. Although areas of boundary layer convergence are often evident in radar data as thin lines in clear-air radar reflectivity and convergence lines in Doppler velocity, it is not straightforward to automatically detect these areas and the clear-air coverage is often limited to within 50–70 km or so from the radar. Using a large set of predictor fields and manually inserting the location of boundary layer convergence lines in NCAR's AutoNowcaster (ANC) (Mueller et al. 1993), Wilson et al. (2004) demonstrated an ability to predict storm initiation up to one hour in advance. The ANC system uses fuzzy logic[5] to combine predictor fields that reflect the atmospheric environmental conditions and boundary layer forcing based on observations and numerical models. Active research is being conducted to show the inadequacy of the current operational models to provide accurate high-resolution information of the atmospheric

[5] Fuzzy logic is a probabilistic method to combine storm predictors that are specified based on conceptual models of storm evolution.

stability, such as convective available potential energy (CAPE), convective inhibition (CIN), and humidity, for the nowcasting application. Research is also being conducted to determine if ANC nowcasts of storm initiation, growth, and decay can be improved utilizing analyses of high-resolution boundary layer convergence and vertical motion obtained from a four-dimensional variational data assimilation (4D-Var)-based technique that assimilates Doppler radar data on a 15-min update cycle (Sun et al. 2010).

In the paper reporting on the Beijing 2008 Forecast Demonstration Project, Wilson et al. (2010) summarized that significant improvement in the nowcasting of convective storms depended on methodologies that combined extrapolation, expert systems, and numerical model. It was speculated that the assimilation of high-resolution radar data into numerical models was required if NWP was to be useful in the blending process. One exception where NWP by itself may provide quality predictions for the nowcast period without the aid of convective-scale observations is for strongly forced synoptic situations where local influences are at a minimum (Stensrud et al. 2009).

HIGH-RESOLUTION AND RAPID CYCLE NWP. To meet the need of nowcasting, numerical models have to be run at resolutions of a few kilometers. Wilson and Roberts (2006) found that the 10-km Rapid Update Cycle (RUC10) 3-h forecasts (issued every 3 h) of precipitation initiation during the International H2O Project (IHOP_2002; Weckwerth et al. 2004) were correct at predicting areas of convective initiation only 13% of the time. Although there are several possible factors that can limit the model's ability to predict precipitation initiation, insufficient model resolution could well be one of them. In the last few decades, the steady increase of computing power has made it possible to run operational NWP models with horizontal resolutions in the range of 1–4 km. Models with such resolutions enable the explicit representation of the convective processes without the need of cumulus parameterization schemes and hence are often referred to as "convection-permitting" or "convection-allowing" NWP. It was shown by several studies that forecasts from the convection-permitting models produced more skillful guidance than those from a coarser-resolution model employing convective parameterization (e.g., Done et al. 2004; Kain et al. 2006; Weisman et al. 2008; Clark et al. 2009). Kain et al. (2006) reported that a 4-km Weather Research and Forecasting Model (WRF) run during the spring program 2004 conducted by a joint effort of the Storm Prediction Center (SPC) and National Severe Storms Laboratory (NSSL) received higher ratings than the operational Eta Model on subjective performance measures related to convective initiation, evolution, and mode. More detailed examinations by Weisman et al. (2008) showed that the convection-permitting forecasts often realistically represent the initiation, structure, and evolution of mesoscale convective phenomena.

Although the improved ability of high-resolution NWP in predicting precipitation initiation and structure is notable (cited above), the improvement is inadequate for the nowcasting application due to two general issues. One of them is the inherent model spinup issue that appears when a NWP model is initialized by interpolating a coarser-resolution analysis to a high-resolution grid (e.g., the so-called cold start initialization) due to the initial condition's inability to represent the physical processes at the convective scale. The typical spinup period for a convection-permitting model is 3–6 h, making the forecast in this period useless for the nowcasting purpose. Beyond the spinup period, NWP models often have some ability to forecast the initiation and mode of convection, but the accuracy (i.e., storm location and timing) often cannot satisfy the needs of nowcasting. Weisman et al. (2008) found, from a subjective comparison of the high-resolution model results to the guidance offered by the operational Eta Model, that the former did not suggest improvement in forecasting the location and timing of the convective systems.

To reduce the period required for model spinup, rapid update cycles are employed in some NWP models to provide the forecast model with a "warm start." Benjamin et al. (2004) described the National Centers for Environmental Prediction (NCEP) operational RUC system that provides frequently updated forecasts by assimilating the latest available observations each hour using the three-dimensional variational data assimilation (3D-Var) technique. [See the next section for descriptions of data assimilation (DA) techniques.] A rapidly cycled 3D-Var system based on WRF was also implemented by the Beijing Meteorological Bureau (BMB) during the 2008 Summer Olympics and has been running operationally since then. It was necessary to apply the digital filter initialization (DFI; Lynch and Huang 1992) to suppress the noise caused by the dynamical imbalance associated with the frequent updates (Benjamin et al. 2004; Huang et al. 2007).

The rapid update cycling reduces the spinup issue such that convective storm initiation can be predicted in the first few hours of the forecast, which results in improved precipitation forecast skill in the nowcasting range. Several studies have shown the benefit of the rapid update cycling in improving convective precipitation forecast skills (i.e., Benjamin et al. 2004; Sun et al. 2012). Figure 2 compares the precipitation skills of three experiments from Sun et al. (2012) conducted over a 1-week period during the IHOP_2002: a cold start initialization by interpolating 1° Global Forecast System (GFS) analysis to a WRF 3-km grid; a similar experiment but using 40-km Eta Model instead of GFS; and a WRF 3D-Var initialization updated every 3 h on the 3-km grid by assimilating only conventional observations. The precipitation skill in Fig. 2 is measured by the fractions skill score (FSS; Roberts and Lean 2008) with a radius of influence of 50 km. It clearly shows the improvement by the 3-hourly cycled 3D-Var initialization. Figure 3 gives an example of the forecasted precipitation patterns from the three experiments at $t = 3$ h. The GFS initialized forecast (Fig. 3c) barely shows any precipitation in the precipitation area indicated by the stage IV analysis (Fig. 3a). The Eta Model initialized forecast (Fig. 3b) spins up a precipitation band by this time, but the pattern deviates from the observed. The rapid cycling warm start experiment produces the precipitation with improved location as early as $t = 1$ h and shows a closer resemblance to the observed pattern at $t = 3$ h (Fig. 3d). As will be discussed in the next section, adding radar observations will further improve the skill of the precipitation forecast.

