Assimilating Surface Mesonet Observations with the EnKF to Improve Ensemble Forecasts of Convection Initiation on 29 May 2012

RYAN A. SOBASH*
School of Meteorology, and Cooperative Institute for Mesoscale Meteorological Studies, University of Oklahoma, Norman, Oklahoma

DAVID J. STENSRUD
NOAA/OAR/National Severe Storms Laboratory, Norman, Oklahoma

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ABSTRACT

Surface data assimilation (DA) has the potential to improve forecasts of convection initiation (CI) and short-term forecasts of convective evolution. Since the processes driving CI occur on scales inadequately observed by conventional observation networks, mesoscale surface networks could be especially beneficial given their higher temporal and spatial resolution. This work aims to assess the impact of high-frequency assimilation of mesonet surface DA on ensemble forecasts of CI initialized with ensemble Kalman filter (EnKF) analyses of the 29 May 2012 convective event over the southern Great Plains.

Mesonet and conventional surface observations were assimilated every 5 min for 3 h from 1800 to 2100 UTC and 3-h ensemble forecasts were produced. Forecasts of CI timing and location were improved by assimilating the surface datasets in comparison to experiments where mesonet data were withheld. This primarily occurred due to a more accurate representation of the boundary layer moisture profile across the domain, especially in the vicinity of a dryline and stationary boundary. Ensemble forecasts produced by assimilating surface observations at hourly intervals, instead of every 5 min, showed only minor improvements in CI.

The 5-min assimilation of mesonet data improved forecasts of the placement and timing of CI for this particular event due to the ability of mesonet data to capture rapidly evolving mesoscale features and to constrain model biases, particularly surface moisture errors, during the cycling period.

1. Introduction

Accurately predicting the location and timing of the development of deep convection, or convection initiation (CI), and thus its associated hazards (straight-line winds, tornadoes, flash flooding, etc.), remains a considerable challenge for operational forecasters (Ziegler and Rasmussen 1998). The occurrence of CI is often a predominant source of uncertainty in many convective weather forecasts, even at forecast lead times as short as 1 hour. While numerical weather prediction (NWP) models can provide valuable forecast guidance for CI, especially those with resolutions capable of permitting convective circulations, cases are routinely encountered where model predictions of CI do not occur or observed CI events are missed (Kain et al. 2013). Given the broad range of applications that would reap benefits from more skillful short-term predictions (0–3 h) of CI (e.g., aviation, hydrology, severe storm warnings), improving the ability of NWP models to anticipate convective development is a worthy goal.

Improving predictions of CI partly depends on adequately observing and simulating the processes that modulate CI in numerical models. These processes act on multiple scales, including large-scale destabilization due to mesoscale and synoptic-scale forcing and smaller-scale turbulent mixing and organized vertical motions induced by circulations in the planetary boundary layer (PBL) such as horizontal convective rolls, drylines, and other surface boundaries. These
latter features can serve to trigger CI, given a favorable larger-scale environment (Weckwerth and Parsons 2006). Resolving the relevant dynamical processes in NWP models would require model and observation network resolutions much finer, both spatially and temporally, than currently permitted. Even so, gains in the skill of short-term CI forecasts could be realized by further exploiting presently available observational datasets that possess information on processes influencing the environment on scales that can be resolved at convection-allowing model resolutions.

For example, the number of mesoscale surface observation networks (i.e., mesonets) have increased during the past several years, and methods to gather, quality control, and distribute these observations in real time have matured. These networks often provide data at higher spatial and temporal resolution than conventional observing systems (e.g., Automated Surface Observing Systems), and are routinely used by forecasters in real time to monitor the evolution of rapidly evolving surface mesoscale features that are important in anticipating and forecasting CI. Thus, it seems possible that assimilating surface mesonet observations into NWP models, especially at frequent intervals, may enhance the skill of short-term CI forecasts by improving the representation of meso-β-scale (Fujita 1981) phenomena.

In general, surface observations have been underutilized in operational data assimilation systems due to challenges with their assimilation (Pu et al. 2013). Height mismatches between the model and surface observations in areas of terrain (Deng and Stull 2007), the degree of coupling between surface observations and the overlying atmosphere (Hacker and Snyder 2005), and biased PBL parameterizations (Coniglio 2013), can all contribute negatively to assimilation performance. Despite these obstacles, several studies have assimilated conventional surface observations at hourly intervals to better represent the environment for convective weather events, including mesoscale surface boundaries and fronts (e.g., Fujita et al. 2007), as well as convectively generated features associated with MCSs (e.g., Stensrud et al. 2009; Wheatley and Stensrud 2010; Wheatley et al. 2012). Ha and Snyder (2014) also noted improved analyses of a surface front and a more accurate convective precipitation forecast by assimilating conventional surface observations. These previous studies used model grid spacings requiring convective parameterization \[O(10) \text{ km}\] and performed data assimilation on intervals of 1 hour or greater.

The impact of mesonet observations on ensemble Kalman filter (EnKF)-generated analyses was investigated by Knopfmeier and Stensrud (2013) by assimilating mesonet and conventional observations each hour during a convectively active two-week period. They determined that the mesonet observations did not provide an added benefit over the analyses generated with only conventional observations. Yet, they suggested that a clearer benefit may emerge by assimilating surface data more frequently. Other studies have assimilated mesonet datasets for the prediction of specific convective events. Xue and Martin (2006, hereafter XM06) and Liu and Xue (2008, hereafter LX08) focused on the skill of short-term model forecasts at predicting CI locations for cases during the International H2O Project (IHOP; Weckwerth et al. 2004). XM06 assimilated routine and special IHOP upper-air and surface observations, including mesonet observations, with some benefits observed in the location and timing of CI. LX08 studied a separate IHOP case and increased the assimilation period to 3-hourly in a sensitivity experiment, with mixed results. They suggest that frequent surface data assimilation (DA) may tend to weaken the surface forcing responsible for CI, leading to a poorer forecast. More recently, mesonet and other surface datasets, along with radar data, have been assimilated at higher frequencies (e.g., Dong et al. 2011; Schenkman et al. 2011; Marquis et al. 2014), but these studies restrict their focus to the period after CI when radar data become available and are primarily used to constrain the evolution of convectively generated surface features, such as cold pools.

