The Numerical Prediction of Severe Convective Storms: Advances in Research and Applications, Remaining Challenges, and Outlook for the Future

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Key Points

- Improved accuracy and timeliness of high-impact severe weather forecasts will yield substantial benefits across many sectors of society.
- Significant progress has been made during the past 30 years in improving the accuracy and timeliness of forecasts of high-impact severe weather, including tornadoes, hail, damage winds and flooding.
- Existing challenges could be overcome via further increases in model and data assimilation efficiency, use of new high-resolution remote-sensing radar and satellite data, and application of machine-learning methods to both data assimilation and numerical prediction.

Synopsis

Accurate and reliable short-range forecasts of hazardous convective weather save lives and reduce property loss. Considerable progress has been made over the past 30 years in improving high-impact severe weather forecasts, including forecasts of hail, damaging winds, flooding, and low-level mesocyclones associated with tornadoes. This progress has primarily been driven by advances in three areas: convective scale Numerical Weather Prediction (NWP) models, high-density storm-resolving observations, and data assimilation (DA) methods. In the development of convective scale NWP models within the US, many early modeling efforts focused on the simulation of convective scale phenomena in idealized environments. Then during the past few decades, the Advanced Regional Prediction System (ARPS) and Weather Research Forecast (WRF) models were developed with the express purpose of forecast applications using real observations. These two model systems inspired a wide variety of research and applications to advance short-term severe weather forecasts. The implementation and ongoing upgrades of the Weather Surveillance Radar-1988 Doppler (WSR-88D) radar network and launch of the Geostationary Operational Environmental Satellite R-series (GOES-R) also have improved short-term severe weather forecasts by providing convective-scale detail for the model initial conditions. Research on variational and ensemble DA methods, especially for the assimilation of radar and satellite data, has further led to significant progress in improving severe weather forecasts. Looking ahead, research leading to better representation of cloud and microphysical processes in NWP models, proper hybridization of ensemble variational DA methods for convective scale phenomena, and effective use of machine learning to improve storm-scale DA and forecast models hold great promise for further improving both the accuracy and efficiency of short-term thunderstorm forecasts.

Introduction

The concept of using "computers" to predict weather (Richardson, 1922; Richardson and Lynch, 2007) predated the emergence of the first electronic, Turing-complete digital computer by some two decades (e.g., Mauchly, 1980). Such computations involve dividing the relevant region of the atmosphere, and possibly other Earth components such as the surface and sub-surface, into an array of discrete points or volumes. At these locations, highly complex equations representing the three wind components, temperature, pressure, liquid and frozen water species, such as rain, hail and snow, solar and terrestrial radiation, surface vegetation, ice and water, and turbulence, are solved in a series of discrete steps that proceed forward in time. Such computations require the most powerful computers available in order to project solutions forward for a sufficiently long period of time, and with the density of the points or volumes at which the weather is computed being sufficiently fine to capture the relevant phenomena of interest.

Today, both numerical weather prediction (NWP) models, and their more complex Earth system model cousins, continue to be among the world's foremost drivers of high-performance computational systems (e.g., Shuman, 1989; Deconinck et al., 2016; Balaji et al., 2017). Numerous NWP models are run at operational centers across the globe, producing forecasts valid for a few hours out to two weeks or even to several months, on scales ranging from local and regional to global (e.g., Kalnay, 2002; Bauer et al., 2015). Such models also are used routinely for research by academic and other institutions, and for commercial purposes, owing to ready access to significant computational resources available locally and via national centers and cloud providers.

During the past few decades, grid spacings in operational NWP models have become ever finer owing to dramatic increases in computational capabilities. Such operational models now marginally resolve deep moist convective storms and their larger aggregates (e.g., Potvin et al., 2019). Not only does 1 km model grid spacing resolve (though marginally so; Bryan et al., 2003) highly energetic local weather, but coarser spacings between 4 and 10 km reside in a "grey zone" for which no meaningful closure assumptions exist for sub-grid scale processes or cloud and precipitation parameterizations (Belair and Mailhot, 2001).

Reliable short-term severe thunderstorm warnings and forecasts, including quantitative precipitation forecasts with NWP models, are fundamentally important to meet society's growing need for actionable weather information. These warnings and forecasts could significantly increase the likelihood of reducing loss of life and property damage from high-impact severe weather phenomena such as flash flooding, large hail, tornadoes, and strong winds—all of which occur worldwide. The explicit numerical prediction of severe thunderstorms, originally considered highly improbable according to classical predictability theory (e.g., Lorenz, 1963a,b, 1969, Lorenz, 1965), was first demonstrated by the Center for Analysis and Prediction of Storms (CAPS), one of the National Science Foundation's first Science and Technology Centers established in 1989 (e.g., Lilly, 1991; Droegemeier, 1997). Subsequent research conducted at CAPS, the National Center for Atmospheric Research (NCAR), the National Oceanic and Atmospheric Administration (NOAA) National Severe Storms Laboratory (NSSL), and other institutions has revealed both the promise and challenges of such prediction.

Predicting deep convective storms with a numerical model benefits tremendously, in most cases, from observations having 3D spatial resolution similar to that of the model. Recognizing this fact, significant progress has been made during the past 30 years, particularly in real time access to high-resolution Doppler radar data (Kelleher et al., 2007), and to high-resolution satellite data from the Geostationary Operational Environmental Satellite R-series (GOES-R)-16/17 (Goodman et al., 2019). Concomitantly, considerable research advances have occurred in assimilating remote sensing data, especially from Doppler radars (e.g., Sun, 2005), for improving model microphysical schemes (e.g., Morrison et al., 2020; Mansell et al., 2010), and also in providing computational, networking, and data storage capabilities needed to attain the spatial resolutions ($\sim$1 km) required to resolve individual convective elements.

All of these advances have illuminated the extraordinary societal benefits of high-resolution storm-resolving forecasts, ultimately leading to the concept and program of "warn-on-forecast" (WoF; Stensrud et al., 2009, 2013). Here, warnings of hazardous weather would be issued not based solely on direct observations (e.g., from radars, human spotters), but also upon short-term NWP forecasts that can provide longer forecast and warning lead times. Indeed, in recent years, the experimental WoF analysis and forecast system developed at NSSL has demonstrated the capability of forecasting the probability for severe weather hazards associated with individual thunderstorms up to 6 h (Heinselman et al., 2024). While improvements to forecasts of severe weather are important, the effective communication of this information to the public is also a critical component of the forecast (i.e., warning process) For this reason, the WoF program is engaging social and behavioral scientists to understand how increased warning lead times may alter public response, especially in unexpected ways (e.g., Hoekstra et al., 2011; Wilson et al., 2021, 2024).

Various convective-scale NWP models and data assimilation (DA) systems have been developed globally, reflecting international efforts to enhance weather prediction capabilities. In Japan, the Meteorological Agency operates a regional mesoscale ensemble prediction system with the aim of supporting disaster prevention and short-range precipitation forecasts (Ono et al., 2021). Similarly, the United Kingdom's Met Office has pioneered the development of a four-dimensional variational data assimilation (4DVAR) and forecast system, with a resolution of about 1 km, specifically designed for short-term severe weather forecasting (Milan et al., 2020). Meanwhile, in France, a convective scale model known as "Application of Research to Operations At Mesoscale (AROME)" has been coupled with a hybrid ensemble variational DA system featuring 1.3 km grid spacing. This effort is aimed at enhancing flash flood prediction capabilities (Montmerle et al., 2018). In the current paper, we focus on reviewing the progress made in several important research areas within US that have transformed the numerical prediction of deep convective storms from vision to reality. This includes the development and refinement of convective scale NWP models, utilization of high-density storm-resolving remote-sensing data, and advancement in DA methods. We then discuss some recent results from ensemble and deterministic forecast systems. Finally, we address some remaining challenges in forecasting high-impact severe storm events and outline future work to address them.

The Development of Convective Scale NWP Models Within US

In the 1960s and early 1970s, only very idealized simulations of convective phenomena, such as precipitating clouds, were performed, usually in two dimensions (e.g., Ogura and Phillips, 1962; Orville, 1965; Takeda, 1971; Schlesinger, 1973). The earliest three-dimensional simulations of deep moist convection started in mid-1970s, with the development of three-dimensional cloud models (e.g., Steiner, 1973; Miller and Pearce, 1974; Schlesinger, 1975; Klemp and Wilhelmson, 1978) with simple warm-rain microphysics. Many more studies were conducted in the 1980s using such models (e.g., Weisman and Klemp, 1982, 1984; Rotunno et al., 1988; Cotton et al., 1982; Tripoli and Cotton, 1982). They increased our understanding of convective storm dynamics and led to the development of two widely used convective/mesoscale models with more complete/sophisticated physics parameterizations, starting in the early 1980s: the Colorado State University's Regional Atmospheric Modeling System (RAMS, Tripoli and Cotton, 1982), and the Pennsylvania State University (PSU) and NCAR Mesoscale Model (Anthes and Warner, 1978; Hsie, 1987; Grell et al., 1994). Hundreds of modeling studies with these two models were published during the 1980s and 1990s (e.g., Anthes, 1990; Pielke et al., 1992; Bossert and Cotton, 1994; Cotton et al., 1994).

Despite the success of early meso- and convective-scale models and their use to simulate severe storms like supercells, squall lines and other mesoscale phenomena, the computational requirements for running these models constrained their use in operational forecast applications. In an effort to focus considerable national resources on the convective-scale prediction problem, the National Science Foundation established CAPS in 1989. The main goal was to demonstrate the practicability of numerically predicting deep convective storms using a complete prototype convective-scale NWP system (Lilly, 1991; Droegemeier et al., 1995, 1997). This initiative led to the development of a comprehensive, three-dimensional, non-hydrostatic prediction system—the Advanced Regional Prediction System (ARPS, Xue et al., 2000, 2001, 2003), that includes full suites of physics parameterizations and DA schemes. ARPS was designed from the beginning for massively-parallel supercomputers so as to accommodate storm-scale predictions for operational testing (Droegemeier et al., 1995).