Several operational and research centers are running convection-permitting NWP models that are equipped with DA schemes with rapid update cycles. Some of them are listed here: the rapid cycled WRF with 3D-Var that is operationally run at the Beijing Meteorological Bureau (Wang et al. 2013a); the Met Office Unified Model with 3D-Var operating at the Met Office and Bureau of Meteorology, Australia (Ballard et al. 2012a); the NCEP 3D-Var–based gridpoint statistical interpolation (GSI) coupled with WRF and operated by National Oceanic and Atmospheric Administration/Earth System Research Laboratory (NOAA/ERSL) (Alexander et al. 2012); Center for Analysis and Prediction of Storms (CAPS) 3D-Var

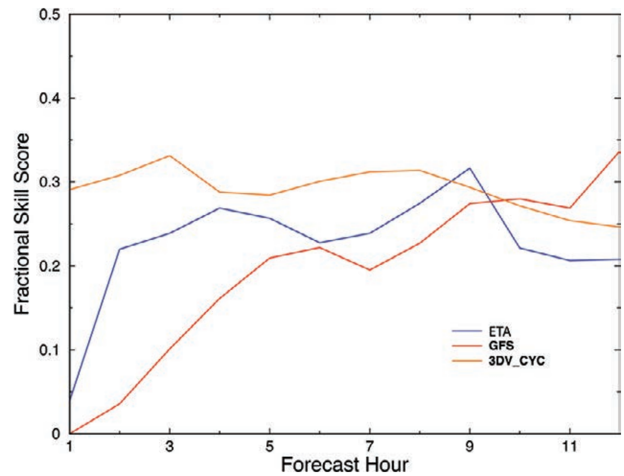

Fig. 2. FSSs of hourly accumulated precipitation from three forecast experiments using WRF. Experiment ETA was run with initial conditions from 40-km Eta Model analysis, experiment GFS from 1° GFS analysis, and experiment 3DV_CYC from WRF 3D-Var 3-hourly cycled analysis without radar DA. The skill score is computed for the threshold of 5 mm with a radius of influence of 50 km over 11 retrospective forecasts between 11 and 15 Jun 2002 during IHOP_2002.

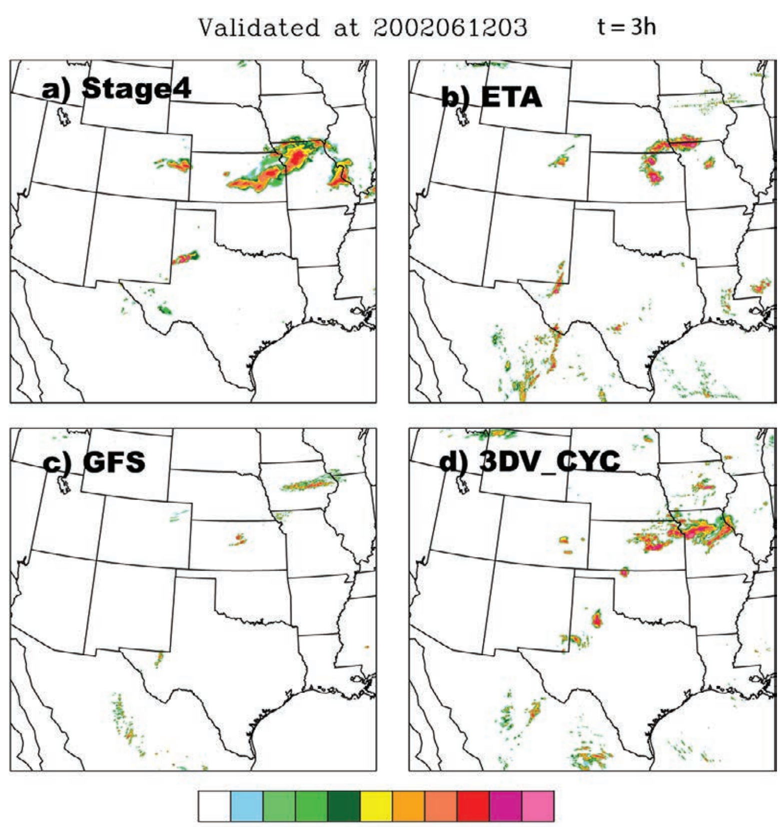

Fig. 3. Comparison of precipitation (mm h^{-1}) patterns at $t = 3$ h from the three experiments of (b) ETA, (c) GFS, and (d) 3DV_CYC in Fig. 2. (a) The Stage4 analysis is shown for verification. The plots are valid for 0300 UTC 12 Jun 2002.

system developed for the Advanced Research and Prediction System (ARPS) model (Gao et al. 2004); Météo-France 3D-Var system coupled with the Application of Research to Operations at Mesoscale (AROME) model (Caumont et al. 2009); a Newtonian nudging-based system for the Consortium for Small Scale Modelling (COSMO) model operating at the German Meteorological Service (DWD) (Stephan et al. 2008); and the Local Analysis and Prediction System (LAPS) developed by NOAA/ESRL (Albers et al. 1996). These systems are run with 1.5–4-km horizontal resolutions and 1–3-h rapid update cycles, assimilating radar observations using different techniques.