LX08 and XM06 are the only studies that have demonstrated a positive impact of assimilating surface observation datasets, including mesonet data, on forecasts of CI and convective evolution using convection-allowing NWP models. Recent advances in DA schemes provide an opportunity to revisit this question and isolate the impact of mesonet data on the subsequent forecasts. In particular, more advanced DA algorithms, including state-of-the-art schemes that provide flow-dependent estimates of the forecast errors from an ensemble (e.g., EnKF), may allow for better use of surface observations in defining the meso-β scale. We extend the work in these previous studies by examining the potential benefit of assimilating mesonet observations at frequent intervals to improve short-term forecasts of CI. Similar to LX08, we have chosen to study an individual case where surface observations are expected to be particularly beneficial. Surface observations are assimilated at short intervals, as often as every 5 min, which may provide additional benefit over hourly assimilation (Knopfmeier and Stensrud 2013), and may be especially salient for capturing rapidly evolving features on the convective scale and taking full advantage of the high observing frequency of mesonet datasets. In addition, short-term ensemble forecasts of CI are used to assess the value of surface observation assimilation, rather than the deterministic forecasts produced in XM06 and LX08.
In section 2, we describe the convective event and the specifics of the methodology used to produce the EnKF analyses and ensemble forecasts. Section 3 highlights the experiment design and describes the differences between the ensemble forecasts, including the impact of the length of the assimilation period and the various surface datasets. The sensitivity of the analyses to the specified localization radius is also discussed in section 3. Section 4 provides a discussion of the results and implications for future assimilation systems that provide convective-scale analyses.

2. Methods

a. Case summary

All forms of severe weather occurred across Oklahoma on 29 May 2012, including hail, damaging winds, and a brief enhanced Fujita (EF)-1 tornado west of Oklahoma City (OKC; Fig. 1), producing nearly $500 million in damage within the state (NCDC 2012). Most of the damage was associated with 5-in. (12.7 cm) diameter hail that was produced by several supercells that affected the OKC metropolitan area. Wind gusts to 80 mph (35.8 m s\(^{-1}\)) were reported with these storms, while later in the event, 60–70 mph (26.8–31.3 m s\(^{-1}\)) wind gusts occurred with a convective line that developed after 0000 UTC across eastern Oklahoma and northeastern Texas.

1) SYNOPTIC AND MESOSCALE ENVIRONMENT

On the synoptic scale, a shortwave trough was located across the northern Great Plains region and progressing eastward (Figs. 2a,b). In the wake of this trough, shortwave ridging and height rises were occurring across the Rocky Mountains. An axis of stronger flow aloft [50–60 kt (1 kt = 0.5144 m s\(^{-1}\)) at 300 hPa] associated with the subtropical jet stream was oriented across the southwestern United States into the southern Great Plains. Associated with this ridging and the subtropical jet stream, there was modestly strong west to northwest flow above the 700-hPa level across the southern Great Plains. No shortwaves were apparent over the south-central United States.

By the afternoon of 29 May 2012, a stationary front was draped across northern Oklahoma and southern Kansas (Fig. 3). An area of low pressure and an associated dryline developed across western Texas, primarily due to strong diabatic heating within the dry air mass across the high plains of eastern New Mexico and western Texas (Fig. 3). By evening, the air mass to the east of this dryline and south of the aforementioned stationary boundary was characterized by moderate to strong instability. The 0000 UTC 30 May 2012 radiosonde launched from Norman, Oklahoma, was representative of this warm sector environment (Fig. 4). Mixed-layer convective available potential energy (MLCAPE) values ranged from 2000 to 4000 J kg\(^{-1}\).
across the warm sector, due to the presence of steep midlevel lapse rates (>7.5°C km⁻¹; Fig. 4) and a moist boundary layer. Deep-layer shear was supportive of organized convection (0–6-km shear >40 kt; Fig. 4) due to the presence of the 30 kt of northwest midlevel flow overlaid on top of the southeasterly surface flow. The presence of a long, straight hodograph was conducive for the development of both left-moving and right-moving supercellular convection (Klemp and Wilhelmson 1978). Modest values of low-level shear (0–1-km shear <10 kt; Fig. 4) and lifted condensation level (LCL) heights (LCLs were near 1.5 km AGL) supported primarily nontornadic supercells, with large hail and severe wind being the most likely threats (Thompson et al. 2003). Thus, if CI were to occur, a range of deep convective modes could be observed with storm motions toward the southeast.
2) CONVECTIVE EVOLUTION

Convection initiated between 2100 and 2200 UTC in three regions near the dryline and stationary boundaries: 1) near the intersection of the stationary front and dryline in southwest Kansas (Fig. 5a), 2) in north-central Oklahoma near and to the north of a dryline bulge and along a well-defined northwest–southeast-oriented boundary layer roll (Fig. 5a), and 3) in southwestern Oklahoma along the dryline, in the presence of several boundary layer rolls (Fig. 5a). In addition, a failed CI attempt occurred in northern Texas (Fig. 5a). For the remainder of this work, these four regions, and their associated CI events, will be denoted as CI1–4, with CI1 being the farthest north and CI4 being the farthest south.

Between 2200 and 0000 UTC several supercells developed within CI1–3. In CI1, an intense supercell moved southeast into northwestern Oklahoma, while weaker convection developed in southwest Kansas (Fig. 6b). This supercell weakened after 2300 UTC and dissipated shortly after 0000 UTC (Fig. 6d). The two areas of CI within CI2 (Fig. 6a) developed into multiple convective cells by 2300 UTC (Fig. 6b). By 0000 UTC, many more convective cells had developed within CI2 on outflow boundaries from earlier convection (Fig. 6c). Of note in this region are several intense supercells on the southern end of CI2 that moved toward the south, passing within and to the west of the OKC metropolitan area (Fig. 6d). Within CI3, two isolated supercells developed and matured between 2200 and 0000 UTC (Figs. 6a–c). The northern storm produced a left split that persisted as it moved northeastward (Fig. 6d) toward OKC. The southern right-moving supercell moved toward the southeast, crossing the Red River into northern Texas (Fig. 6d) and persisted until shortly after 0300 UTC. The left split continued to move northeast until merging with the southeastward-moving convection from CI2. This merger occurred within the OKC metropolitan area shortly after 0100 UTC.
b. Experiment design

1) MODEL CONFIGURATION AND INITIAL ENSEMBLE

The assimilation experiments used a model grid with a horizontal grid spacing of 3 km, while the vertical grid contained 40 vertical levels and was 16 km deep. The domain was 945 km (315 grid points) in the north–south direction, and 885 km (295 grid points) in the west–east direction, and was centered over Oklahoma (Fig. 7). This configuration keeps most of the convection within the domain and away from the lateral boundaries. The initial and boundary conditions for the 50-member, 3-km ensemble originated from downscaled 15-km mesoscale analyses taken from a continuously cycled 50-member EnKF analysis system run in real time at the National Center for Atmospheric Research (NCAR) during the spring of 2012 (Schwartz et al. 2014; Romine et al. 2014). The NCAR assimilation system employed the Advanced Research version of the Weather Research and Forecasting (WRF) Model version 3.3.1 as the forward model (Skamarock et al. 2008) and the data assimilation was conducted using the ensemble adjustment Kalman filter assimilation algorithm within the Data Assimilation Research Testbed1 (DART; Anderson et al. 2009). The NCAR mesoscale ensemble was initialized on 30 April 2012 and conventional observations, including METAR observations, were assimilated every 6 h through the current period of interest.