Starting from mid-1990s, CAPS devoted considerable resources to operational tests of the ARPS in collaboration with several national and international institutions, with a focus on using Weather Surveillance Radar-1988 Doppler (WSR-88D) radar observations to initialize the model (Janish et al., 1995; Droegemeier et al., 1996a,b; Xue et al. 1996a,b; Carpenter et al., 1998). Such efforts provided an early foundation for the explicit prediction of the initiation and evolution of individual convective storms. Given the intermittent and often highly localized nature of severe thunderstorm events, Droegemeier (1997) suggested that relocatable models, run "on-demand" to target areas of particularly active weather, might prove effective. This strategy has been adopted in the experimental WoF system (Stensrud et al., 2013; Gao et al., 2013; Hu et al., 2021; Heinselman et al., 2024).

In the late 1990s, a collaborative partnership was initiated to bridge the gap between the research and operational communities, recognizing the need for this unity. Several institutes, including NCAR, NOAA National Centers for Environmental Prediction, NOAA Earth System Research Laboratories (ESRL), and the University of Oklahoma (represented by CAPS), joined forces to develop the Weather Research and Forecasting (WRF) modeling system. This state-of-the-art mesoscale and convective scale NWP system was designed to serve both atmospheric research and operational forecasting applications. The PSU modeling system comprises the Advanced Research WRF (ARW, Skamarock et al., 2005) and non-hydrostatic mesoscale model (NMM, Janjic, 2003) dynamic cores. As the collaboration progressed, additional contributions came from the Federal Aviation Administration (FAA), US Air Force, and Naval Research Laboratory.

The WRF system, particularly its ARW version, is a versatile tool catering to a broad spectrum of meteorological applications, ranging from cloud to synoptic and even hemispheric scales (Powers et al., 2017). Emphasizing horizontal grid spacings of 1−10 km (Klemp, 2006), WRF has become a cornerstone in operational forecasting due to its flexibility and computational efficiency (Michalakes et al., 2004). WRF owes its adaptability to the incorporation of recent advancements in model physics, numerics, and DA, which have been contributed by developers from research and application communities worldwide. Widely adopted globally, especially in forecasting configurations, the ARW version of WRF is utilized by numerous research and operational institutes. One notable application is the High-Resolution Rapid Refresh (HRRR), a convection-allowing forecast system developed by NOAA/Global Research Laboratory. Operating on a 3-km grid spacing with hourly updates, HRRR is based on WRF ARW (Dowell et al., 2022; James et al., 2022; Weygandt et al., 2022). The WRF model has been also instrumental in short-term (0−6 hour) convective scale forecasts at a 3 km grid spacing through the NOAA/NSSL's WoF analysis and forecast system (Jones et al., 2018a, 2019, 2020;

Wang et al., 2019; Hu et al., 2019, 2021; Pan and Gao, 2022; Wheatley et al., 2015; Yussouf et al., 2015, 2016, 2020a,b; Yussouf and Knopfmeier, 2019). Another WRF version, the NNM dynamic core, was mainly developed and operationally used by NOAA/ National Centers for Environment Prediction for its Short Range Ensemble Forecast project (SREF, Du et al., 2015).

The development of unified global and regional NWP models for both the US research and operational communities is now ongoing, with leadership provided by NOAA and NCAR. A finite-volume cubed-sphere (FV3) nonhydrostatic dynamical core, originally developed by the Geophysical Fluid Dynamics Laboratory (GFDL) of NOAA (Lin, 2004), was the first model selected for use in the Unified Forecast System (UFS; https://ufscommunity.org). Following its operational use for global NWP, it is currently used in the first pre-operational version of the Rapid Refresh Forecasting System (RRFS) which covers the North America domain and be run at ~ 3 km grid spacing with hourly update as an ensemble (RRFS, Banos et al., 2022; Carley et al., 2023). The FV3 system was first tested and evaluated at convection-allowing resolutions with 3 km grid spacing in 2017, which helped establish its possible usefulness for convective-scale predictions (Harris et al., 2019; Snook et al., 2019; Zhang et al., 2019a). Additionally, NCAR has developed the nonhydrostatic Model for Prediction Across Scales (MPAS; Skamarock et al., 2018) that uses unstructured Voronoi meshes and is suitable for both global and regional applications. MPAS is now being considered for one of the next generation models within the UFS, particularly with respect to convective-scale prediction of individual thunderstorms.

Convection-Resolving Remote Sensing Observations

For accurate thunderstorm forecasts, another crucial component involves obtaining observations that are both dense and frequent enough to reveal information about the internal structure of the storm. WSR-88D (Crum et al., 1998) and GOES-R (Goodman et al., 2019) are capable of generating high-resolution observations of convection with very fine temporal (~5 min) and spatial (~250−500 m) scales. In numerous studies over the past several decades, these high-resolution observations have been assimilated into convective-allowing/resolving NWP models in real time, employing high-frequency cycles (5−15-min cycles). This assimilation process aims to provide an accurate analysis of convective thunderstorms, and the details will be discussed in **Research on Convective Scale DA** and **Highlights of Some Recent Research Progress in Severe Thunderstorm Prediction** sections. In the following, we briefly review how and when these high-resolution remote-sensing data became available and why they are so important for high-impact severe weather forecasts.

The Importance of Establishing Real-Time WSR-88D Radar Network

In the US, the most important observations that can resolve convective storms and be used for initializing convective-scale NWP are from the WSR-88D radar network. Its ~160 Doppler radars, upgraded to dual polarimetry in 2013 (Crum et al., 2013), have been used with great success in the real-time detection and warning of multi-season weather hazards, as well as for convective-scale NWP. However, accessing, receiving, and processing huge volumes of WSR-88Ds in real-time was a tremendous challenge over 20 years ago. In late 1999, several federal and state government entities, universities, and private-sector entities, including NSSL and CAPS, joined together to form the Collaborative Radar Acquisition Field Test (CRAFT) Project (Kelleher et al., 2007).

The CRAFT project essentially established the WSR-88D radars as a real-time network, providing robust real-time Next Generation Weather Radar (NEXRAD) data acquisition, archive, and dissemination services for all Level II data. The project enabled the delivery of NEXRAD data to users at a low cost by the Internet. In addition, it demonstrated that the permanent archive of Level II data at the National Centers for Environmental Information (formerly National Climate Data Center) could be more effectively accomplished via Internet-based transmission. The CRAFT testbed successfully addressed important issues for sustained research and operational use. The success of this project not only ensures that NEXRAD data, now including radial velocity, reflectivity, spectral width, differential reflectivity, co-polar correlation coefficient, differential phase and/or its range derivative, can be used in real-time by National Weather Service (NWS) forecasters issuing severe weather warnings and hazards ahead of time. It also benefits a wide range of severe weather research and applications, paving a way for future operational high-resolution local severe storm forecasts with convective-scale NWP models.

The GOES-R Series Products

In the last 50 years, observations from satellites have become increasingly important for global NWP, emerging as the dominant source of atmospheric observations assimilated by major world operational meteorological centers (Eyre et al., 2020, 2021). Among them, in a joint effort by the National Aeronautics and Space Administration (NASA) and NOAA, GOES-R series were developed, launched, and operated and have been in operation since 1975. However, due to relatively low data quality and resolution in the early years, satellite data were not used in convective scale NWP for severe thunderstorm prediction. The new GOES-R series represents significant advancements in satellite observation capabilities. The latest operational GOES-R includes GOES-16 (or GOES-West) and GOES-18 (or GOES-East). The GOES-R satellites can provide images every few minutes from 16 channels within the visible and infrared spectrum. The two primary instruments are the Advanced Baseline Imager (Schmit et al., 2017) and the Geostationary Lightning Mapper (GLM, Goodman et al., 2013; Rudlosky et al., 2019). At the time of their launchings, both sensors provided new observations and had significant potential for use in convective-scale NWP.

The data provided by the Advanced Baseline Imager is five times faster in temporal resolution and four times greater in spatial resolution, in comparison with the previous GOES satellites (Schmit et al., 2017). The more frequent updates are extremely important for thunderstorm monitoring and forecasting because they enable the nearly continuous identification and monitoring of cloud and atmospheric conditions. The Advanced Baseline Imager provides the following observations and products that are useful for thunderstorm monitoring and forecasting (https://www.goes-r.gov/products/overview.html):

Radiances: GOES-R observes radiances at high spatial and temporal resolution in 16 spectral bands. These high-resolution radiance data can help to distinguish cloudy and cloud-free regions, and provide very useful information on temperature and moisture, especially for cloud-free regions. Many studies have been done in recent years to investigate the usefulness of radiance for improving thunderstorm forecasts (e. g. Jones et al., 2018a; Zhang et al., 2018; Zhu et al., 2023).

Cloud Top: The infrared bands can be used to determine cloud top height, cloud top temperature, and cloud top pressure for a cloudy pixel and is helpful for cloud initialization in NWP models (e. g., Kerr et al., 2015; Zhang et al., 2018).

Total Precipitable Water (TPW): This derived product provides environmental information on the horizontal variation of the total moisture field, which is fundamentally important for convective scale NWP (e. g., Pan et al., 2018).

Derived Motion Winds: This product provides tropospheric wind information at high resolution over ocean and land (Goodman et al., 2019). The assimilation of this product has been shown to improve NWP forecasts of tropical cyclones (e. g., Langland et al., 2009). This product also can provide near-storm environmental wind information with high temporal frequency and high spatial resolution, making it helpful in initializing convective scale NWP models (e. g., Zhao et al., 2021a,b).

GLM Total Lightning: The instrument measures total lightning, which includes in-cloud, cloud-to-cloud, and cloud-to-ground lightning (Goodman et al., 2013), from which derived information, such as water vapor mass mixing ratio and flash extent density, can be used to improve thunderstorm forecasts (e. g. Fierro et al., 2019; Kong et al., 2022).

Other GOES-R products, such as cloud particle size distribution and estimated rainfall rate, could be useful for severe thunderstorm forecasts as well. For more information on these products, the reader can refer to GOES-R products overview (https://www.goes-r.gov/products/overview.html). In general, the GOES-R Series offers tremendous opportunities for forecasters and researchers to explore the usefulness of various new products for monitoring and predicting severe thunderstorms, complementing the National WSR-88D radar network.