DATA ASSIMILATION AT THE CONVECTIVE SCALE. Traditional nowcasting techniques largely relied on radar observations because Doppler radar is the only operational instrument that can frequently sample the detailed structure of convective storms. It has been recognized that the effective use of radar observations to initialize NWP models is one of the keys to the success of the explicit prediction of convective storms (Droegemeier 1990; Lilly 1990). Doppler radars provide three-dimensional high-resolution observations of the atmosphere at the convective scale, but these measurements were limited to radial velocity and variables associated with hydrometeors. Hence, earlier works that began in the 1990s focused on the proof-of-concept studies to investigate whether it was feasible to retrieve the full three-dimensional wind and temperature field from radial velocity observations of single-Doppler radar (e.g., Sun et al. 1991; Qiu and Xu 1992; Shapiro et al. 1995; Gao et al. 1999) and the microphysics from reflectivity observations (e.g., Sun and Crook 1997, 1998). The promising results from these studies encouraged efforts on the assimilation of radar observations into operational NWP models using various DA techniques. While advanced DA techniques, such as 4D-Var and ensemble Kalman filter (EnKF), showed promise and are being actively studied for radar DA, other relatively simple yet computationally efficient techniques are also quite popular. In the following, we provide a brief review of some DA techniques that are used at the convective scale.

Diabatic initialization based on reflectivity. The simplest way to use radar observations for the initialization of an NWP model is to extract information from reflectivity data. The radar reflectivity can be linked to hydrometeor content or precipitation rate through theoretical or empirical relations. Latent heat released by condensation can be estimated from derived hydrometeor content or precipitation rate. Further, the humidity can be specified by assuming saturation wherever the reflectivity exceeds a prespecified value (Wang et al. 2013a). Techniques to assimilate these estimated quantities from reflectivity are developed for operational models, including latent heating nudging (e.g., Jones and Macpherson 1997; Stephan et al. 2008), diabatic digital filter initialization (DDFI; Weygandt et al. 2008), and complex cloud analysis (e.g., Albers et al. 1996; Xue et al. 2003; Hu et al. 2006a). These techniques, in one way or another, apply the concept of diabatic initialization (Krishnamurti et al. 1991) in which the diabatic effect is accounted for through the assimilation of latent heat and/or humidity estimated from radar reflectivity observations (and often also from satellite and surface observations) by assuming saturation in cloud regions. It has been demonstrated that the diabatic initialization techniques based on reflectivity data are able to reduce the precipitation spinup problem and hence improve the forecast skill at least in the first few hours (e.g., Hu et al. 2006a; Stephan et al. 2008; Weygandt et al. 2008; Dixon et al. 2009; Schenkman et al. 2011a,b; Wang et al. 2013a). Figure 4 gives an example of the improved precipitation forecast skill when latent heat nudging based on reflectivity observations was used in NCAR's Real-Time Four-Dimensional Data Assimilation (RTFDDA; Liu et al. 2008) system with a 3-km grid spacing, for a 1-week period on a domain over the Front Range of the Rockies. The hourly accumulated precipitation forecast skill, as measured by FSS, from the experiment with radar reflectivity assimilation is initially significantly higher than that without reflectivity. The skill, however, decreases rather quickly in the first five hours, likely due to the lack of convective-scale dynamical response in the initialization. The RTFDDA with latent heat nudging is running operationally at a proving ground of the U.S. Army Testing and Evaluation Command, and the real-time performance is being evaluated.

The assimilation techniques based on the diabatic initialization provide practical and computationally efficient ways to use information contained in reflectivity observations for the improvement of NWP precipitation forecast in the nowcasting range. Several operational centers, including the Met Office of the United Kingdom and DWD of Germany, operate rapid cycle systems that include reflectivity data assimilation through the diabatic initialization.

Variational radar DA. The above techniques for reflectivity data assimilation are often combined with a 3D-Var technique that is capable of assimilating radial velocity observations. The 3D-Var is currently a commonly used data assimilation technique by operational NWP systems because of its computational efficiency and its ability to assimilate various indirect observations (such as satellite radiance and radar radial velocity). To assimilate radar radial velocity and reflectivity in a 3D-Var system, the original cost function is modified to include additional observation terms that measure the discrepancy between the model-derived radial velocity and reflectivity and the respective observations. Direct assimilation of radar reflectivity through the 3D-Var cost function can only have minimal impact because the three-dimensional balances used in 3D-Var techniques cannot fully represents those in the convective scale and hence storms may not be effectively sustained. Therefore, a common practice is to include the diabatic initialization using one of the techniques mentioned in the previous section to enhance the impact of the reflectivity observations. Encouraging results from 3D-Var radar DA have been shown through case studies and real-time demonstrations as well as operations (Gao et al. 2004; Xiao et al. 2005, 2007; Hu et al. 2006b; Hu and Xue 2007; Xue et al. 2008; Kain et al. 2010; Rennie et al. 2011; Sun et al. 2012).

The impact of radar DA on short-term precipitation forecasts using WRF initialized by the 3D-Var developed at CAPS of the University of Oklahoma (Xue et al. 2003; Gao et al. 2004) is shown by Fig. 5, which compares the Gilbert skill score (GSS) of three model runs for the threshold of 2.5 mm over 36 forecasts starting at 1200 UTC from 15 April to 6 June 2008 (run only during weekdays). There was no continuous rapid cycling in this real-time exercise, which is believed to be the cause of the rapid drop of skill as can be observed in Fig. 5. However, the skill scores clearly show the benefit of assimilating radar observations. The 3D-Var system includes a diabatic initialization scheme via the cloud analysis method described by Hu et al. (2006a). More detailed description of the real-time exercise for storm prediction during the NOAA Hazardous Weather Testbed 2008 spring experiment can be found in Xue et al. (2008) and Kong et al. (2008). Similar operational systems that assimilate radial velocity and reflectivity using a 3D-Var with the aid of a diabatic initialization have also shown some success, including the Met Office 3D-Var (Ballard et al. 2012a,b) and WRF 3D-Var (Sun et al. 2012; Wang et al. 2013a).