To create the initial conditions for the 3-km ensemble, the posterior ensemble member states valid at 1800 UTC 29 May 2012 were downscaled onto the 3-km model grid. To produce boundary conditions for the nested domain, each member of the 15-km

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1 DART software is available online at http://www.image.ucar.edu/DARES/DART.
The mesoscale ensemble was advanced 6 h to 0000 UTC 30 May 2012 using boundary conditions from the Global Forecast System (GFS) initialized at 1800 UTC. Boundary conditions for the 3-km domain were updated every 30 min. Thus, the initial ensemble for all experiments consists of the 50 downscaled ensemble states valid at 1800 UTC 29 May 2012. Several experiments were designed to assimilate various combinations of surface data between 1800 and 0000 UTC, as discussed in section 3.

As in the NCAR assimilation system, version 3.3.1 of the WRF Model was used for the assimilation and forecast experiments on the 3-km domain. The Morrison double-moment scheme (Morrison et al. 2009) was used to parameterize cloud microphysics. Boundary layer parameterization was implemented with the Mellor–Yamada–Janjic (MYJ) scheme (Janjic 1994). The Rapid Radiative Transfer Model for global climate models (RRTMG; Iacono et al. 2008) handled shortwave and longwave radiation. Other details of the model configuration are provided in Table 1. Surface fields such as 2-m temperature, 2-m mixing ratio, 10-m wind speed, along with composite reflectivity, were saved at 5-min intervals for verification.

2) OBSERVATION SOURCES AND PROCESSING

Surface data were obtained from the NOAA Global Systems Division Meteorological Analysis and Data Ingest System (MADIS; Miller et al. 2005). These data included observations from sites that produce METARs and various mesoscale networks (mesonet observations). The MADIS system does not archive Oklahoma

![Figure 5](image-url)
Mesonet data, thus these data were added separately. Temperature, dewpoint temperature, altimeter, and the horizontal wind components \((U, V)\) were assimilated. A rigorous quality control procedure, including spatial and temporal consistency checks, was applied to the observations within the MADIS system. Only those MADIS observations that have passed all MADIS quality control checks were assimilated in the present experiments. Figure 8 shows the spatial distribution of surface observations at 1800 UTC 29 May 2012.

Observation error standard deviation for \(U, V, \) temperature, and altimeter observations are shown in Table 2. Dewpoint observation uncertainty is computed with the root-sum-of-squares method using temperature and relative humidity uncertainties [following Lin and Hubbard (2004), their Eq. (4a)]. Observation errors for MADIS mesonet data were assigned to be slightly larger than METAR and Oklahoma Mesonet data due to the variety of mesonet data sources with unknown error characteristics within the MADIS dataset.

FIG. 6. Composite reflectivity (dBZ) at (a) 2145, (b) 2245, (c) 2345, and (d) 0045 UTC. Panels (a)–(c) correspond to the same time as Figs. 5b–d.
c. Assimilation details

The assimilation experiments were conducted with the sequential parallel version (Anderson and Collins 2007) of the deterministic ensemble adjustment Kalman filter (Anderson 2001, 2003). In this framework, observations are assumed to have independent errors, and are assimilated serially.

Covariance localization is used to eliminate spurious covariances due to sampling error. Determining proper localization for surface observations is challenging, especially in the vertical, where the coupling between surface observations and the overlying atmosphere is variable in time and space. Given the relatively dense observational network due to mesonet data across the portion of the domain where most convection is observed, a horizontal localization length scale that is somewhat smaller than those chosen in other studies (e.g., Fujita et al. 2007; Ha and Snyder 2014) is implemented here (60-km horizontal cutoff), using the Gaspari–Cohn localization function (Gaspari and Cohn 1999). An 8-km vertical localization cutoff is used in the vertical (these cutoff lengths are the distances where the covariances are forced to zero). The sensitivity of the analyses and forecasts to localization values is examined in a later section. The sampling error was also accounted for through the use of a sampling error correction (Anderson 2012).

In addition to localization, adaptive prior inflation (Anderson 2009) was used to counteract the tendency for spread values to decrease during the data assimilation update. The adaptive inflation algorithm produces an inflation field that varies in time and space. The specific parameters used in the inflation algorithms, along with other DART settings, are provided in Table 3.

3. Surface data assimilation experiments

a. Experiment design

Available surface observations were assimilated every 5-min between 1800 and 2100 UTC. The reporting frequency varied among data sources. Oklahoma Mesonet data were available every 5 min, while MADIS mesonet data, consisting of multiple data sources, were available at intervals ranging from 5 min to 1 h. METAR data are typically available hourly, although some stations report at 20-min intervals. Observations taken in the 5-min window centered on the DA time are used.