Research on Convective Scale DA

In the last two sections, we reviewed the development of convective-scale NWP models and high-resolution remote-sensing observations capable of providing direct or indirect information on internal structures of severe storms. In this section, we focus on convective DA methods, which blend information from early model forecasts and observations in a natural way to produce initial conditions for numerical thunderstorm forecasts. Advanced DA methods have seen notable success at most operational NWP centers worldwide, primarily in the context of large-scale hydrostatic flows. However, extending these techniques to fine-scale non-hydrostatic flows, such as those associated with deep convective storms, presents several challenges. Firstly, the high temporal and spatial intermittency of convective storms invalidates the types of error statistics typically derived from historical data and applied to larger-scale hydrostatic flows. Secondly, assimilating high-resolution remote-sensing data into NWP models faces significant hurdles, including strong nonlinearity in the relationship between observations and model-predicted variables, such as reflectivity and dual-polarimetric radar observations, as well as lightning data from GLM (Gao and Stensrud, 2012; Fierro et al., 2019; Zhang et al., 2019b). Thirdly, convective-scale model physics used within DA systems are still under continued development, especially in addressing systematic errors in representing cloud and precipitation microphysical processes (Morrison et al., 2020). These differences drive research challenges and opportunities for future research, as many operational high-resolution DA systems still inherit methodologies developed for synoptic or large-scale applications. The progress of research and development leading to methods suitable for convective scale DA are briefly reviewed below.

Considerable progress has been made over the past three decades in convective-scale DA using variational methods, both in three dimensions and four dimensions (3DVAR and 4DVAR; e.g., Sun and Crook, 1997, 1998; Gao et al., 1999, 2004; Barker et al., 2004, 2012; Sun, 2005; Ge et al., 2005, 2011, 2012; Hu et al., 2006a,b; Xiao et al., 2007; Zhao et al., 2008; Xu et al., 2010; Michel et al., 2011; Wang et al., 2013a; Fierro et al., 2014, 2016, 2019; Wattrelot et al., 2014; Sun et al., 2010, 2014, 2016, 2020; Wang and Wang, 2017; Liu et al., 2019, 2020). Barker et al. (2004) described a 3DVAR system developed for the Penn State-NCAR MM5 model. Building on this, a variational data system was developed for the WRF model (named WRF-3DVAR, Barker et al., 2012). Xiao et al. (2007) implemented a direct reflectivity DA scheme into WRF-3DVAR. While their study showed that assimilating both WSR-88D radial velocity and reflectivity led to improved quantitative precipitation forecasts for Typhoon Rusa at landfall, the impact of reflectivity alone produced mixed results. A different approach was taken by Wang et al. (2013a), who introduced an indirect reflectivity DA scheme within WRF-3DVAR. Their approach successfully enhanced the development of convective systems and significantly improved the subsequent prediction of precipitation location and intensity in various real-data case studies. In general, WRF-3DVAR is relatively flexible and easy to use in both research and operational environments and has been operationally implemented at the US Air Force Agency and several other international agencies (Barker et al., 2012).

Another 3DVAR system was developed at CAPS for the ARPS model system, initially assimilating radar radial velocity data together with other conventional observations (Gao et al., 1999, 2004; Hu et al. 2006a,b; Zhao and Xue, 2009; Stensrud and Gao, 2010; Ge, 2011, 2012). The ability to directly assimilate reflectivity data variationally has been further developed at NSSL (Gao and Stensrud, 2012; Gao et al., 2013, 2016, 2017) and at CAPS (Liu et al., 2019, 2020). This 3DVAR system was designed for convective-scale weather. Utilizing a mass continuity equation and additional constraints incorporated into a cost function, the system produces analyses of three wind components and various other model variables. To accurately capture intermittent convective storms, Gao et al. (2004) and Schenkman et al. (2011) employ multiple analysis loops with different spatial influence scales. Ge et al. (2010) took a further step by introducing considerations for beam broadening and earth curvature into the radar radial velocity forward operator of the convective-scale DA system. The inclusion of earth curvature, in particular, was observed to significantly enhance analysis accuracy, especially for wind variables located beyond 150 km from radar positions. Additionally, Gao and Stensrud (2012) introduced a forward operator designed for radar reflectivity, leveraging a background temperature field supplied by an NWP model to facilitate automatic hydrometeor classification. The implementation of this forward operator was found to enhance the convergence of the analysis, notably reducing the spin-up problem. To improve the effectiveness of reflectivity assimilation in the 3DVAR DA system, Liu et al. (2019) introduced height/temperature-dependent hydrometeor background errors to help produce physical hydrometeor partitioning, while Liu et al. (2020) introduced several special treatments including logarithmic transform for hydrometeor control variables to help alleviate some serious problems related to the high nonlinearity of the radar reflectivity forward operator.

Research also has been conducted on convective-scale DA using the 4DVAR method, particularly by scientists from NCAR utilizing a simple cloud model and the WRF model (Sun and Crook, 1997, 1998, 2001, 2005; Huang et al., 2009; Sun and Wang, 2013). Sun and Crook (1997, 1998) showcased the feasibility of initializing state variables in a cloud-scale model through a 4DVAR that assimilates single-Doppler radar observations. The effectiveness of this system was tested in real time during various field programs, producing analyses at scales of 2−5 km (Sun and Crook, 2001; Crook and Sun, 2002). A 4DVAR for the WRF model was also developed (Huang et al., 2009) with its capability for convective-scale radar DA examined (Wang et al., 2013a; Sun and Wang, 2013). However, the inclusion of the tangent linear and adjoint models only for the Kessler warm-rain microphysics scheme was noted. Despite some encouraging results, the application of 4DVAR for convective-scale purposes has typically been restricted to simple microphysics, primarily due to the challenge of handling the strong nonlinearities associated with ice phase microphysics during the minimization process. Reported difficulties, such as slow convergence, were highlighted by Honda and Koizumi (2006) when attempting to incorporate an ice microphysics within their 4DVAR system for the JMA nonhydrostatic model.

Extensive work has been conducted over the last two decades using Ensemble Kalman filter (EnKF) methods for convective-scale DA. The earlier studies testing and evaluating EnKF assimilation of radar radial velocity and/or reflectivity data include Snyder and Zhang (2003) and Dowell et al. (2004). Within the US, four EnKF systems capable of assimilating radar data were subsequently developed for convective-scale NWP and have gained widespread use in the research community. These developers include CAPS (Tong and Xue, 2005; Jung et al., 2008a,b), NCAR Data Assimilation Research Testbed (DART, Anderson et al., 2009), PSU (Zhang et al., 2009; Weng and Zhang, 2012), and NOAA/ESRL (Hamill et al., 2011; Wang and Lei, 2014; Johnson et al., 2015; Liu et al., 2018). Houtekamer and Zhang (2016) provide a review of EnKF methods and applications in atmospheric DA. The EnKF codes developed by CAPS, Penn State and NOAA/ESRL are all based on a serial Ensemble Square Root Filter algorithm (Houtekamer and Mitchell, 2001; Whitaker and Hamill, 2002), while DART uses an ensemble adjustment Kalman filter (EAKF, Anderson, 2001). Much of the initial proof-of-concept research for WoF used DART (Yussouf et al., 2013; Wheatley et al., 2014; Jones et al., 2013, 2014, 2015, 2016) and the work has transitioned to using GSI-EnKF as the program moves towards operational testing (Skinner et al., 2018; Flora et al., 2019; Yussouf et al. 2015, 2016, 2020a,b; Yussouf and Knopfmeier, 2019; Jones et al. 2018a,b, 2019, 2020; Guerra et al., 2022; Pan and Gao, 2022; Wang et al., 2022; Heinselman et al., 2024). As another example, Zhu et al. (2023) assimilated GOES-R ABI all-sky brightness temperature data using GSI EnKF and found that frequent cycled assimilation of the data can correctly build up observed mesoscale convective storms within the model and remove spurious storms in model background effectively, leading to improved forecasts. The EnKF system developed at CAPS also has the capabilities to directly assimilate polarimetric radar data (Jung et al. 2008a,b, 2010; Putnam et al., 2019, 2021) and GEOS-R GLM lightning data (Kong et al., 2020, 2023).

In recent years, hybrid ensemble variational (EnVar) DA methods have gained substantial attention in both global and regional NWP (Lee and Barker, 2023). These methods aim to overcome limitations and leverage advantages offered by both ensemble and variational approaches (Hamill and Snyder, 2000). They have found extensive use in assimilating radar and satellite data into convective-scale NWP models (e.g., Gao and Stensrud, 2014; Wang et al., 2013b; Hamrud et al., 2015; Gao et al., 2016; Liu and Xue, 2016; 2019, 2020; Wang and Wang, 2017, 2020; Kong et al., 2021, 2023; Pan et al., 2021; Li et al., 2022). For instance, Kong et al. (2021) demonstrated that a hybrid EnKF-variational approach for the assimilation of radar data yields a better analysis compared to pure variational or pure EnKF methods for a significant severe weather day in Oklahoma. Another hybrid ensemble-3DVAR DA system has been developed over the past decade at NSSL (Stensrud and Gao, 2010; Gao and Stensrud, 2014; Gao et al., 2016; Wang et al., 2019; Pan et al., 2018, 2021). This system can assimilate Doppler radar, GOES-R derived satellite products, and other conventional data into NWP models such as ARPS and WRF. Multiple analysis loops are employed with various spatial and temporal scales to accurately represent intermittent convective storm features. This system, along with the 3DVAR component, underwent testing as part of the spring NOAA Hazardous Weather Testbed (HWT) in recent years (Wang et al., 2019; Hu et al., 2021; Gao et al., 2021, 2022; Carpenter, 2022; Carpenter et al., 2023).

Highlights of Some Recent Research Progress in Severe Thunderstorm Prediction

In the previous sections, we delved into three critical components essential for successful severe thunderstorm forecasting: the development of convective-scale NWP models, advancements in observational capabilities, and various DA methods which link the model's state variables and observations. The noteworthy progress in these domains, coupled with the substantial augmentation of computing power, promises significant improvements in short-term, high-impact severe thunderstorm forecasts. In the subsequent subsections, we highlight several recent research findings and applications pertaining to short-term severe convective storm predictions.