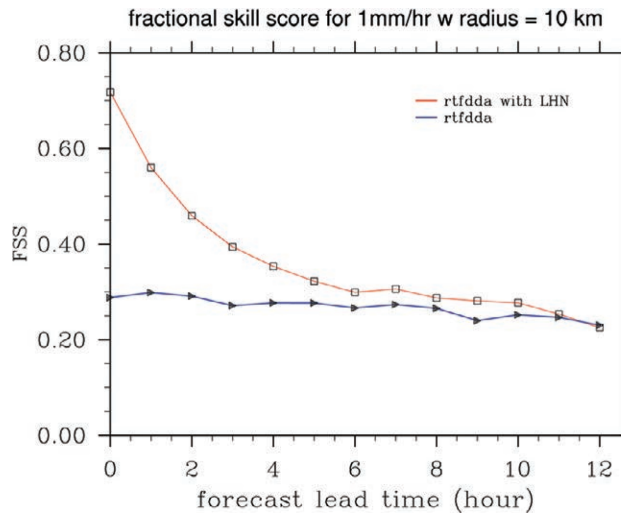

Fig. 4. FSSs of hourly accumulated precipitation from two WRF runs over a Front Range domain initialized with RTFDDA without (blue) and with (red) radar reflectivity nudging. The FSS is computed for the threshold of 1 mm with a radius of influence of 10 km over 24 forecasts from 11 to 17 Jun 2009.

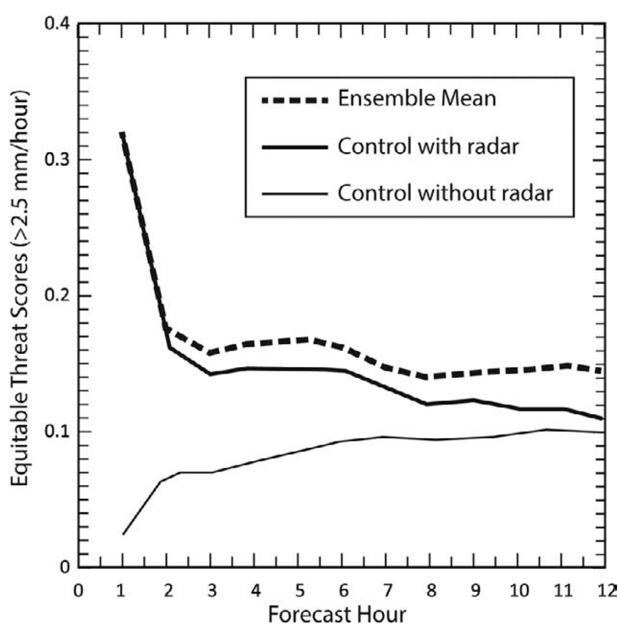

Fig. 5. Equitable threat scores (ETS) for hourly accumulated precipitation (>2.5 mm) from two forecast experiments at 4-km grid spacing, with (thick solid line) and without (thin solid line) radar radial velocity and reflectivity DA using the ARPS 3D-Var DA system and the Advanced Research core of WRF forecast model (ARW). The ETSs are computed over 36 forecasts between 15 Apr and 6 Jun 2008 (no forecast on weekends) over a domain covering 80% of the continental United States. The thick dashed line shows the ETS for the ensemble-mean precipitation over nine ensemble members with radar DA.

While the studies described above have shown that the assimilation of the radial velocity is technically feasible in 3D-Var, critical questions remain as to how the 3D-Var technique can retrieve the unobserved tangential wind component. Sugimoto et al. (2009) demonstrated, using an observing system simulation experiment (OSSE) and WRF 3D-Var, that the 3D-Var technique has a limited ability in retrieving the tangential wind when a radar network only has single-Doppler coverage. They found that the retrieved tangential component only had a correlation of ~0.4 with the simulated observations. In contrast, some previous studies (e.g., Sun et al. 1991; Sun and Crook 1994) have suggested that 4D-Var has a good ability in retrieving the unobserved tangential component of wind.

The basic concepts of the 3D-Var and 4D-Var are the same except that the 4D-Var technique employs an additional set of prognostic equations as a strong constraint. Moreover, the 4D-Var minimizes a cost function that is defined over a time window, and hence it uses data at more than one time step to produce an analysis. Since the 4D-Var technique can use a full NWP model that includes the time tendency term as the constraint, it can potentially be a superior technique for the convective-scale DA because convective weather has a large temporal change that can cause significant errors if neglected. The capability of the 4D-Var technique in radar DA was demonstrated in several studies by Sun et al. (1991) and Sun and Crook (1997, 1998), using a cloud-scale model with warm rain physics and its adjoint. Sun (2005) and Sun and Zhang (2008) showed that analyses by 4D-Var radar DA successfully initialized convective storms and hence improved their forecasts. A 4D-Var radar DA system has recently been developed for WRF, assimilating both radial velocity and reflectivity with an adjoint model that includes microphysics. Initial tests in a case study showed that the system had a good potential to improve 0–6-h forecasts of convective storms (Sun and Wang 2013; Wang et al. 2013b). Figure 6 shows a comparison of precipitation forecast skills (FSS with a radius of 8 km) between WRF 4D-Var, WRF 3D-Var, and an enhanced WRF 3D-Var by a diabatic initialization scheme. It clearly shows that the initial analysis skill by the 4D-Var is maintained during the 6-h forecasts and, in contrast, the skills of the 3D-Var schemes decrease in the first forecast hour due to dynamical readjustments. Sun and Wang (2013) found that the WRF 4D-Var was able to analyze the low-level cold pool as well as the midlevel latent heating, while the enhanced 3D-Var missed the low-level cold pool.