To assess the impact of various lengths of the data assimilation period on forecasts of CI, 50-member ensemble forecasts were launched at 1900 (SFC1H), 2000 (SFC2H), and 2100 UTC (SFC3H). This encompasses CI and the early evolution of convection. These experiments are summarized in Fig. 9. In addition to the three ensemble forecasts, a control ensemble forecast (CNTL) was initialized with the 1800 UTC initial conditions from the downscaled NCAR mesoscale ensemble. No DA was used within this control forecast. Forecasts were also initialized from separate experiments to test various aspects of the surface DA, including delaying the start of the DA period, the impact of assimilation frequency, and sensitivity to covariance localization choices. Among these experiments, emphasis will be placed on the differences in the forecasts of CI and early convective evolution during the 3-h forecast period from 2100 to 0000 UTC.

b. Methods of forecast comparison

In both model output and observed radar data, convection was identified as areas where composite reflectivity (CREF) exceeded 25 dBZ (abbreviated as observed and forecast CREF25). This threshold was chosen to identify early signs of convective development and to identify convection in the ensemble mean, where...
**CREF values may not exceed higher thresholds due to averaging among members, especially at longer forecast lead times. Several ensemble fields derived from forecast CREF25 were produced to evaluate differences between experiments and observations, including 1- and 3-h ensemble probabilities of CREF25 (denoted PROB1H-CREF25 and PROB3H-CREF25, respectively). The PROB1H-CREF25 forecast was computed from the hourly maximum CREF forecast, while the PROB3H-CREF25 forecast was computed from the 3-hourly maximum CREF forecast derived with the individual hourly maximum CREF fields over three consecutive hours. At each grid point, the fraction of members where CREF exceeded 25 dB$\ Z$, using the 1- or 3-h maximum CREF field, determined PROB1H-CREF25 and PROB3H-CREF25.**

Two methods were developed to enable a more refined inspection of ensemble forecast CI timing errors. In the first method, areas where ensemble mean CREF exceeded 25 dBZ, using the 1- or 3-h maximum CREF field, determined PROB1H-CREF25 and PROB3H-CREF25.

Two methods were developed to enable a more refined inspection of ensemble forecast CI timing errors. In the first method, areas where ensemble mean CREF exceeded 25 dBZ (denoted by MEAN-CREF25) were plotted at 15-min intervals with earlier areas plotted on top of later areas. This provided a simple way to visually interpret ensemble mean timing errors. The second method used the 15-min CREF output to compute the centroid of each CREF >40-dBZ object within each ensemble member. These points are color coded in time to provide a sense of the variation among ensemble members in timing and location of convection. A size threshold of 10 contiguous grid points was used to remove small CREF objects. The same procedure was applied to the observed CREF field to produce a verifying centroid track.

**TABLE 2. Summary of observation errors for surface datasets.** The dewpoint temperature observation error is assigned using Lin and Hubbard (2004).

<table>
<thead>
<tr>
<th>Data source</th>
<th>$U$ (m s$^{-1}$)</th>
<th>$V$ (m s$^{-1}$)</th>
<th>$T$ (K)</th>
<th>Altimeter (hPa)</th>
</tr>
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<tbody>
<tr>
<td>METAR</td>
<td>1.75</td>
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<td>1.75</td>
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<td>1.75</td>
<td>0.75</td>
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<tr>
<td>MADIS Mesonet</td>
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<td>2.5</td>
<td>2.5</td>
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</table>

**FIG. 8. Spatial location of (a) mesonet and (c) METAR observations at 1800 UTC 29 May 2012 and the number of total observations between 1800 and 2100 UTC falling within 70-km grid boxes for (b) mesonet and (d) METAR observations. The black circles in (b) and (d) correspond to CI regions.**
c. CNTL ensemble forecast

The CNTL forecast between 2100 and 0000 UTC produced nonzero values of PROB3H-CREF25 clustered near the areas of convective development in the three CI regions. Within CI1, PROB3H-CREF25 values exceeded 80% (Fig. 10a), with the spatial coverage of probabilities suggesting uncertainty in the placement of convection. CNTL largely failed to initiate convection in CI2 during the 3-h period. Low values of PROB3H-CREF25 exist along the western edge of the observed CREF25 contour in CI2, associated with convection that develops late in the 2100–0000 UTC period. The convective development in CI3 was well captured in CNTL, depicting two distinct locations of CI, with slightly larger probabilities for the southern storm (Fig. 10a). The extension of probabilities to the north and east with the northern supercell suggests the development of northeastward-moving convection (i.e., left-moving supercells).

CNTL also produced spurious convection in several regions, the most notable being near CI4 in north-central Texas. Here, a focused area of higher PROB3H-CREF25 values (>65%) existed where a majority of ensemble members predicted the development of isolated convection, a scenario that was not observed, although visible satellite imagery indicated attempts at convection near 2100 UTC in proximity to the PROB3H-CREF25 maximum (Fig. 5a). Other areas of spurious convection in CNTL existed along the stationary boundary in southeast Kansas and in association with terrain across western Arkansas. While several isolated, short-lived areas of convection were observed in these locations, PROB3H-CREF25 from CNTL overestimated convective coverage.

The PROB1H-CREF25 and MEAN-CREF25 fields both reveal timing differences between forecast and observed CI in CNTL. Within CI1 and CI2, no ensemble members forecast CREF25 within the 2100–0000 UTC period, during the period when CI occurred (Fig. 11a). By 2200–2300 UTC, a large area of low PROB1H-CREF25 values developed, centered on CI1 (Fig. 12a). This was also reflected in the MEAN-CREF25 field, with the earliest MEAN-CREF25 area occurring

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**TABLE 3. Summary of DART options used in the assimilation experiments. Localization choices vary in some sensitivity experiments as described in the text. A full description of the adaptive inflation is provided by Anderson (2009).**

<table>
<thead>
<tr>
<th>DART setting</th>
<th>Value</th>
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<td>Filter type</td>
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<td>Ensemble members</td>
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</tr>
<tr>
<td>Outlier threshold</td>
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<tr>
<td>Adaptive prior inflation</td>
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<tr>
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<tr>
<td>Localization type</td>
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<tr>
<td>Sampling error correction</td>
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</tr>
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</table>

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**FIG. 9. Summary of data assimilation experiments. Red lines indicate surface DA period with black dots indicating an assimilation time, while the black lines indicate 50-member ensemble forecasts initialized at different points during the DA period. The three pairs of experiments in the gray boxes represent the experiments testing sensitivity to 1) observation type/assimilation frequency, 2) initialization time, and 3) horizontal localization.**
near 2230 UTC (Fig. 14a). By 2300 UTC, PROB1H-CREF25 magnitudes were largest near CI1 within the eastern half of the area where CREF25 was observed (Fig. 13a). The low values of PROB1H-CREF25 along the western edge of CI2, noted in the previous section (Fig. 10a), developed within this hour. Thus, the ensemble members that produced convection in this region initiated storms more than an hour later than observations.

