Using Blue Waters To Assess Non-Tornadic Outbreak Forecast Capability by Lead Time

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ABSTRACT

Derechos are a dangerous, primarily non-tornadic severe weather outbreak type responsible for a variety of atmospheric hazards. However, the exact predictability of these events by lead time is unknown, yet would likely be invaluable to forecasters responsible for predicting these events. As such, the predictability of nontornadic outbreaks by lead time was assessed. Five derecho events spanning 1979 to 2012 were selected and simulated using the Weather Research and Forecasting (WRF) model at 24, 48, 72, 96, and 120-hours lead time. Nine stochastically perturbed initial conditions were generated for each case and each lead time, yielding an ensemble of derecho simulations. Moment statistics of the derecho composite parameter (DCP), a good proxy for derecho environments, were used to assess variability in forecast quality and precision by lead time. Overall, results showed that 24 and 48 hour simulations had similar variability characteristics, as did 96 and 120 hours. This suggests the existence of a change point or statistically notable drop-off in forecast performance at 72-hours lead time that should be more fully explored in future work. These results are useful for forecasters as they give a first guess as to forecast skill and precision prior to initiating their predictions at lead times of out to 5 days.

Keywords

Non-tornadic severe weather, stochastic initial condition perturbation, numerical weather prediction, ensemble forecasting, derecho forecasting

1. INTRODUCTION

Predicting severe weather occurrence continues to be a difficult forecasting challenge, despite many advances in this research area and the importance of the research problem. Many severe weather studies have considered tornadoes the primary hazard associated with major severe weather outbreaks owing to the catastrophic damage associated with tornado impacts. Receiving less attention are non-tornadic outbreaks of severe weather, which still have tremendous impacts from their known hazards, particularly derechos. Derechos are defined as a widespread, convectively induced windstorm, which can contain tornadoes but has a primary hazard of straight line wind damage (Johns et al. 1986). Derecho hazards are often as costly as many tornado and hurricane events that affect the United States (Ashley et al. 2005). For instance, on 4 April 2011, there was a severe derecho outbreak that impacted over twenty states and caused over $16.5 million dollars in property damage, $320,000 in crop damages, 3 deaths, and 13 injuries (Storm Database). Despite their importance, derecho predictability remains difficult in many instances, particularly as it relates to the timing of the event (Gallus et al. 2005).

Numerous studies have assessed the climatological aspects of non-tornadic severe weather events (including derechos). Coniglio et al. (2003) suggested that warm-season (summer) derechos tended to be confined to northern latitudes, while cool season derechos primarily impacted southern states. Ashley et al. (2005) noted an elevated occurrence probability for derechos when a previous derecho had impacted a region recently. These efforts gave insight into the basic characteristics of derechos, but offered little in terms of predictability.

Initial efforts at predicting derecho extent and timing have centered around the use of localized sounding observations (Cohn et al. 2007, Coniglio et al. 2004, others). These efforts have centered around predictability of a single event (i.e. Cohn et al. 2007) or identification of parameters useful in identifying and predicting derecho environments (Coniglio et al. 2004). Doswell et. al (2003) also noted that that the initial mechanism by which convection begins is likely a major contributing factor to a mesoscale system evolving into a derecho. These studies supported initial work that identified a typical environment conducive for derecho formation, which requires a 1-2 km surface based stable layer, an elevated mixed layer of 2-4 km, and an upper tropospheric layer of intermediate stability extending up to the tropopause (Schmidt et al. 1991). These characteristics typically result in a storm system known referred to as a "bow echo" as the wind stress behind the line causes the line to bow outward (Przybylinski et al. 1995). These advances are certainly important to explain the current state of knowledge and fundamental characteristics of derecho events, but their applications in forecasting are limited, owing to data constraints and the impracticality of launching soundings into every derecho event. The availability of an accurate forecast model would

DOI: https://doi.org/10.22369/issn.2153-4136/8/3/5

certainly help meteorologists improve predictions of future derecho events.

Recent work in numerical modeling of derecho events (e.g. Kain et al. 2004) has found good predictability for the strongest events. Mercer et al. (2009) explored the discrimination capability of machine learning methods in identifying tornadic and non-tornadic environments within numerical weather prediction simulations, the first effort in diagnosing outbreak mode outside of a forecast office. Their results showed overall good discrimination capability (with forecast skill scores exceeding 0.7). They also noted only a slight degradation in classification performance by lead time (out to 72-hours), motivating a research question regarding non-tornadic outbreak predictability by lead time.

Forecasters have long assumed that outbreak forecasting limitations exist in the short-term without properly quantifying that time period (though the 72-hour results in Mercer et al. 2009 are a first guess). This lack of specificity, combined with the results of Mercer et al. (2009), motivate the current research objective. The primary objective of this project is to identify model forecast uncertainty within non-tornadic severe weather outbreaks as it relates to outbreak lead time. It is hypothesized that variability patterns within outbreak lead times of 3 days and shorter will be statistically significantly different than lead times of 4 – 5 days. To demonstrate this, a set of 5 major non-tornadic outbreaks will be simulated with the Weather Research and Forecasting model using 9 stochastically varied initial conditions at lead times of 24, 48, 72, 96, and 120 hours. Shifts in the variability associated with the 9 simulations per lead time will help assess forecast precision by lead time, which will be useful for forecasters to identify the maximum skill within their forecasts.