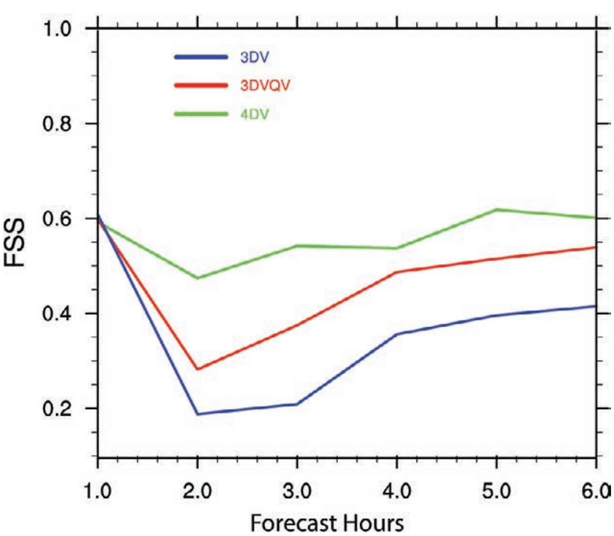

Fig. 6. FSSs for hourly accumulated precipitation (>5 mm) from three forecasts using WRF initialized with radar observations via WRF 3D-Var (blue), WRF 3D-Var with a diabatic initialization (3DVQV), and WRF 4D-Var for the squall line case of 12 Jun 2002 occurred during IHOP_2002.

Some early implementations of the 4D-Var technique for high-resolution operational models have shown encouraging results. The Japan Meteorological Agency (JMA) has been running a mesoscale 4D-Var system, assimilating hourly precipitation data analyzed by the JMA's radar network and automated meteorological data acquisition system with a 5-km resolution. It was reported that the threat score of the 4D-Var in the preoperational experiments significantly surpassed those of the routine system (Koizumi et al. 2005) even beyond the nowcasting range. The upgrade to a convection-permitting nonhydrostatic model (JMA-NHM; Honda et al. 2005) that assimilates radial velocity and reflectivity is planned and is now in the research mode. Kawabata et al. (2007, 2011) reported promising results in two case studies using the new 4D-Var radar DA system. Since the end of March 2012, the Met Office has been running a real-time demonstration hourly cycling 4D-Var system over a domain covering southern England and Wales. The forecasts were made available for assessment during some of the many flooding events in May–November 2012 and during the 2012 London Summer Olympics. This system currently assimilates radar radial velocity in the 4D-Var, but the reflectivity is assimilated with a diabatic initialization (Jones and Macpherson 1997; Dixon et al. 2009; Ballard et al. 2012a,b). The 4D-Var analysis uses a 3-km grid, whereas the forecast is conducted with a 1.5-km version of the unified model. There were some spectacular successes (e.g., the outbreak of a line of thunderstorms on 28 May 2012 that produced flooding and lightning; see Fig. 7). In this case, the 4D-Var system correctly initiated the storms when nothing was present at $T + 0$. In the example shown, the 5-h forecast from the hourly cycling 4D-Var system has a very good forecast of the location of the line of convection (Fig. 7a), the 5-h current operational blended nowcast has nothing (Fig. 7c) because the latest U.K. 4-km forecast from 0300 UTC that it was blended with had no convection at 1500 UTC, and the latest available forecast from the 3-hourly cycling 1.5-km 3D-Var has some convection but too far east and not extensive enough (Fig. 7d). The hourly cycling 4D-Var system is able to assimilate Doppler radial wind observations from five radars, 6 times per hour, as well as other observations from wind profilers and satellites every 15–60 min. For the case presented here, the improved forecast does not come from radar observations because there was not much radar data at the initialization time. In other cases, however, the benefit of the radar assimilation can be seen with the skill of the location of convection increasing at successively shorter lead times. From subjective and objective assessment of the forecasts, it is clear that in some cases the impact of the hourly cycling 4D-Var is limited by the small domain size as the weather systems are advected in and out of the forecast domain so it is hoped to extend the system to cover the whole United Kingdom.

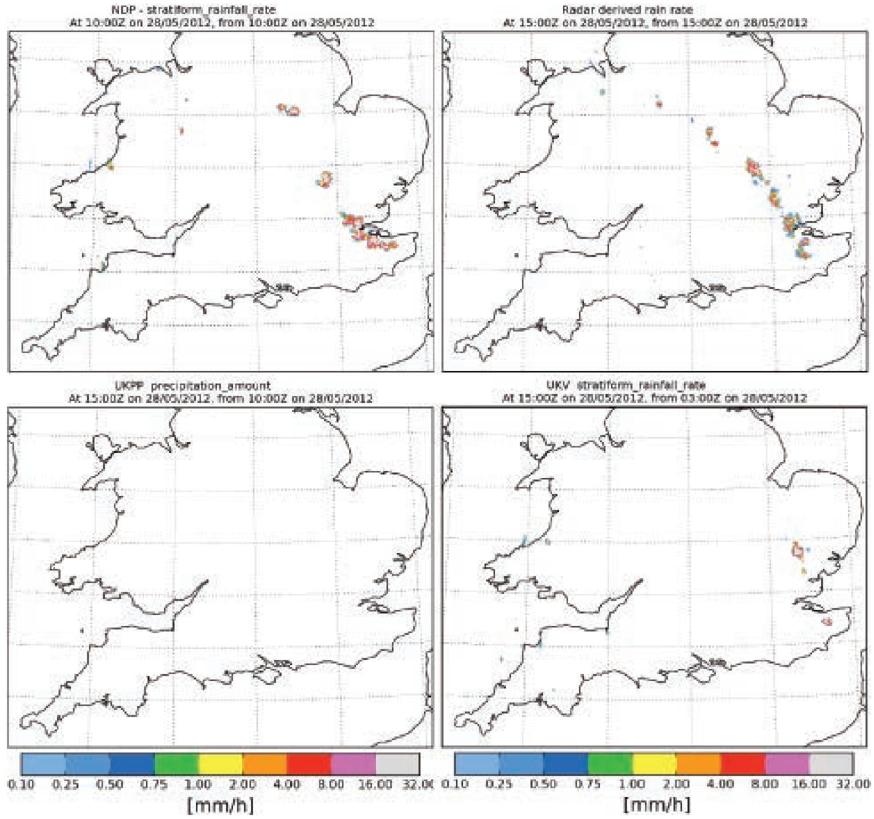

Fig. 7. Comparisons of (b) the observed U.K. radar derived surface precipitation rate at 1500 UTC 28 May 2012 with (a) the 5-h forecast from the 1000 UTC Met Office 4D-Var hourly cycling 1.5-km NWP system, and (c) the current operational nowcast from 1000 UTC using extrapolated radar derived rain rates blended with a 4-km resolution U.K. forecast from 0300 UTC, and (d) the latest available real-time forecast from the 3-hourly cycling with 3D-Var 1.5-km U.K.-wide system that is a 12-h forecast from 0300 UTC. The figure shows the comparison on the domain of the hourly cycling Met Office NWP system.