In CI3, PROB1H-CREF25 values were below 20% in the 2100–2200 UTC period, but in good agreement with the locations of initial development (Fig. 11a). MEAN-CREF25 areas were only associated with the southern storm in CI3, where PROB1H-CREF25 values were higher (this demonstrates the disadvantage of using ensemble mean forecasts for low probability events; Fig. 14a). In CI3, nonzero PROB1H-CREF25 values expanded and increased in magnitude during the following hour, with the southern supercell having larger probabilities (Fig. 12a). Later, the PROB1H-CREF25 envelope broadened within CI3, with some members producing convection west of the observed CREF25 area during this period, resulting in low probabilities (Fig. 13a). The lower PROB1H-CREF25 values in CI3 compared to the probabilities in CI1 imply uncertainty in either the development of convection or the placement of convection within CI3.

d. Results from SFC1H, SFC2H, and SFC3H

The largest differences between the three ensemble forecasts occur within CI2 and CI3. For CI3, improvements are evident in the ensemble mean, as the development of the northern storm within CI3 is captured in the MEAN-CREF25 field in SFC2H and SFC3H (Figs. 14c,d), while it is not in CNTL and SFC1H (Figs. 14a,b). Second, as the DA period is increased, a westward shift occurs in the placement of CI within CI3, in better agreement with observations. Finally, the timing of CI is much improved, especially in SFC3H, with MEAN-CREF25 areas occurring as early as 2130 UTC for the northern storm (Fig. 14d), while CNTL, SFC1H, and SFC2H delay initiation to 2200 UTC or later in this region (Figs. 14a–c).

Less substantial changes in the forecasts of MEAN-CREF25 occur for CI2. The MEAN-CREF25 area shifts westward in CI1 as the DA period is increased, but the timing of CI is further delayed, well after the time of observed CI shortly after 2100 UTC (Fig. 14d). Very small areas of MEAN-CREF25 occur within CI2, the size and timing of which are nearly unchanged between the three experiments. The spurious convective development in CI4 is also unchanged across the set of four experiments. An area of spurious convection also exists in east of CI4, near Dallas, Texas, in SFC3H that is not present in
Differences between the CNTL and SFC3H forecasts of PROB3H-CREF25 provide more insight into the differences in the MEAN-CREF25 forecast between the experiments (Fig. 10). In CI3, where the largest changes to MEAN-CREF25 occurred, PROB3H-CREF25 values are greater in SFC3H, especially associated with the northern storm (probabilities >80%). Here, an axis of higher probabilities (35%–50%) exist associated with ensemble members that produce and maintain a left split that moves toward the northeast. This was also evident in CNTL, but the PROB3H-CREF25 values are more focused, and more members predict this forecast scenario. While very small differences existed in the MEAN-CREF25 field within CI2 between the four experiments, the PROB3H-CREF25 values are larger in SFC3H than CNTL. The areas of nonzero PROB3H-CREF25 values in SFC3H coincide with the western edge of CI2, with between 35% and 50% of ensemble members indicating CI, including a right-moving supercell (not shown). The envelope of probabilities associated with CI1 is shifted westward and is more refined, matching well with the observed area of CREF25, although PROB3H-CREF25 magnitudes are reduced in SFC3H. In CI4, one area of CI was forecast in CNTL, but several additional areas are indicated in SFC3H, although PROB3H-CREF25 magnitudes are smaller in SFC3H in CI4.

The forecast centroids suggest a large amount of uncertainty in the placement of convection within CI1 in both CNTL and SFC3H (Fig. 15). Centroid points are more widely scattered in CI1 compared to the other CI regions, although the observed centroids fall within the envelope of ensemble centroid tracks. In SFC3H, some members produce convection earlier in the period (i.e., more blue centroid points in SFC3H than CNTL), and these are located farther to the northwest in SFC3H by approximately 10–20 km. While PROB3H-CREF25 values were near zero in CNTL within CI2, several ensemble members did produce convection near the end of the forecast period in this region, as indicated by red centroid points within CI2, although these are distributed across several counties. This is in stark contrast to the tightly clustered track of forecast centroid points in SFC3H, which match closely with the location and time of observed CI.

The centroids indicate a high degree of certainty in the placement and tracks of convection in CI3 in both CNTL and SFC3H (Fig. 15). In SFC3H, the number of forecast centroid points associated with the northern storm has increased and the locations are more clustered. Further, a larger number of members produce a northeastward-moving storm associated with a left split. Differences in the position and timing of the forecast centroid points for the southern storm are less compared to the northern storm between the two experiments. Within CI4, the forecast centroid points also indicate that the spurious PROB3H-CREF areas in SFC3H are
associated with the development of three areas of convection; in CNTL, most members only predict spurious convection in one location.

e. Discussion

Taken together, the MEAN-CREF25, PROB3H-CREF, and forecast centroid tracks demonstrate that surface DA improved the forecasts of CI occurrence and timing within CI2 and CI3, while providing less benefit within CI1 and CI4. The CNTL ensemble was clearly deficient in producing convection within CI2 and had delayed CI in CI3. A potential reason for the delayed CI within CI3 in CNTL is the westward bias in the placement of the surface dryline (Fig. 17); CNTL does not mix...
the dryline far enough east during the afternoon hours. Other studies have found that convection-permitting models mix the dryline too far to the east (Coffer et al., 2013). The present case is different in that the dryline is not associated with a synoptic-scale low pressure system, thus its evolution is likely more sensitive to PBL estimates of vertical mixing. The dryline and moisture biases will be discussed in section 3g.
Another potential reason forecasts were most improved in CI2 and CI3 are due to observation availability. CI2 and CI3 are relatively well observed (primarily by the Oklahoma Mesonet), while fewer surface observations are available outside of Oklahoma within CI1 and CI4 (Fig. 8). Also, errors above the surface (e.g., in the magnitude of a capping inversion) cannot be corrected solely with surface data assimilation. This may be to blame for poor forecasts in CI4. Yet, overall, the trends in CI timing and placement as the DA period increases are encouraging, especially within CI2 and CI3. The PROB3H-CREF25 magnitudes increase and become more refined as the time of CI approaches.

In a real-world setting, probability trends between subsequent ensemble forecasts can give forecasters confidence in a particular forecast outcome. The precise effect of DA in these experiments is difficult to extract, since the forecast lead time is not consistent. Thus, the differences in the above ensemble forecasts are likely due to a combination of changes in initial condition accuracy during DA and reduced predictability error with shorter lead times, making it difficult to disentangle each source of error on the resulting forecast. Two additional experiments were conducted in an attempt to understand these sources of error.

f. Impact of the length of the DA period

In a subsequent set of experiments, surface DA was delayed by 1 and 2 hours (assimilation period of 1900–2100 and 2000–2100 UTC), so the end of the assimilation period coincides with 2100 UTC. A cleaner comparison of the effects of DA length can be made with these two experiments (SFC2H-19UTC and SFC1H-20UTC), combined with SFC3H.