High-Resolution Short-Term Forecast With US National WSR-88D Radar Network

As mentioned earlier, CAPS developed the ARPS model during the 1990s and started the development of 3DVAR DA system for ARPS in the late 1990s, and EnKF in the early 2000s. These systems were designed for initializing high-resolution convective-scale thunderstorm forecasts, with a primary focus on assimilating radar data (Xue et al., 2000, 2001, 2003, 2006; Gao et al., 1999, 2004; Hu et al., 2006a,b; Tong and Xue, 2005). The 3DVAR system was designed to assimilate observations from multiple scales, including traditional sounding and surface observations sampling the larger scales, with radar data sampling the smaller scales, through the effective use of different assimilation loops (Gao et al., 2004). Additionally, an interface with the WRF model was developed for the 3DVAR system, reflecting CAPS' involvement in the development of the WRF model in the early 2000s. CAPS EnKF system also directly supports both ARPS and WRF models (Tong and Xue, 2005).

To realize the crucial value of assimilating quality-controlled, rapidly received radar data from the US national WSR-88D network, CAPS started systematic real-time convective storm forecast experiments in the spring season of 2008, after initial efforts in mid- and late 1990's (Droegemeier et al., 1996a,b; Xue et al., 1996a,b). In 2008, one member within a 10-member ensemble at 4 km grid spacing, and one forecast at 2 km grid spacing, were run with the WRF ARW model daily for 30 h, assimilated radar data. Radar data from all WSR-88D radars within a domain covering about $^2/_3$ of the continental US were assimilated using the combined 3DVAR-cloud analysis method (Xue et al., 2008). Standard quantitative precipitation verification scores suggested a significant positive impact of WSR-88D observations for up to 9 h, with relatively small score differences between the 4 km and 2 km forecasts (Schwartz et al., 2009).

Realizing the need for improved convective forecasts through accurate resolution of internal storm structures, the CAPS team conducted real-time forecasts applying 1 km grid spacing and assimilating radar data from mid-April through early June 2009 (Xue et al., 2009, 2013). The forecasts, using 9600 processor cores of a Cray XT5 supercomputer at the National Institute of Computational Science, University of Tennessee, featured daily 30-h predictions. Preparatory tests in spring 2008 marked the first instance of generating forecasts at a 1 km grid spacing for the entire continental U.S. domain. In Xue et al. (2013), a comparison of forecasts from 1 km and 4 km configurations of the WRF model demonstrates the advantage of 1 km grid spacing in resolving convective-scale structures within a long narrow squall line in the Southern Plains (**Fig. 1**A—D). In this case, using 1 km grid spacing, the model accurately captures narrow squall-line structures and predicts the bow-echo in the Missouri-Arkansas region (**Fig. 1**A vs B). In contrast, the 4 km resolution WRF model, while capturing a similar broad convection pattern, lacks many fine-scale details, demonstrating the advantage of the 1 km model grid spacing in resolving convective-scale structures (**Fig. 1**C). The 3-h forecast without assimilating WSR-88D data at 4 km resolution is notably inferior at 3 h **Fig. 1**D). CAPS real-time experiments with high-resolution convective-scale NWP (mostly with 1 to 4 km grid spacings) during the late 2000s and early 2010s suggested that the impact of assimilating data from the WSR-88D network lasts about 9 to 12 h, with the radar data influence fading away after 12 h during the 32-h forecast period (Kong et al., 2008; Kain et al., 2010). These real-time demonstrations at NOAA/HWT inspired further studies on high-resolution thunderstorm forecasts, fostering collaboration between CAPS, NSSL, and NOAA Storm Prediction Center (SPC) and resulting in many research publications (e.g., Schwartz et al., 2009; Kain et al., 2010; Clark et al., 2010; 2011, 2012; Johnson et al., 2014).

Ensemble Convective Storm Forecasts With WSR-88D and GOES-R Radiance Data

The PSU WRF—EnKF cycling DA and forecast system (Meng and Zhang, 2008a,b; Zhang et al. 2009, 2018, 2019; Weng and Zhang, 2016) was developed with WRF model ARW core. It uses the ensemble square root filter, a type of EnKF approach, proposed by Houtekamer and Mitchell (2001) and Whitaker and Hamill (2002). Initially designed to assimilate surface, wind profiler, and standard rawinsonde observations into a mesoscale domain with a horizontal resolution of 30 km (Meng and Zhang, 2008a,b), the system was expanded by Zhang et al. (2009) to incorporate the assimilation of WSR-88D radar data for simulating Hurricane Humberto with cloud-resolving modeling at a 1.5 km grid spacing for the WRF inner domain. The study revealed that the EnKF analysis, incorporating radial velocities from three radars along the Gulf coast, closely aligned with the observed best-track position and intensity of Humberto. The deterministic forecasts, initialized from the EnKF mean analysis, successfully predicted the rapid formation and intensification of the storm. Notably, this research marked the first instance showcasing the effectiveness of EnKF in assimilating observations with diverse spatial and temporal scales, achieved through the application of different localization radii. In a subsequent study by Zhang et al. (2016), the community radiative transfer model (CRTM, Han et al., 2006), a rapid forward model used to convert the model state into a corresponding set of synthetic radiances, was integrated into the PSU EnKF DA system. This study marked the first exploration of the positive impacts of GOES-R all-sky radiances on hurricane prediction through both two idealized cases and a real-data case in convection-resolving modeling.

Expanding on the initial success of the PSU EnKF DA system, Zhang et al. (2018) undertook groundbreaking research by assimilating all-sky GOES-16 ABI infrared brightness temperature observations into the WRF Model, at 1 km horizontal resolution. The study centered around a tornadic thunderstorm event spanning Wyoming and Nebraska on June 12, 2017. The assimilation of

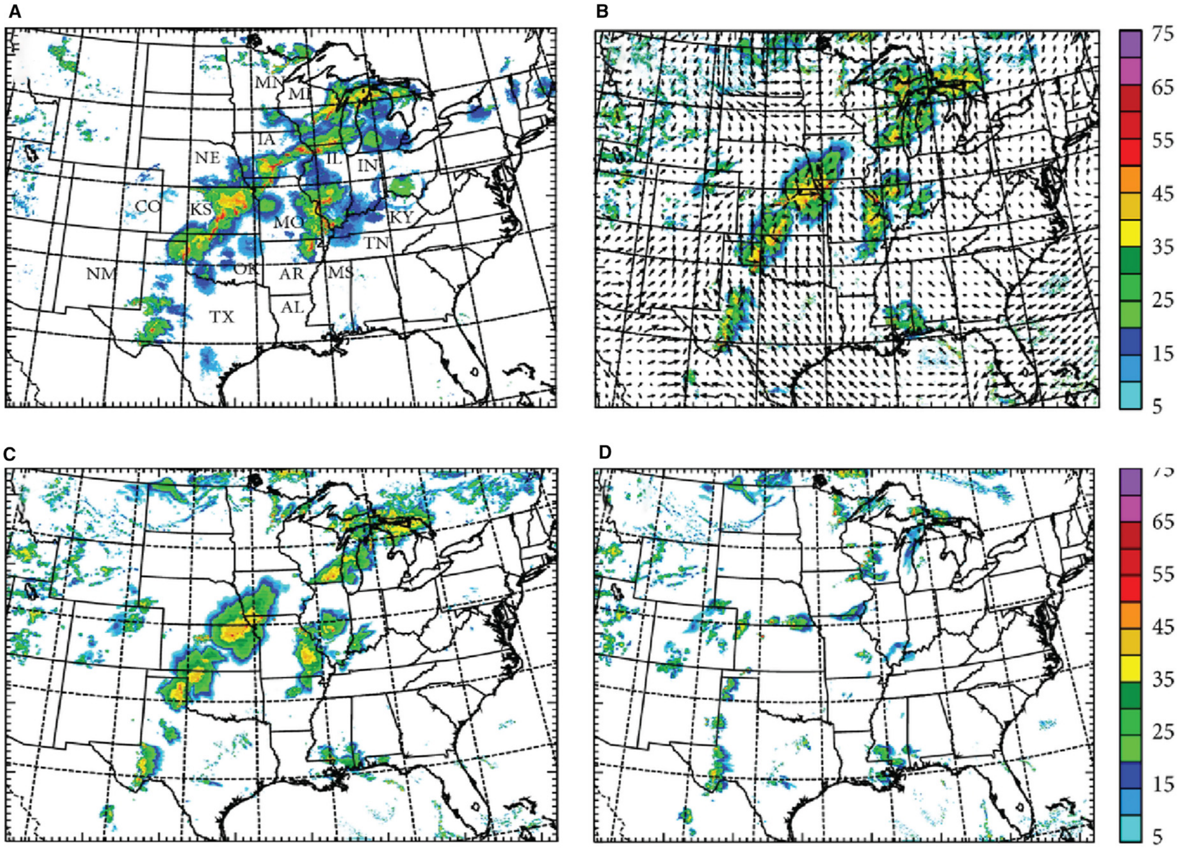

Fig. 1 Observed composite radar reflectivity at 0300 UTC, May 26, 2008 (A), and 3-h forecasts of the same field valid at the same time from (B) the 1-km resolution run with radar DA, (C) the 4- km resolution run with radar DA, and (D) the 4- km resolution run without radar DA, using the CAPS realtime variational DA and forecast system. Panel (B) includes surface wind vectors at 10 m AGL plotted at every 80th grid point. From Xue et al. (2013), Courtesy from Advances in Meteorology.

spaceborne observations from GOES-16 led to notable enhancements in forecasts, specifically improving predictions related to the timing and location of convection initiation. Additionally, both deterministic and probabilistic forecasts of midlevel mesocyclones and low-level vortices generated by the WRF Model closely aligned with reported tornado occurrences, indicating the potential to improve weather predictions of severe weather.

In a subsequent study, Zhang et al. (2019c) explored the benefits of assimilating infrared radiance observations from GOES-16 alongside WSR-88D radar observations for analyzing and predicting the same tornadic supercell thunderstorm event. The research highlighted that satellite observations could provide valuable information about clouds even before the formation of precipitation particles, particularly in instances where in-storm radar observations were not available yet. Additionally, satellite data offered insights into the broader environment surrounding the thunderstorms. The assimilation of satellite observations demonstrated the potential to extend forecast lead times for severe weather events when compared to relying solely on radar observations. Furthermore, assimilating both types of observations yielded better forecasts and longer lead times than assimilating them separately, particularly in terms of updraft helicity track forecasts, which indicate the rotational strength of thunderstorm updrafts (**Fig. 2**). This emphasized the complementary nature of satellite and radar data in enhancing the understanding and prediction of severe weather events. Recent research, exemplified by studies conducted by Eure et al. (2023) and Mykolajtchuk et al. (2023), has shifted its focus toward leveraging satellite and clear-air WSR-88D observations to enhance predictions of convection initiation. Results from a realtime application of the PSU EnKF ensemble DA and forecast system can be found in Zhang et al. (2023).