There is no doubt that we are only in the early stage to demonstrate the capability of the 4D-Var technique in initializing high-resolution operational models. However, we anticipate that more operational testing will be conducted in the next decade for nowcasting applications to confirm the ability of the 4D-Var technique in improving convective forecasting. The 4D-Var technique has been successfully used for large-scale models and longer-term forecasts in several of the major operational centers throughout the world, including European Centre for Medium Range Weather Forecast (ECMWF), Met Office, Japan Meteorological Agency, and Environment Canada. For the convective scale, however, the progress is slow, although its potential has been shown through case studies and real-time demonstrations described above. Besides the high computational cost to run a high-resolution 4D-Var system, the main obstacle is its large demand in resource to develop and maintain a 4D-Var system. This is due to the need for an adjoint model and the potential difficulties dealing with highly nonlinear yet very important microphysical processes in the adjoint model at the convective scale (Zou 1997). Although these issues are not insurmountable, some operational centers opt to develop the four-dimensional analysis system based on the EnKF approach, which requires much fewer resources to develop and maintain compared to a 4D-Var system.

EnKF radar DA. The EnKF DA method was applied to the convective-scale radar DA initially by Snyder and Zhang (2003) for an "identical twin" problem with a perfect prediction model and simulated radial velocity observations, after promising results were shown by Evensen (1994) and Houtekamer and Mitchell (1998) for large-scale problems. Unlike the traditional Kalman filter that explicitly evolves the background error covariance in time using a covariance prediction equation (e.g., Evensen 1992), the method uses a forecast ensemble to evolve and estimate flow-dependent background error statistics through the DA cycles. Zhang et al. (2004) further showed that the initial position error of a storm can be effectively corrected by the EnKF DA cycles, producing analyses with good quality. The ability of the EnKF in accurately analyzing microphysical species associated with a multiphase ice scheme, and in assimilating reflectivity observations, was first demonstrated by Tong and Xue (2005) using a fully compressible cloud model and simulated radar observations. EnKF was shown to be able to reestablish the model storm after a number of assimilation cycles, and the best results were obtained when both radial velocity and reflectivity data, including reflectivity information outside of the precipitation regions, are used.

The application of EnKF to real observations also showed progress in recent years. Dowell et al. (2004) first applied the EnKF technique to real radar observations and obtained EnKF analyses of vertical velocity and vorticity within a supercell storm that are similar to those of dual-Doppler analyses. Tong (2006) documented difficulties in maintaining accurate prediction of an EnKF-analyzed supercell storm beyond 30 min for a supercell storm. Lei et al. (2009) demonstrated the importance of including surface mesonet data to obtain an improved 1-h prediction of a tornadic supercell storm, indicating the importance of accurate analysis of both convective-scale storms and their mesoscale environment.

One challenge for the application of EnKF to the convective scale is to properly account for model errors because the nonlinear error grows rapidly in a convective system and the EnKF technique relies on the model to produce flow-dependent error covariance. Several studies examined methods to properly account for model errors within the EnKF system for the convective-scale DA. Increased covariance inflation using various methods can help make the ensemble spread more consistent with the ensemble-mean error (e.g., Dowell and Wicker 2009), while the use of multiple microphysics schemes in the forecast ensemble has also proven to be beneficial (Snook et al. 2011). Figure 8b shows a 2-h precipitation forecast of the tornadic mesoscale convective system studied by Snook et al. (2011). Comparing with the observed storm (Fig. 8a), the ensemble-mean forecast predicts the dominant convective mode reasonably well and the location of tornadic mesovortices with some success, which is a great improvement over a control that does not use radar observations (not shown). An alternative approach is to correct model error through parameter estimation. Tong and Xue (2008a,b) showed that it is possible to estimate

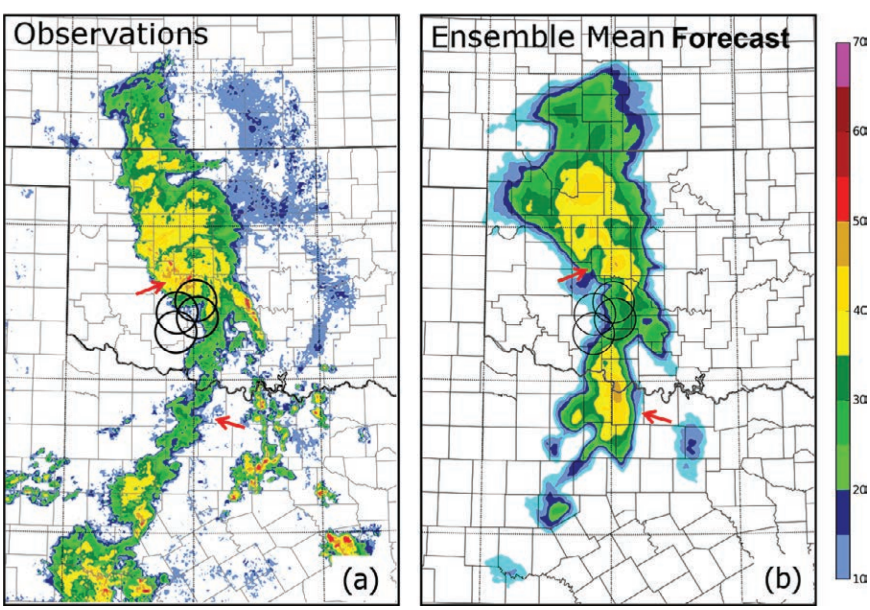

Fig. 8. (a) Reflectivity observations of a tornadic storm at 0400 UTC on 9 May 2007 in Oklahoma; (b) 2-h ensemble-mean forecast from 40 members initialized by an EnKF. The black circles indicate the ranges of Engineering Research Center for Collaborative Adaptive Sensing of the Atmosphere (CASA) X-band radars that are also assimilated in the experiment.

parameter uncertainties associated with microphysical species within an ice microphysics scheme together with the state estimation using EnKF, although the estimation becomes more difficult when multiple parameters contain error. The addition of polarimetric radar measurements is shown to improve the parameter estimation as the measurements provide an additional observation constraint on the estimation problem (Jung et al. 2010).