One hour of surface DA in SFC1H-20UTC has a clear impact on the PROB3H-CREF25 magnitudes compared to CNTL (cf. Figs. 10a and 16a). One hour of DA adjusts the envelope of probabilities westward.
within CI1, but magnitudes are reduced from >80% to <50%. Near and within CI2, two areas of >50% probabilities are produced, compared to near-zero probabilities in CNTL. In CI3, PROB3H-CREF25 values increase by 40%–50% compared to CNTL. A swath of probabilities is present in CI3 associated with the members producing a left split. After additional hours of surface DA (Figs. 16b,c), PROB3H-CREF25 magnitudes increase within CI1, but are observed to decrease in other areas. In CI3 and CI4, PROB3H-CREF25 values remain similar to SFC1H-20UTC for the northern supercell within CI3, while PROB3H-CREF25 values decrease for the southern supercell. This is true for several areas of spurious convection within CI4 as well, although the probabilities increase associated with the spurious storm just to the south of the southern supercell in CI3.

SFC1H-20UTC and SFC2H-19UTC provide a clearer interpretation of the effect of multiple hours of surface DA on short-term forecasts of convection. In CI2 and
CI3 probability values within SFC1H-20UTC are similar to those from SFC3H, thus, it appears that in these two areas, the primary source of forecast improvement was the 1 hour of surface DA between 2000 and 2100 UTC, immediately prior to CI (Figs. 16a–c). Extending the DA period to 2 or 3 hours (as in SFC2H-19UTC and SFC3H) either has a small benefit, or is slightly detrimental to the PROB3H-CREF25 probabilities (e.g., reduction of magnitudes between SFC2H-19UTC and SFC3H). As noted before, a major role in these differences may be due to observational availability. In areas that are well observed (e.g., CI2 and CI3, Fig. 8), the relatively high-density of observations, combined with frequent assimilation cycles, is able to adjust the state more quickly, thus reducing the need for a longer assimilation period. More sparsely observed areas (e.g., CI1) may rely on model dynamics to spread observation information.

g. Surface moisture analyses

The CI can be especially sensitive to the distribution of boundary layer moisture (Crook 1996; Weckwerth 2000), as specific humidity variations of 1 g kg$^{-1}$ can impact the occurrence of CI. Differences in the ensemble mean dewpoint field between CNTL and SFC3H were analyzed to gauge the impact of surface DA on the distribution of surface moisture (Fig. 17). Also, the ensemble mean dewpoint RMSE and bias was computed every 5 min during the assimilation period (using the prior ensemble mean) and forecast periods with METAR and mesonet observations (Fig. 19).

RMSE for the CNTL experiment increases from 3.1° to 4.1°C between 1800 and 2100 UTC, while in SFC3H the prior-state RMSE decreases to just above 2°C for the entire period (Fig. 19). The CNTL and SFC3H ensemble mean 2-m dewpoint temperature forecasts at the beginning of the assimilation period both possess an approximately 1.2°C domain-average moist bias. This bias remains constant during the assimilation period in SFC3H, while the CNTL 2-m dewpoint temperature bias increases by 1.5°C, growing to 2.8°C by the end of the assimilation period. During the free forecast, the surface moisture bias in both experiments increase with time.

The largest 2-m dewpoint temperature errors are located in two regions (Fig. 18a). The first is associated with the surface dryline, where observations indicate that the placement of the dryline in the forecast is too far west (Fig. 19). The second is an axis that stretches from south-central Kansas into southeast Oklahoma, near and to the northeast of a weak stationary boundary. In SFC3H, the errors in both of these regions are reduced compared to CNTL.

The improvements in CI in these areas between CNTL and SFC3H are likely driven by these differences in the surface moisture field and the simulated dryline circulation. Not only is the dryline placement improved in SFC3H, but the magnitude of the differences between the theta-e of the two air masses is also larger, due to lower dewpoints behind the dryline across southwest and northwest Oklahoma and little to no change in the surface dewpoint ahead of the dryline.
in western Oklahoma. The increased theta-e difference in SFC3H is associated with a stronger dryline circulation and surface mass convergence in the areas where convection was observed to initiate. This is further reflected in the ensemble mean surface wind field differences between the two experiments in the vicinity of the surface dryline. Three hours of surface DA resulted in increased westerly momentum behind the dryline and easterly momentum ahead of the dryline (Fig. 18a).

h. Impact of mesonet data and frequent cycling

Two additional assimilation experiments were conducted to assess the impacts of both the mesonet dataset and the 5-min assimilation interval on the analyses. In the first experiment, mesonet data were withheld; the remaining METAR observations were assimilated at 5-min intervals from 1800 to 2100 UTC (SFC3H-NOMESO). METAR observations are available as frequently as every 20 min for some locations, while other stations report hourly near the top of the hour. Because of this, several times did not possess any observations in SFC3H-NOMESO. In a second experiment, observations were assimilated once per hour (SFC3H-HOURLY). In SFC3H-HOURLY, METAR observations taken between 15 min before and 15 min after the top of the hour were assimilated, along with mesonet observations within 2.5 min of the top of the hour. The smaller mesonet assimilation window in SFC3H-HOURLY was chosen to ensure that each mesonet observing site only contributed, at most, one observation per assimilation cycle. SFC3H-HOURLY was designed to mimic hourly, cycled, DA systems that have been used in previous studies (e.g., Wheatley et al. 2012).

The 2100 UTC ensemble mean 2-m dewpoint temperature and 10-m wind field differences from (a) SFC3H minus CNTL, (b) SFC3H-HOURLY minus CNTL, and (c) SFC3H-NOMESO minus CNTL. Full wind barbs indicate a wind difference of 5 m s$^{-1}$, while half barbs indicate a difference of 2.5 m s$^{-1}$. The observed position of the surface dryline is indicated by the brown scalloped line.