Ensemble Forecasts With WSR-88D, Cloud Water Path, and GOES-R Radiances

In the pursuit of providing accurate short-term severe weather forecasts, scientists at NSSL, as part of NOAA's WoF project (Stensrud et al., 2009, 2013), have developed an experimental ensemble analysis and forecast system known as the WoF System (WoFS, Heinselman et al., 2024). Since 2017, this system has been used experimentally in operations and during the Spring Forecast Experiment (SFE), hosted by the NOAA/HWT (Clark et al., 2021, 2022, 2023). The WoFS advances capabilities and contributes to the understanding and prediction of severe weather events. In early versions of the WoFS, the WRF model was chosen as the convective scale NWP model. For DA, the system employed the DART EAKF system developed by NCAR (Anderson et al., 2009). DART EAKF has the

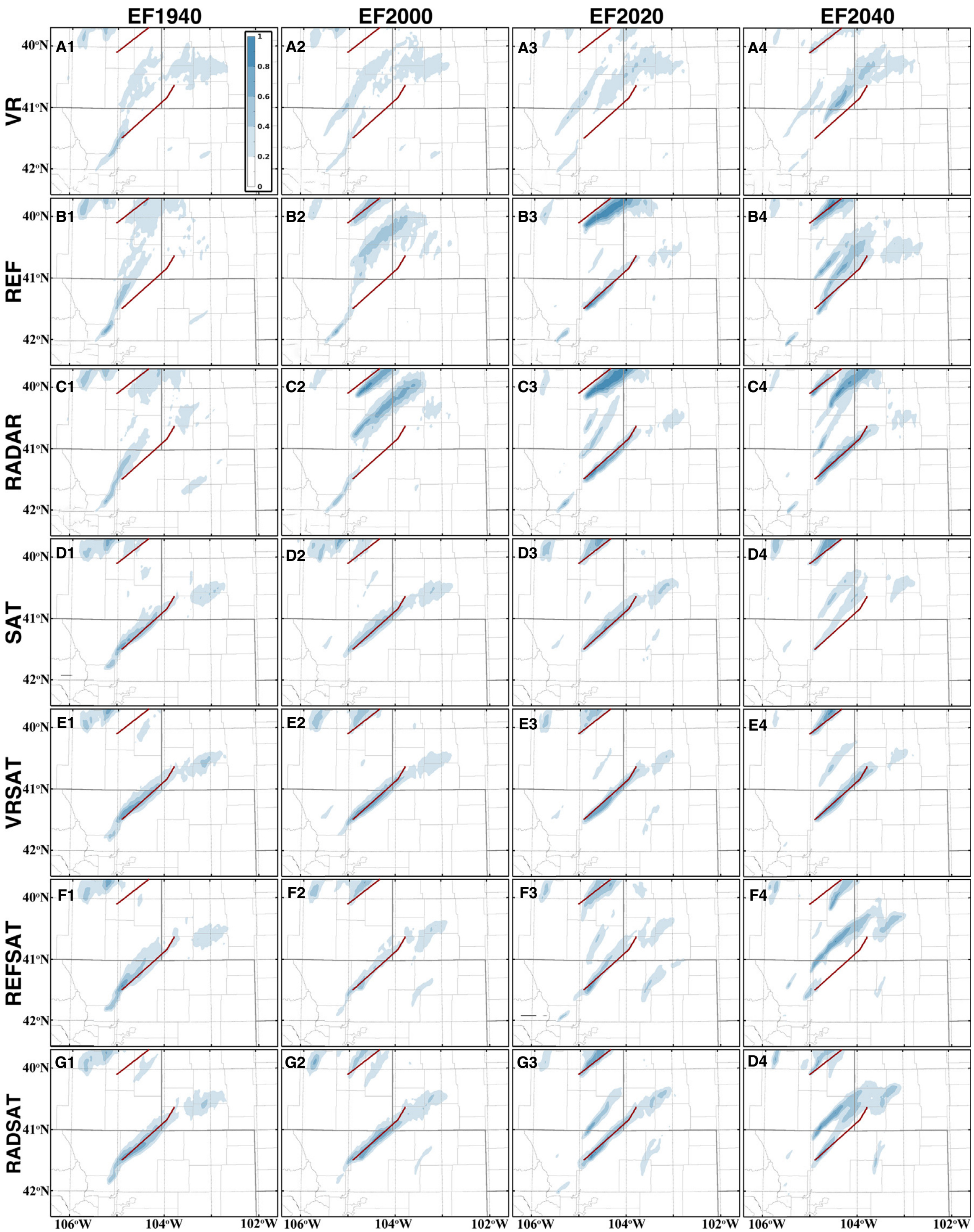

Fig. 2 Ensemble neighborhood probability of forecast updraft helicity tracks (exceeding 200 $m^2 s^{-2}$, shaded) over the period between 2100 UTC 12 June and 0000 UTC 13 June, 2017 from (A) Radial Velocity only (VR), (B) Reflectivity only (REF), (C) Radar data only (RADAR), (D) Satellite data only (SAT), (E) Radial Velocity & Satellite data (VRSAT), (F) Reflectivity & Satellite data (REFSAT), and (G) Radar & Satellite data (RADSAT) experiments using the PSU-EnKF DA and forecast system. The EF1940, EF2000, EF2020, and EF2040 represent ensemble forecasts initialized from 1940, 2000, 2020, and 2040 UTC respectively. Red solid lines are observed mesocyclone tracks identified manually from WSR-88D observations. From Zhang et al. (2019c), courtesy of the American Meteorological Society.

capability to assimilate a broad range of observations, including traditional sounding and surface observations, as well as data from the WSR-88D radars and satellite. The NSSL WoF research team extensively utilized DART EAKF to assimilate radial velocity and reflectivity data from the WSR-88D radar network. These studies demonstrated the significant improvements in short-term storm prediction achieved through the assimilation of WSR-88D radar data (Wheatley et al., 2015; Yussouf et al., 2013, 2015, 2016). Additionally, advancements were made in assimilating data from GOES-R. Jones et al. (2013) developed a forward operator for cloud water path (CWP) retrievals in DART EAKF. CWP refers to the column-integrated quantity of cloud water, encompassing both liquid and ice forms, confined between a cloud's base pressure and its top pressure. The assimilation of CWP, in addition to radar data, was shown to improve storm forecasts in severe weather events (Jones et al., 2013, 2015).

Since 2018, NSSL has incorporated GSI-EnKF into its WoFS for research and applications, following the selection of GSI-EnKF as NOAA's community-supported DA system. Some developments from the DART EAKF system were transferred to the GSI-EnKF DA system (Hu et al., 2019). With an increase in NSSL's available computational resources in 2018, the WoFS expanded from its original domain of 750 × 750 km to cover a larger area (900 × 900 km) with its traditional 3-km horizontal grid spacing and 51 vertical levels. The 2018 version of WoFS has the capability to assimilate various observations, including data from the WSR-88D radar network, GOES-R satellite, and conventional observations (such as Mesonet, Automated Surface Observing System, etc.) at 15-min intervals from early afternoon to late evening (Yussouf and Knopfmeier, 2019; Jones et al., 2020). Initial and boundary conditions are obtained from an experimental High-Resolution Rapid Refresh (HRRR) ensemble developed by collaborators from the Global Systems Laboratory (Dowell et al., 2022; James et al., 2022). The current WoFS has 36 members and is continuously cycled every 15 min for 15 h each forecast day. The WoFS generates a new forecast ensemble using the first 18 analysis members every 30 min, providing a rapidly-updating, probabilistic high-impact weather forecast out to 6 h. The ensemble approach provides not only an estimate of the occurrence of an event and its potential intensity (e.g., rotation, precipitation, winds), but also a measurement of the uncertainty associated with that event.

Recent research with the updated WoFS expanded its application to extreme rainfall events. Yussouf and Knopfmeier (2019) conducted a study focused on 0−6-h probabilistic rainfall forecasts for heavy rainfall events in 2015 and 2016. They demonstrated that the updated WoFS could predict intense rainfall at the right locations and timings, particularly during the first 0−3 h. This work, and feedback from forecasters (Yussouf et al., 2020b; Martinaitis et al., 2023), suggests the system's potential capability to help forecasters in issuing warnings or short-term forecasting of flash flood threats. Jones et al. (2020) investigated the impact of assimilating GOES-16 all-sky radiances on top of conventional, level-II WSR-88D radar data, together with cloud water path. Their findings indicated that assimilating both radar and satellite data improved forecasts compared to radar-only assimilation experiments, consistent with data-denial studies performed by Zhang et al. (2019c). Jones et al. (2020) noted that assimilating WSR-88D radar data, cloud water path, and clear-sky radiances resulted in the best overall forecast performance. This specific configuration is used in the current WoFS real-time experiments. While assimilating all-sky radiances improved convective initiation forecasts of severe storms in several instances, it may occasionally produce spurious cells (Jones et al., 2020).

WoFS has demonstrated its potential to provide accurate ensemble forecasts of storm intensity, location, timing, and rotation characteristics for various high-impact weather cases examined over the last several years. Severe weather events, including those leading to damaging winds, hail, and tornadoes, are often associated with strong rotation and updraft, which can be indicated by the updraft helicity tracks. **Fig. 3** provides several examples. In all four cases, the 6-h forecasted ensemble 90th percentile of 2−5 km updraft helicity tracks closely aligned with the NWS/SPC storm reports. For instance, the forecast initialized at 2100 UTC May 5, 2020 generated a updraft helicity track along or south of reported tornadoes and hail events near the North Carolina/South Carolina border (**Fig. 3**A). In the forecast initialized at 1900 UTC May 23, 2021, the generated track aligned with tornado and hail reports from the northeast Colorado to the southwest Nebraska, and these tornados knocked down a total of 20 power poles but produced no property damage because they occurred in open fields (**Fig. 3**B). The forecast initialized at 1900 UTC May 20, 2022, produced a updraft helicity track along the tornado damage path in central Michigan (**Fig. 3**C). This tornado caused several deaths and dozens of injuries about 50 min into the forecast. Similarly, the forecast initialized at 2100 UTC May 30, 2022 produced updraft helicity paths that covered a large area in Minnesota and coincided with reported EF3 tornadoes, damaging winds (140 mph), significant property and tree damage, and power outages. For a more detailed and comprehensive review of the WoFS development and applications, refer to Heinselman et al. (2024).