EnKF has been shown to have a particular strength in handling complex physical processes. Xue et al. (2010) showed that both mixing ratios and the total number concentrations of multiple microphysical species of a two-moment microphysics scheme can be successfully "retrieved" from radar radial velocity and reflectivity data using EnKF. For a real case, Jung et al. (2012) further demonstrate the ability of EnKF in properly estimating microphysical state variables when using a two-moment microphysics scheme; in such a case, the EnKF system is even able to capture polarimetric radar signatures within a supercell storm. More accurate EnKF analysis of another real storm using a two-moment microphysics scheme is documented in Stensrud et al. (2012).

Although encouraging results of EnKF have been shown for convective-scale DA, further development and evaluation are necessary to prove the ability of EnKF in improving 0–6-h precipitation nowcasting before it can be used operationally. An advantage of EnKF over 3D-Var and 4D-Var is that it is able to produce an ensemble of analyses that can serve as initial conditions for ensemble forecasting. This has been successfully demonstrated by Aksoy et al. (2010), Snook et al. (2012), and Dawson et al. (2011) for convective storms and by Zhang et al. (2011) and Dong and Xue (2012) for hurricanes. A relatively new, promising approach that attempts to combine the strengths of variational and ensemble methods is the hybrid DA method that utilizes ensemble-derived flow-dependent error variance within a 3D-Var or 4D-Var framework. Preliminary studies have been conducted recently using such an approach (Li et al. 2012) and demonstrated promise.

FUTURE CHALLENGES. Although significant progress has been made in using NWP models toward the nowcasting application, there are still many challenges ahead of us. We discuss three of them in this section: the predictability of precipitation systems, the need for improved mesoscale observation networks, and the improvement of rapid update NWP and DA systems.

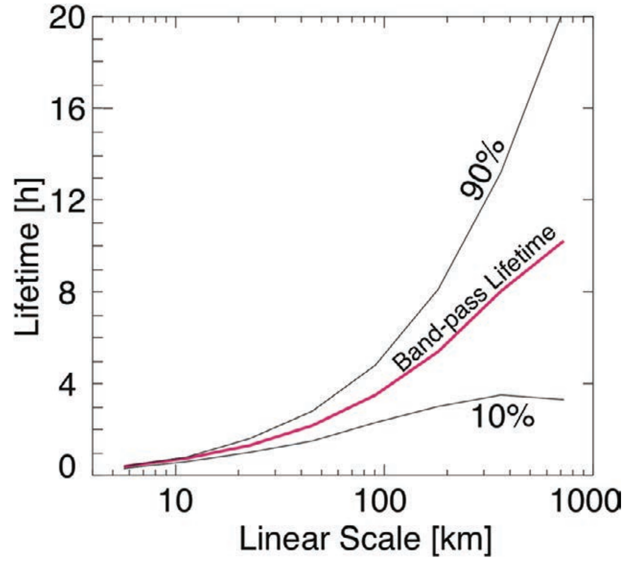

Fig. 9. Scale dependence of wavelet bandpass lifetime of fields of reflectivity (dBZ). The average over 1,424 h of warm season radar rainfall data and the 10th and 90th percentiles are shown.

Predictability of precipitation systems. Lorenz (1969)'s theoretical study on the predictability of flows with many scales was widely accepted as a reference for understanding the range of predictability of atmospheric motion. Recently, Germann et al. (2006) examined the predictability of precipitation and its scale dependence based on the lifetime of precipitation patterns derived from continental-scale radar images. The lifetime of rain patterns is defined here as the time at which a given scale in the precipitation field decorrelates to 1/*e* in coordinates moving with the precipitation. Thus, if the nowcast method is simply Lagrangian persistence (LP), such as the McGill Algorithm for Precipitation Nowcasting by Lagrangian Extrapolation (MAPLE; Turner et al. 2004), the predictability for a given scale is its lifetime. Figure 9 shows the lifetime as a function of scale computed from 1,424-h warm season rainfall datasets from U.S. radar composites (Germann et al. 2006). Here, wavelet decomposition was used for scale decomposition of reflectivity (dBZ). As seen, the smallest scales resolvable by radar data (a few kilometers) have a lifetime of less than one hour with very little variability. As scales increase, their lifetime increases and becomes more and more case dependent. The simplest way of increasing nowcasting skill is by filtering out the smallest scales of precipitation. This is sometimes done inadvertently when two methods of forecast are blended: the blending process may eliminate small scales. As shown in Germann et al. (2006), there is also a strong dependence on geographic location, with the central United States having the highest lifetime and Florida the lowest. To a good extent this can be attributed to the diurnal cycle of precipitation and the advection of precipitation patterns across the continent as described in Carbone et al. (2002) and Surcel et al. (2010). Predictability also strongly increases with the strength of large-scale forcing that organizes precipitation spatially. This is true for NWP as well as for LP. Thus, it should not be surprising that predictability by MAPLE and NWP is in fact correlated: more persistent systems are more organized, have greater areal coverage, and are more predicable by the two methods of forecast.