FIG. 18. Difference fields for the ensemble mean 2-m dewpoint temperature (shaded; °C) and 10-m wind field at 2100 UTC 29 May 2012 from (a) SFC3H minus CNTL, (b) SFC3H-HOURLY minus CNTL, and (c) SFC3H-NOMESO minus CNTL. Full wind barbs indicate a wind difference of 5 m s$^{-1}$, while half barbs indicate a difference of 2.5 m s$^{-1}$. The observed position of the surface dryline is indicated by the brown scalloped line.
Through the assimilation period, CNTL and SFC3H-NOMESO possess similar ensemble mean 2-m dewpoint temperature RMSE and bias values (Fig. 19) while the SFC3H-HOURLY RMSE is slightly smaller. The differences in error between the experiments at the end of the DA period continue throughout the forecast. Following a period of fairly rapid error growth during the first 30 min of the forecast, the RMSE for all experiments stabilize. Although SFC3H-NOMESO has a slightly smaller RMSE than CNTL at 2100 UTC, this difference is lost after 15 min and CNTL and SFC3H-NOMESO have similar RMSE values through the rest of the forecast. The SFC3H-HOURLY RMSE is approximately midway between SFC3H and CNTL through the forecast. This behavior is also true for the 2-m dewpoint bias statistics.

In this case, assimilating METAR and mesonet observations once per hour cuts the 2-m dewpoint temperature RMSE in half, with an equal amount of RMSE reduction if the observations are assimilated every 5 min. In the latter case, the benefits are primarily due to the ability to utilize the full mesonet dataset in both time and space. Given that neither experiment is capable of reducing the moisture biases nor fully adjusting the position and magnitude of the dryline, it appears that the combination of frequent assimilation cycles and higher-resolution mesonet data provides the largest impact on the analyses.

PROB3H-CREF25 values for SFC3H-NOMESO and SFC3H-HOURLY generally fall in between CTRL and SFC3H (Fig. 20). One notable exception is the probabilities associated with CI2; in this area both SFC3H-HOURLY or SFC3H-NOMESO are similar to the CTRL in that they produce little to no convection. Only SFC3H has ensemble members that develop sustained convection within CI2.

To compare the subjective impressions of the forecast with an objective metric, PROB3H-CREF25 for these four experiments were also verified by computing the area under the relative operating characteristic (ROC) curve (AUC), as in Snook et al. (2012). All four experiments (CNTL, SFC3H, SFC3H-HOURLY, and SFC3H-NOMESO), possess AUC values above 0.7, indicating skillful forecasts. Among the four, SFC3H had the largest AUC (0.82), while CNTL and SFC3H-NOMESO had the lowest AUC (0.77), matching the subjective impression that SFC3H produces the best forecast. The larger AUC for SFC3H likely is due to the higher forecast probabilities within CI2, while the differences in other CI areas are more modest, with lesser impact on the AUC score.
i. Sensitivity to horizontal localization cutoff

The choice of an appropriate length scale for covariance localization is a complex function of observation type, density, state variable, etc. The inclusion of mesonet data in the current study results in a varying observation density across the domain (Fig. 8). The horizontal localization cutoff in all of the experiments so far (i.e., 60 km) was chosen to be approximately double the distance of the average observation spacing within Oklahoma, the region of relatively high-density observations due to the presence of the Oklahoma Mesonet. More sparsely observed regions (e.g., CI1 and CI4) might benefit from a larger horizontal cutoff. To test this hypothesis, SFC3H was repeated using a horizontal localization cutoff increased to 120 km (SFC3H-H120V8) and 240 km (SFC3H-H240V8).

The differences in the ensemble mean dewpoint RMSE between the three experiments at the 2100 UTC are relatively modest (Fig. 19). Compared to SFC3H, the RMSE is smaller in both SFC3H-H120V8 and SFC3H-H240V8 for most of the analysis and forecast period. Larger differences emerge later in the forecast period, primarily after 2130 UTC. Both SFC3H-H120V8 and SFC3H-H240V8 have smaller ensemble mean dewpoint RMSE than SFC3H, with SFC3H-H240V8 having the smallest of the three experiments.

The forecast RMSE implies that the SFC3H-H120V8 and SFC3H-H240V8 analyses both have better representations of the surface dewpoint field, yet these benefits do not necessarily extend into better short-term forecasts of convection. In fact, fairly large differences exist between the three experiments. In general, increasing the horizontal localization cutoff reduces probabilities of convection throughout the domain in the 2100–0000 UTC period (Fig. 21). One exception to this is in CI1, where PROB3H-CREF25 magnitudes are increased. In CI2, forecast probabilities are reduced to near zero in SFC3H-H240V8, while in CI3 a similar reduction occurs, although <25% of the ensemble continues to produce two areas of convection, albeit placed farther away from the observations than in SFC3H or SFC3H-H120V8. In CI4, the reduction in forecast probabilities is beneficial since no convection is observed in this region. All three experiments continue to produce large values of PROB3H-CREF25 east of CI4; forecast probabilities are less sensitive here to localization than in other areas of the domain. The AUC values for the two horizontal localization experiments match the subjective impressions of the PROB3H-CREF25 values, with SFC3H-H240V8 having a much smaller AUC (0.65) than SFC3H (0.82) or SFC3H-H120V8 (0.79).

The behavior of the forecast probabilities can potentially be explained by the reduction in spread that results from using larger localization. As localization increases, the ensemble spread is reduced as state points are influenced by more observations (not shown). As members cluster around solutions where convection develops or is suppressed, probabilities of convection would likely be drawn to lower or higher values. This behavior is observed in the three experiments, with CI1 CREF25 probabilities increasing (almost all members produce convection in this location), and probabilities decreasing in areas along the dryline in Oklahoma and Texas.
j. Sensitivity to observation type

To isolate the impact of the thermodynamic and wind observations, two experiments were conducted: one where temperature and dewpoint temperature were not assimilated (SFC3H-NOTMP) and in another the horizontal wind observations were not assimilated (SFC3H-NOWIND). All other configuration settings were identical to SFC3H.

Overall, SFC3H-NOTMP performed slightly better than SFC3H-NOWIND, especially in CI1 and CI2 (Fig. 22). PROB3H-CREF25 values were larger in CI1 and CI2 in SFC3H-NOTMP compared to SFC3H-NOWIND and higher probability values better fill the observed CREF25 contour, especially in CI1. PROB3H-CREF25 values are reduced with the northern supercell in CI3 in SFC3H-NOTMP, but are quite large (e.g., >80%) in SFC3H-NOWIND. RMSE values for wind are larger in SFC3H-NOWIND throughout the 3-h forecast (not shown). This is also true for the RMSE of temperature in SFC3H-NOTMP. These results suggest that assimilating wind observations, especially in the northern part of the domain, are responsible for a majority of the forecast improvement through adjustments to the placement of the dryline and strength of the associated dryline circulations. In regions to the south (e.g., CI3 and CI4), removing either wind or temperature observations both slightly reduce the quality of the forecast.