Deterministic Forecasts With WSR-88D Data, GLM Data, and Precipitable Water

Scientists at NSSL also have been involved in developing a deterministic analysis and forecast system using a 3DVAR DA approach (Gao et al., 2013; Stensrud et al., 2013). An early application of this system was a high-resolution (1 km) and high-frequency (5 min) 3D storm analysis using a weather-adaptive relocatable domain. This 3DVAR analysis system assimilates radar observations from multiple WSR-88Ds and results indicate an ability to identify robust mid-level circulations embedded within thunderstorms (Gao et al., 2013). During the NOAA HWT/Experimental Warning Program evaluation period from 2010 to 2012, the 3DVAR system was used to analyze the life cycles of 218 supercell thunderstorms on 27 event days, providing multiple products including vertical velocity, vertical vorticity, and updraft helicity to forecasters (Smith et al., 2014). The analysis of participant responses conducted by Calhoun et al. (2014) found that 3DVAR analyses were extremely useful to forecasters in blending data rather than having to analyze multiple radars separately, especially when range folding obscured the raw data from one or more radars. They also found, however, that data latency was a big issue for the real time use of this product by forecasters at that time, as the

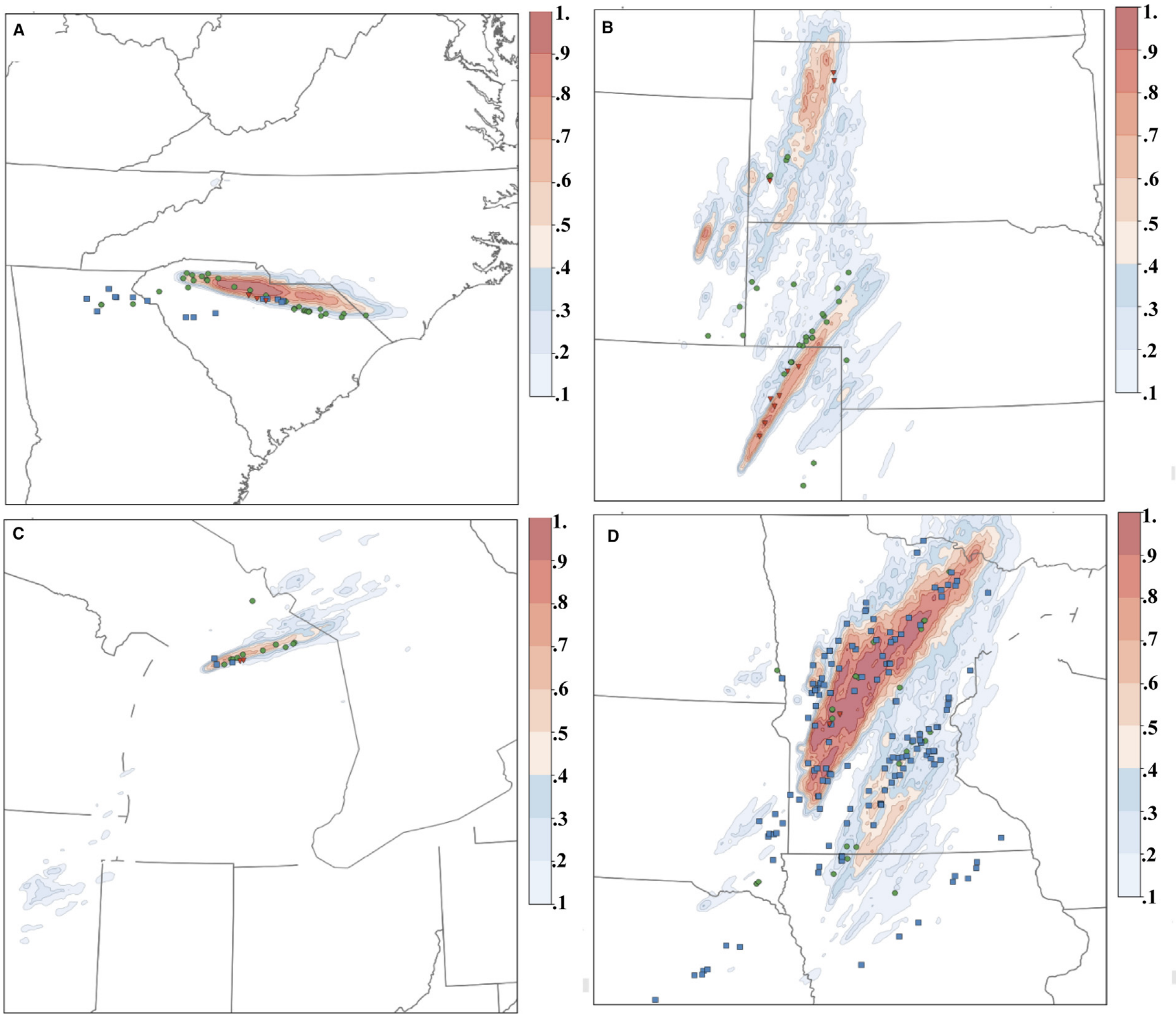

Fig. 3 The 6-h forecasts for the ensemble 90th percentile of 2–5 km updraft helicity tracks (shading) from the NSSL WoFS ensemble initialized, respectively, (A) at 2100 UTC on May 05, 2020, (B) at 1900 UTC on May 23, 2021, (C) at 1900 UTC on May 20, 2022, (D) at 2100 UTC on May 30, 2022. The red triangles, green circles, and blue squares represent observed tornados, hail, and wind damage, respectively, during the forecast periods from National Weather Service/Storm Prediction Center storm reports.

4–6 min needed to create the analysis reduces the utility of the products when new radar scans are available. We believe that with the computation power increases, the data latency issue could be significant reduced.

In recent years, the 3DVAR system has undergone upgrades to assimilate a broader range of observations. These enhancements include the assimilation of: (1) GOES-R derived CWP and TPW (Pan et al., 2018), (2) pseudo-observations for q_v derived from radar based vertical integrated liquid water (Lai et al., 2019; Chen et al., 2021; Hu et al., 2023), (3) pseudo-observations for q_v derived from GOES-R GLM lightning data (Fierro et al., 2019; Hu et al., 2020), and (4) GOES-R derived AMV (Zhao et al. 2021a,b, 2022). This 3DVAR system also incorporates ensemble-estimated covariance in a variational framework (Gao and Stensrud, 2014; Gao et al., 2016). Building on the insights gained from these studies, a real-time dual-resolution hybrid ensemble and variational WoF analysis and forecast system, referred to as WoF-Hybrid has been developed at NSSL (Wang et al., 2019; Pan et al., 2021; Gao et al., 2021, 2022). Complementing the ensemble-based WoFS, WoF-Hybrid incorporates flow-dependent background error covariances derived from the ensemble forecasts of WoFS. It provides a deterministic analysis and forecast product using 1.5 km grid spacing, serving as a supplement to the baseline WoFS, which operates using 3 km grid spacing. The assimilation is carried out through high-frequency, 15-min DA cycles, running in parallel with WoFS. To enhance the accuracy of these assimilated observations, the error statistics for these observations are adjusted and optimized based on a sensitivity study using retrospective cases from 2018 to 2019.

In 2019 SFE/HWT the above system was informally tested with the variational DA component only. The forecast performance for various high-impact severe weather events in May 2019 was reported in Hu et al. (2021); including a damaging straight-line wind event over the New England area on May 29, 2019. Fig. 4 displays 3-h forecasts of wind speeds at 500 m above ground level,