The most likely origin of the scale dependence of precipitation predictability discussed above is the small-scale variability of low-level humidity as well as wind and temperature (Weckwerth 2000; Ge et al. 2013). Current observation networks are clearly inadequate to address these small-scale variations. This implies that it would be difficult for either extrapolation-based nowcasting techniques or NWP models to forecast convective storms with scales less than ~30 km beyond 1–2 h. The improvement of nowcasting through enhanced data assimilation and NWP models would be most possibly seen beyond the 1–2-h forecast range. Sun et al. (2012) found that the impact of the assimilation of Doppler radars had a clear diurnal variation in a consecutive 6-day forecasting experiment during IHOP_2002 with a larger impact on the forecasts starting at evening and smaller impact on the forecasts initialized at early morning. A possible cause for such a variation is because nighttime convective systems are more organized and have larger-scale patterns than those in the early morning for the study period. The more organized systems are better initialized as a result of more Doppler radar data coverage and they are intrinsically more predictable.

The temporal variability of predictability means that the usefulness of convective-scale forecasts will vary from day to day, dependent on the strength of the larger-scale forcing. This temporal variability is apparently a result of the intrinsic uncertainty of the convective precipitation processes. This argues for an inherently probabilistic approach to forecasting at this scale. Several operational centers are currently developing or testing ensemble prediction systems based on the convection-permitting models. Given the inherent uncertainty of convective systems and the temporal variability of predictability, research is required to answer the question how to discriminate the scales that are predictable from those that are not as a function of lead time. Data assimilation techniques should be developed to optimize the predictable scales with available observations while quantifying the uncertainty of the unpredictable scales.

Needs for improved mesoscale networks. One of the challenges of mesoscale (rapid update cycling) analysis and forecast systems is to provide them with a sufficient amount and spatial coverage of observations of high spatial and temporal resolution. Detailed observational information on moisture, wind, and temperature in the boundary layer and the midlevel is considered to be particularly relevant for constraining the initial state of mesoscale models. In past years, much progress has been made in the assimilation and impact assessment of radar precipitation, reflectivity, and radial wind velocity data, using a variety of assimilation techniques. However, Doppler radars have a limited ability in detecting mesoscale environmental conditions (because of the lack of reflectors) that are critical for a successful analysis that leads to improved precipitation forecasts beyond just a few hours. Dabberdt et al. (2005) summarized the observational needs for improved nowcasting, including enhanced surface network, polarimetric radar, enhanced Doppler radar coverage by integrating Weather Surveillance Radar-1988 Doppler (WSR-88D), Terminal Doppler Weather Radars (TDWR), and X-band radars, and profiling the boundary layer. Other operational observation types that have been shown to be beneficial in mesoscale rapid update cycling systems are the Global Navigation Satellite System (GNSS) meteorological network, ground-based GPS receiver, satellite IR/visible imagery, and aircraft data. For each of these data sources, a strict quality control and bias treatment is of critical importance to achieving a positive impact in mesoscale analysis systems. Several new (not yet operational) data sources, like Mode-S aircraft observations or boundary layer water vapor lidars, seem very promising for operational use in mesoscale rapid update cycling systems and deserve to be studied further.

Improvement of DA and rapid update NWP. While variational and ensemble-based DA methods have shown great promise, including measurable impacts in real-time storm-scale forecasting, many challenges remain to obtain optimal, well-balanced, dynamically consistent state estimations in the presence of complex model physics and to produce accurate and well-calibrated deterministic and ensemble forecasts. The dynamically consistent initial conditions (i.e., produced by 4D-Var; Sun and Wang 2013) are able to maintain the forecast skill of the initial convection, avoiding the rapid drop as shown by some of the simpler methods. The challenges are both theoretical and practical. Theoretical challenges include the best approaches to dealing with model error, and effective ways of ameliorating the impact of sampling error, proper fitting of the analysis to dense observations, while correcting errors at multiple scales (Lorenc 2003). Data quality control, bias removal, nonlinearity, and non-Gaussian error are other aspects that require careful research. Given the predictability issue of the precipitation systems described above, it is important to design a data assimilation system that aims to resolve the predictable scales while accounting uncertainties of the unpredictable scales.

Practical issues include the design and implementation of computationally efficient algorithms that can execute fast enough on large parallel computers so as to produce rapidly updated forecasts that meet the needs of nowcasting and very-short-range forecasting of severe storms. We envision that the 4D-Var and hybrid of variational method and EnKF hold great promise for the future improvement of NWP for the convective scale because of their abilities in obtaining initial conditions that contain convective-scale balances. However, both approaches require further development and research to make them computationally efficient for operational implementations. The sub-hourly rapid update cycling is another development that is required by the nowcasting application, which is currently still unachievable in most of the operational systems that are mainly 3D-Var based.

Improvement of convective-scale modeling is no doubt another area that is required for the successful application of NWP for nowcasting. The performance of NWP can be quite sensitive to physical parameterizations of microphysics, planetary boundary layer, and land surface characteristics even in the very short range. Further research is needed to examine the sensitivity of these processes and their parameterization schemes in high-resolution rapid cycled NWP.

Another area that is not addressed in this paper but deserves attention is the proper evaluation of the performance of NWP and nowcasting skills for QPF. The use of the appropriate metrics of forecast skill and careful application of statistics are important to determine where and when improvement occurs and how much confidence can be assigned to the improvement. New methods and metrics have been developed in recent years (Gilleland et al. 2009) and they should be more widely implemented by the nowcasting community in the future.

The use of NWP for nowcasting precipitation will experience continued rapid development in the decades to come. While the traditional nowcasting techniques will continue to be developed, they will more and more depend on the short-term high-resolution NWP that is initialized by radar observations. The combination of the two techniques as described in the first section will be the key to producing seamless nowcasting that takes advantage of both techniques. With the continued improvements of high-resolution data assimilation, numerical modeling with rapid cycles, and computation efficiency, it is anticipated that the precipitation nowcasting skill by NWP will continue to be improved, giving an increased weight in the blended nowcasting. The greatest challenges are to skillfully handle the predictability issue that is scale dependent, to improve mesoscale observations especially in the lower levels, and to produce initial conditions that are dynamically balanced at the mesoscale and convective scale.

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