4. Summary and discussion

To assess the ability of high-frequency surface observation assimilation to improve ensemble forecasts of CI, several surface DA experiments of the 29 May 2012 convective event were performed in the present work. In the primary experiment, SFC3H, surface data, including conventional (e.g., METAR) and mesonet surface observations, were assimilated into the WRF Model using the ensemble Kalman filter. Observations were assimilated every 5 min during a 3-h period from 1800 to 2100 UTC 29 May 2012, prior to CI, to take advantage of the high temporal resolution of the mesonet observations. High-frequency assimilation of surface data led to improvements in ensemble forecasts both in the timing and placement of initial convective development. These improvements extended into the short-term forecast period due to a more accurate representation of the surface moisture field, the strength of the dryline, and a reduction of errors due to model biases. Additional experiments that only assimilated routine surface observations (i.e., METAR), or only assimilated observations each hour, did not see the same improvements in the forecasts of CI. Finally, increases to the horizontal localization cutoff for the assimilated surface observations led to forecast probabilities of CI that were drawn toward higher and lower values for this case.

The 3 hours of surface data assimilation improved the ensemble predictions of the dryline location by shifting it eastward. This produced more skillful forecasts of CI, particularly in areas where convection initiated near the dryline across north-central Oklahoma that went on to impact the OKC metropolitan area. Here, the control forecast contained little convection. Withholding the mesonet data produced little change in dryline location
compared to the control forecast, while assimilating all observations at hourly intervals resulted in some improvements to the placement of the dryline, but not as significant as the experiment using 5-min DA intervals. The differences in the surface moisture field persisted in the ensemble forecasts initialized with the final analyses. During the forecast period, the control and conventional-only experiments possessed similar ensemble mean dewpoint RMSE, approximately 1.5–3 K larger than the 5-min mesonet DA experiment. The forecast ensemble mean dewpoint RMSE using analyses produced from hourly DA fell in between these two extremes, demonstrating some benefit to assimilating mesonet data at hourly intervals.

For this particular convective event, the assimilation of surface data from mesonets appears to provide a clear benefit for forecasts of CI compared to traditional approaches that assimilate conventional observations at less frequent intervals (e.g., hourly). This is the first time that high-frequency mesoscale surface data have been assimilated, with a rapid cycling period using the EnKF, for the explicit goal of predicting CI for a real convective event. The benefits described herein are hypothesized to occur primarily through two mechanisms. First, the higher-resolution mesonet dataset, in both space and time, provided information on the evolution of meso-α- and meso-β-scale features such as the diurnal progression of the surface dryline that mixed eastward during the afternoon hours and played an important role in the development of convection for this event. The variability of the dryline position on the meso-β scale, such as dryline surges, is captured by the mesonet observations and thus introduced into the model initial conditions through the data assimilation procedure, resulting in a better short-term forecast of CI.

Second, surface DA also improves the analyses in this work by constraining model biases near the surface, which can be particularly large in the PBL and accumulate in a cycled DA system. The MYJ PBL parameterization scheme used within these experiments produced forecasts with a positive moisture bias, as noted in previous evaluations (Hu et al. 2010). A similarly configured mesoscale ensemble system to the one used herein also contained a positive moisture bias within the PBL that impacted forecasts of convection (Romine et al. 2013). In cycled DA systems, like the system that provided the initial and boundary conditions for the present experiments, these model errors can persist and grow with each analysis cycle, unless observations are regularly assimilated to constrain the model solution. It appears the 5-min cycling frequency used herein is able to constrain the magnitude of the moist bias during the cycled DA period more so than DA periods of 1 hour. The benefit of this persisted through the 3-h forecast period, leading to improvements to not only CI, but short-term convective evolution.

**FIG. 22.** As in Fig. 10, but for (a) SFC3H-NOWIND and (b) SFC3H-NOTMP.
Although surface DA constrains the model biases near the surface, these errors impose a fundamental limitation on the accuracy of analyses near the surface and likely results in the suboptimal use of observations (Dee and Da Silva 1998). In addition to the surface moisture biases described above, biases affect the adjustments that surface observations create on the overlying free atmosphere. While surface fields, such as low-level moisture, may be improved, the state above the surface may not necessarily be more accurate. Further research is crucial to fully understand and correct model errors due to PBL parameterization and to develop strategies to properly handle surface observations and their impact above the surface.

Assimilating surface observations remains important following CI, when radar observations become available for assimilation. The EnKF has been used to assimilate radar datasets in an effort to produce accurate short-term predictions of convection and convective hazards (Stensrud et al. 2013), but many studies have relied upon simplified representations of the mesoscale environment (e.g., Dowell et al. 2011; Dawson et al. 2012). Realistic, accurate mesoscale environments are critical to produce reliable short-term forecasts of convection (e.g., Stensrud and Gao 2010). For example, if radar observations are assimilated in regions where the mesoscale environment is unsupportive of convection, for instance, due to errors in the placement of critical surface boundaries, then convection may fail to become established in the model and dissipate rapidly in any forecasts initialized with these analyses. Additionally, in many cases, predicting the track and intensity of convection is sensitive to both the three-dimensional heterogeneous structure of the environment and its temporal evolution during the forecast period. Assimilating surface observations can ensure that the simulated environment supports convection leading to improvements in the forecasts of convective evolution, intensity, and demise.

Situations may exist where the assimilation of surface datasets have less benefit on the analysis compared to the results demonstrated herein. These include instances where model biases near the surface are minimal, especially in fields that are important for CI such as surface moisture. Also, CI during the 29 May 2012 convective event was largely driven by forcing from surface features rather than larger-scale forcing from shortwaves, fronts, etc. In these cases, assimilating surface observations should be especially important, while in situations that are strongly forced, benefits may be reduced. Finally, this event occurred over a region possessing a rich set of surface mesonet observations (i.e., Oklahoma); in areas where mesonet observations are not available, have larger errors, or have lesser density, surface observations would be less impactful. This work supports and demonstrates the benefit of continued expansion of current mesonets and the creation of new mesoscale networks across the United States.

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REFERENCES


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