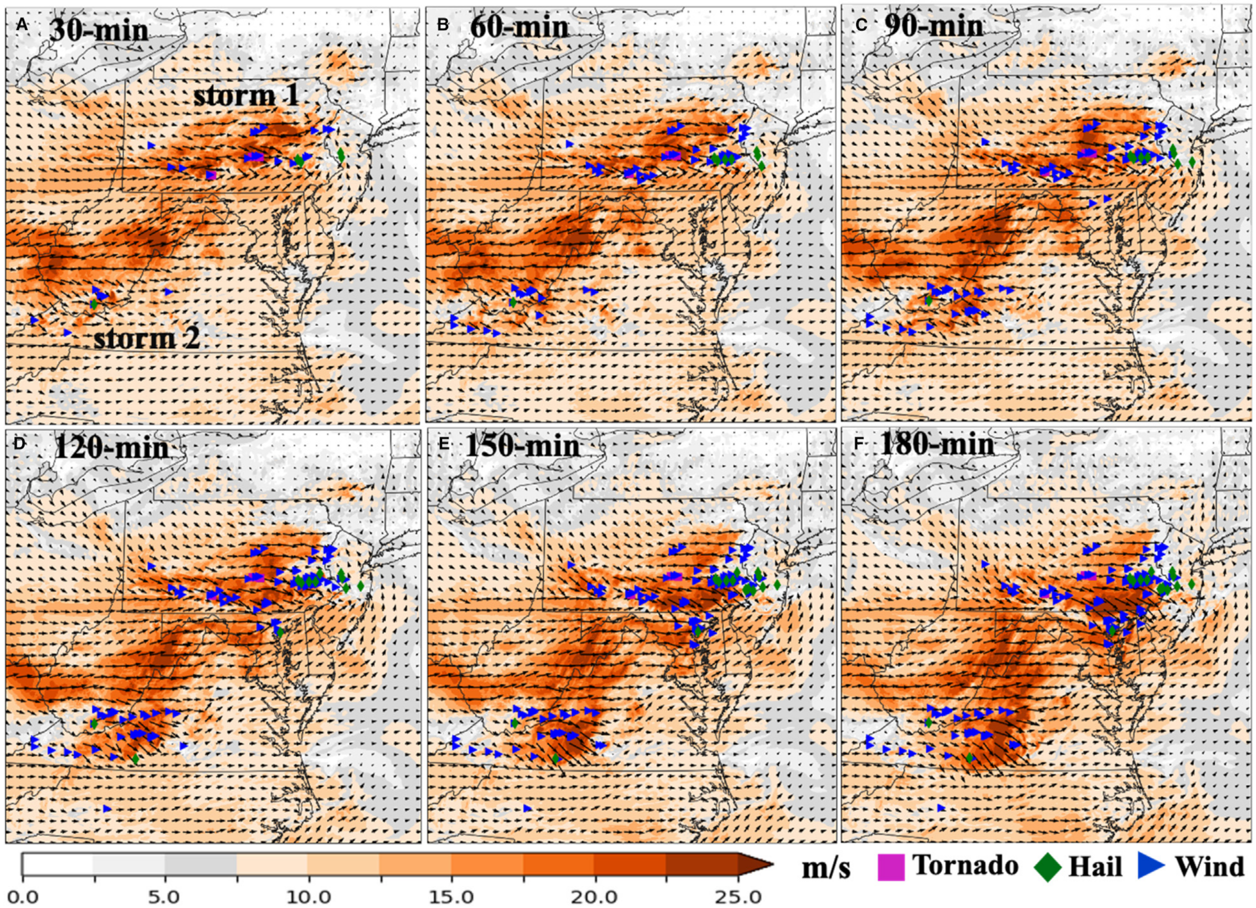

Fig. 4 The 3-h forecasts of wind at 500 m above ground level (AGL) from the deterministic WoF-Hybrid DA and forecast system, initialized from 2000 UTC May 29, 2019. It is valid for the period 2000 UTC until (A) 2030, (B) 2100, (C) 2130, (D) 2200, (E) 2230, and (F) 2300 UTC May 29, 2019. The blue triangles, green rhombi, and pink square represent observed wind, hail, and tornado damage, respectively, during the forecast periods from National Weather Service/Storm Prediction Center storm reports. Hu et al. (2021), Courtesy from Q. J. R. Meteorol. Soc., and John Wiley & Sons.

initiated at 2000 UTC, with an output frequency of 30 min. The forecast shows that the primary storm in Pennsylvania intensified over time while moving eastward/southeastward. The maximum wind speeds, as predicted by the system, were closely aligned with NWS/SPC severe weather reports. Specifically, the simulation captures the leading edge's progression from West Virginia to Virginia, matching the NWS/SPC damaging wind reports in those regions. This example highlights the system's ability to predict the evolution and intensity of hail and damaging wind events, which may enhance forecasters' ability to issue more accurate and timely forecast and warning products.

In the 2020 and 2021 NOAA SFE/HWT, the WoF-Hybrid system was formally tested and evaluated by forecasters, utilizing its hybrid capability with 50% static covariances and 50% flow-dependent covariances derived from the WoFS ensemble. Hourly deterministic 6-h forecasts were launched using the analyses generated between 1700 UTC on day one and 0300 UTC on day two. The selection of the daily domain was based on the region where severe weather was anticipated, covering a 900 km by 900 km area influenced by the SPC Day 1 Convective Outlook. The forecasters were provided with deterministic, physically-consistent gridded analyses and forecasts to supplement the ensemble-based WoFS products. Forecasters were asked if WoF-Hybrid provided additional value in addition to the randomly selected member of WoFS based on 0–6 hour forecast initialized from 2100 UTC and 2300 UTC during 2021 HWT/SFE. The average of subjective ratings indicates that the WoF-Hybrid performed slightly better than the random member of WoFS for 2100 UTC initializations although for 2300 UTC initializations both systems' forecasts were determined to be quite similar. Because of its generally higher resolution (with 1.5 km grid spacing) it was possible that WoF-Hybrid was able to better depict storms in their early development stages; the ratings suggest that the forecasters believed that the WoF-Hybrid provided value in terms of storm structure. However, the forecasters also noticed that WoF-Hybrid often produced spurious convection in the analyses and suggested that this should be a high priority area for improvement (See Clark et al., 2022 for more information).

Both quantitative and qualitative evaluations of composite reflectivity and updraft helicity forecasts for several highlighted events indicated that WoF-Hybrid can realistically predict reflectivity patterns and updraft helicity tracks. Detailed forecast

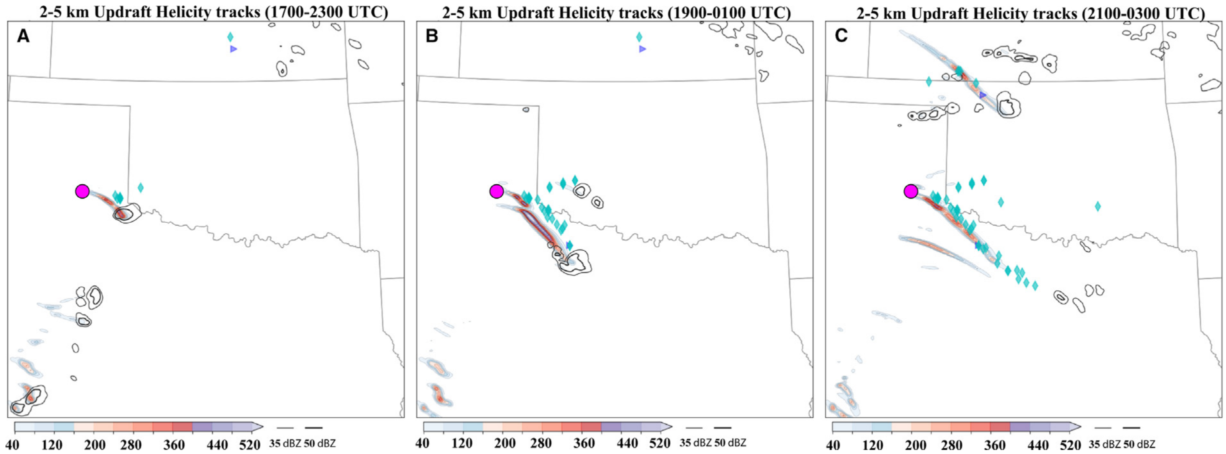

Fig. 5 The 6-h forecasts of 2—5 km updraft helicity tracks (color-shaded) from the WoF-Hybrid system for a hail storm May 7, 2020 case, north Texas storm. The forecast initialized from (A) 1700 UTC, (B) 1900 UTC, (C) 2100 UTC. The forecast started from 1700 UTC had a very good CI predicted 4 h into the model forecast. Forecast started from 1900 UTC had CI predicted in 2 h into the model forecast. And forecasts started from 2100 UTC when CI happened has less location errors in comparison with National Weather Service/Storm Prediction Center report. The green rhombi, and blue triangles represent observed hail, and wind damage, respectively, during the periods. The pink circle represents the CI location.

performance evaluations for these two years can be found in Gao et al. (2021, 2022), Carpenter (2022) and Carpenter et al. (2023). An illustrative example from the 2020 real-time runs involves a hail storm event that occurred on May 7, 2020, in North Texas. Forecasts initialized at three different times predicted the storm initiation (indicated by the red circle in the domain) around 2100 UTC. The first forecast (**Fig. 5**A) and the second forecast (**Fig. 5**B) predicted the storm initiation 4 h and 2 h ahead of time, respectively. This case exemplifies the system's effectiveness in predicting storm cell initiation. Another example pertains to a high-impact weather event on 10—11 December 2021, which resulted in 89 fatalities and almost $4 billion in damage. The most impactful thunderstorm was the so-called "Quad State Supercell," which produced tornadoes for almost 7 h along its more than 400-mile path (**Fig. 6**A). Damage in Mayfield, Kentucky was particularly devastating (**Fig. 6**B). The forecasts, based on two 6-h deterministic runs launched from the WoF-Hybrid analysis at 2300 UTC on December 10 (**Fig. 6**C) and 0100 UTC on December 11 (**Fig. 6**D), captured the major supercell and other multiple storms. The forecasts aligned well with SPC/NWS storm reports for tornadoes, hail, and damaging winds, demonstrating the system's ability to reasonably predict significant severe weather events.

Discussion and Future Outlook

While the advancements highlighted in the last section are promising, challenges and issues exist. An overview of these challenges and possible ways to address them are provided below.

Convective Scale NWP Models

The progress made in developing convective-scale NWP models, particularly in representing various physics processes that resolve internal convective structures, are significant. However, since clouds are influenced by many factors, such as radiation, orography, and physical parameterizations, inaccuracies in these representations within convective-scale NWP models can lead to the generation of spurious storms in short-term severe weather forecasts. The representation of clouds, especially in model radiation physical processes, remains an area that requires significant improvement.

The wealth of high-resolution data provided by WSR-88Ds and GOES-R can expedite research aimed at refining cloud representation in convective-scale NWP models. These observations serve to enhance our understanding of cloud physical and dynamics processes and the diagnosis of systematic errors within model simulations. Ideally, better understanding of these processes will enable the development of advanced parameterizations that represent cloud dynamics more realistically, contributing toward improvement in accuracy and reliability of short-term severe weather forecasts.

Assimilation of Radar and Satellite Observations

As discussed earlier, use of data from the WSR-88D network in research and development has resulted in significant improvements in the initial conditions of short-term severe thunderstorm forecasts within convective scale NWP models. The addition of dual-polarization capability to the WSR-88D network in 2013 has enabled advancements in severe weather detection, hydrometeor

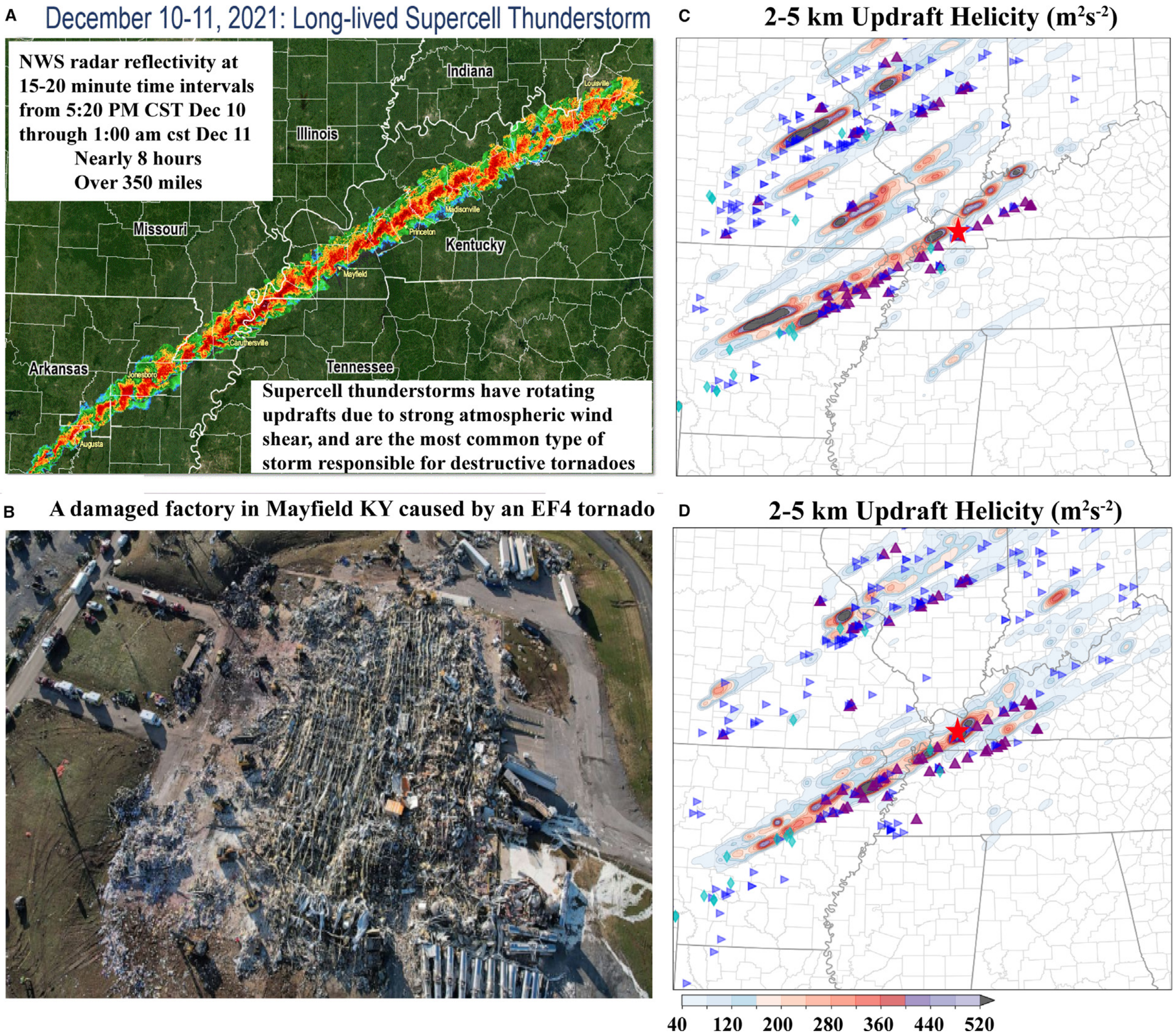

Fig. 6 Observations and forecasts of the "Quad-State Supercell" on 10–11 December 2021. (A) successive radar reflectivity images overlaid for nearly 8 h, (B) damage in Mayfield, KY. Panels (C) and (D) depict 6-h forecasts of 2–5 km updraft helicity tracks (shading) from the WoF-hybrid system initialized, respectively, at 2300 UTC on December 10, 2021, and at 0100 UTC on December 11, 2021. The red triangles, green rhombi, and blue triangles represent observed tornadoes, hail, and wind damage, respectively, during the periods shown from National Weather Service/Storm Prediction Center storm reports. The red star indicates the location of Mayfield, Kentucky.

classification, understanding of winter precipitation processes, and quantitative precipitation estimation (Kumjian and Ryzhkov, 2008; Chandrasekar et al., 2013; Zhang et al., 2019b). Although the use of polarimetric radar data for improving thunderstorm forecasts with convective-scale NWP (Jung et al. 2008a,b, 2010, 2012, 2021) has also progressed, several challenges to the integration of these data into real-time NWP applications remain. One major challenge is the development of accurate and efficient forward operators that can effectively link NWP model variables with polarimetric radar data (Zhang et al., 2019b). This scientific challenge is driven by the nonlinearity inherent in these relationships. One approach worth exploring is the development of methods to reduce the nonlinearity of forward operators, ideally enabling the derivation of more useful information from polarimetric radar observations than is currently possible. Another challenge is that dual-polarimetric radar features are often much smaller in scale than the reflectivity structures that are currently assimilated within prediction systems using 3 km grid spacing. We anticipate positive impacts on forecast performance will result from assimilating these observations using model grid spacing of 1 km or finer. The third major challenge is the ability for the NWP model and microphysics to correctly produce observed polarimetric radar signatures so that the minimization of the difference between observed and simulated signatures can lead to correct improvement to the multi-moment microphysical state variables. This is a necessary condition for effective direct assimilation of polarimetric radar parameters (Jung et al., 2012; Putnam et al., 2013) that still evades a solution.

The launch of GOES-R and the subsequent generation of high-resolution satellite data, including radiance, various derived products, and GLM lightning data, present significant opportunities for improving short-term thunderstorm forecasts. While substantial progress has been made in assimilating some of these data, particularly satellite radiance, an ongoing challenge is the accurate representation of microphysics. The exploration and development of advanced DA methods, with hydrometeors as control variables, promise to more effectively assimilate all-sky radiance data, especially when frequent DA cycles are implemented. Given that GLM lightning data offer information about hydrometeor species (especially ice), updraft strength, and moisture content, the assimilation of these data may further improve the representation of microphysics. However, the relationship between lightning data and NWP model variables is nonlinear and complex. Research efforts focused on deriving appropriate proxy products, such as flash extent density and minimum flash area (e.g., Kong et al., 2022; Pan and Gao, 2022), which might be more effectively assimilated or used in conjunction with NWP models. Developing strategies to more effectively represent microphysics through the assimilation of the satellite products into convective-scale NWP models could contribute to better understanding and forecasting of thunderstorms.

Improve Convective DA Methods

The EnKF methods, while capable of providing valuable probabilistic information, have the drawback of requiring time to fully capture and represent ongoing storms, as discussed by Guerra et al. (2022). On the other hand, the variational-based hybrid DA techniques, although can not provide probabilistic information, offer flexibility and the ability to integrate flow-dependent information from various sources, including ensemble forecasts within EnKF or mesoscale ensemble products like the HRRR ensemble products (Lorenc, 2003; Penny, 2014). Two-way coupling of EnKF methods and Hybrid ensemble variational methods may help provide both deterministic and probabilistic information, making it potentially valuable for public dissemination. This approach was demonstrated in synoptic scale DA with ECMWF hybrid EnKF and 4DVAR DA system (e.g., Bonavita et al., 2015). For the convective scale, the two-way coupling of WoFS and WoF-Hybrid was tested recently and it was found that this approach has potential to improve the forecasts for storm location and intensity with a few real data cases (Gao et al., 2023). The comparative analysis using this and other DA methods underscores the need for ongoing research to refine and tailor convective-scale DA and modeling approaches. The ultimate goal is to develop systems that combine the strengths of different assimilation techniques to produce more accurate and timely forecasts of convective storms, ultimately improving severe weather warnings and predictions.

Within the US, there is ongoing community effort to develop the next-generational DA framework, the Joint Effort for Data Assimilation Integration (JEDI), as part of the UFS effort. JEDI adopts object-oriented programing methodology that promises more rapid system development. JEDI's ensemble DA employs the local ensemble transform Kalman (LETKF) filter algorithm, and an initial result on implementing and testing radar DA capabilities within JEDI LETKF are reported in Park et al. (2022).

Use Machine Learning to Improve Thunderstorm Forecasts

The challenge of providing fast and timely forecasts for convective weather events, especially high-impact severe weather events, has led researchers to explore the potential of machine learning (ML) and artificial intelligence (AI) in improving predictions. While running a large number of high-resolution ensemble forecasts to improve the skill of probabilistic forecasts of severe weather hazards remains resource-intensive, ML techniques have shown promise in predicting various aspects of thunderstorms and associated hazards using less resources (McGovern et al., 2023). However, given the infrequent occurrence of high-impact extreme hazard events, statistically-based ML techniques may face challenges in identifying and forecasting them accurately, especially for rare events.

Combining ML with DA (Geer, 2021), which shares theoretical similarities in terms of statistical optimization, could be a promising avenue for improving convective-scale analysis and thunderstorm forecasts. For example, Bonavita and Laloyaux (2020) explored ML methods to estimate model errors for use in 4DVAR. The integration of machine learning with DA and the exploration of novel forecasting techniques offers exciting prospects for improving the accuracy and efficiency of severe weather predictions.

Summary

This paper provides an overview of the progress made in short-term thunderstorm forecasting over the past two to three decades, with a particular focus on US severe weather forecasting systems and efforts. It underscores the research and development toward improved NWP forecasts for convective storms in the 0−6 hour time frame. This progress is a direct result of advances in three key research areas, including convective scale NWP models, high-density storm-resolving observations, and DA methods.

The development of convective scale NWP models began with idealized simulations of convective scale phenomena in many early modeling studies. Subsequently, ARPS and WRF models were developed in the US with a view toward predicting high-impact weather using real observations, especially high-resolution radar data. Beginning some 30 years ago, these two models have inspired a wide variety of research and applications to advance short-term severe weather forecasts. The implementation and modernization of the WSR-88D radar network and the continuous launch of the GOES-R Series have granted real-time access to high-resolution remote-sensing observations. This technological evolution has significantly improved the accuracy of severe weather forecasts and warnings. Research on advanced variational and ensemble DA methods for convective scale, especially for the assimilation of radar and satellite data, has further led to significant progress in improving short-term severe thunderstorm forecasts. In this paper, some recent strides in research and applications of severe thunderstorm forecasts within several US institutes are highlighted. These research and applications have demonstrated the substantial potential of the convective scale NWP in enabling NWS forecasters to improve severe weather forecasts and warnings.

Looking forward, some challenges still exist. For the convective scale NWP models, research on better representation of clouds and microphysics schemes remains an area that requires significant improvement. For high-resolution remote-sensing observations, developing accurate and efficient forward operators that can effectively link convective scale NWP model variables with remote-sensing data, such as polarimetric radar data, still requires a lot of research. Furthermore, the proper hybridization of using ensemble Kalman filter methods and variational DA methods for convective scale may combine the strengths of different assimilation techniques to produce more accurate and timely forecasts of convective storms. Finally, ML/AI is an emerging and powerful tool to improve thunderstorm DA and forecasts and holds great promise for further improving short-term thunderstorm forecasts in both accuracy and efficiency.

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