This research is part of the Blue Waters Undergraduate Internship Experience. As such, the paper contains not only information about the resulting research, but aspects of the internship including lessons learned and reflections. Section 2 contains a summary of data and methods used in this research, while section 3 shows the results from multiple non-tornadic outbreak simulations at varying lead times. Section 4 contains discussion regarding important results and lessons learned from the internship, while section 5 contains reflection information on the internship experience. Section 6 summarizes the results and provides important conclusions from the research.

2. DATA AND METHODS

2a. Data

As the primary objective of this project was the diagnosis of forecast variability by lead time for major non-tornadic outbreaks, a set of outbreak events was required. For this study, five major derecho events from the Storm Event database (Storm Data) recorded by the National Climatic Data Center were selected, all of which spanned multiple states over a multi-hour period. The 19 June 1979 event included 137 severe thunderstorm wind reports (those in excess of 58 mph) occurring over 9 states, with a peak wind speed of 90 mph. The 30 May 2004 affected 19 states, resulting in 578 individual severe wind reports, with a peak wind speed of 97 mph. The major derecho of 4 April 2011 had 1318 wind reports across 18 states with a maximum wind speed reported at 90 mph. On 21 June 2011, a derecho impacted 21 states and resulted in 604 wind reports with a peak speed of 81 mph. Finally, the 29 June 2012 derecho event (e.g. Fig. 1) affected 15 states with 1195 wind reports and a maximum observed wind speed of 93 mph.

Once a case set was established, continuous atmospheric data for each event was required for input into the WRF model. Since many of the predictors used for convective forecasting are mesoscale, a mesoscale analysis dataset, the North American Regional Reanalysis (NARR) was used to initialize the WRF. NARR data are provided on a 32-km Lambert conformal North American grid with 29 vertical levels and 3-hourly temporal resolution from 1979 to present. NARR data valid at 24, 48, 72, 96, and 120 hours prior to conclusion of the outbreak were retained.

2b. Model Configuration and Simulations

The proper simulation of a non-tornadic severe weather outbreak requires a gridded, convection allowing non-hydrostatic atmospheric model. The Weather Research and Forecasting (WRF – Skamarock et al 2008) version 3.8 was used to simulate the 5 outbreaks mentioned previously. Since the primary objective of this project was the diagnosis of variability of outbreak forecasts by lead time, each event was simulated at 24, 48, 72, 96, and 120 hours prior the end of a given event (as described previously). This timing ensured the peak outbreak time, which typically occurred on or after 0000 UTC on the event day, was sufficiently captured. Traditional model parameterizations for severe weather events were selected for the WRF simulations, including:

- The Yonsei University Planetary Boundary Layer scheme [YSU] for all five cases (Hong et al. 2005)
- The WRF Single-moment 6-class micro physics scheme [WSM6] (Hong et al. 2006)
- No cumulus parameterization
- The Dudhia Shortwave Radiation Scheme (Dudhia et al. 1989)
- The RRTM Longwave Radiation Scheme (Mlawer et al. 1997)
- The 5-layer Thermal Diffusion Land Surface Scheme (Dudhia et al. 1996)

The simulation domain was centered on a kernel density estimated outbreak center provided by the results from Shafer et al. (2012) and formulated on a 250 x 150 12-km grid-spacing grid with 45 vertical levels (e.g. Fig. 1). While the domain size was the same for each event, the geographic location of each simulation varied based on the storm report estimated outbreak center.

While event simulations were useful to depict overall environmental characteristics associated with each outbreak, a measure of variability was required to assess forecast precision by lead time. Variability was introduced into the WRF simulations using the Stochastic Kinetic Energy Backscattering Scheme (SKEBS, Berner et al. 2009) built into WRF 3.8. SKEBS adds random noise to potential temperature and stream function fields within the NARR input data, introducing perturbations and adding simulation variability via generation of an initial condition ensemble. At model initialization, only NARR are used, but SKEBS introduces random noise throughout the rest of the simulation, ensuring maximum spread in ensemble output and providing a direct measure of model variability. The SKEBS routine was used to generate nine initial condition ensemble members for each of the 5 lead times for each case, for a total of 225 individual model simulations.

The resulting simulations provided multiple diagnostic variables which are useful for addressing general weather variability, but derived severe weather parameters were required to assess environmental proneness to non-tornadic severe weather. One well known parameter, the derecho composite parameter (DCP – Evans and Doswell 2001) was computed on all gridpoints within each simulation domain to identify those locations which had elevated risk for derecho impacts (e.g. Fig. 1). The DCP is based on the following equation (from Evans and Doswell 2001):

$$DCP = \left(\frac{DCAPE}{980\frac{J}{kg}}\right)\left(\frac{MUCAPE}{2000\frac{J}{kg}}\right)\left(\frac{\Delta\vec{V}_{0-6}}{20\ kt}\right)\left(\frac{\vec{V}_{0-6\ km}}{16\ kt}\right)$$

Here, DCAPE refers to downdraft CAPE (a measure of positive stability associated with strong downdrafts and potential for extreme straight-line winds), MUCAPE is a maximum measure of instability, $\Delta\vec{V}_{0-6}$ refers to the vertical wind shear over the 0-6 km layer, and $\vec{V}_{0-6\ km}$ is the mean wind vector over the 0-6 km vector. Evans and Doswell (2001) defined this formula based on a large database of derecho proximity sounding data. They showed that the DCP was attuned at identifying atmospheric environments that were favorable for cold pool wind events through four mechanisms:

1. Cold pool production [DCAPE]
2. Ability for strong storms to be sustained along the leading edge of a gust front, the strongest section of a gust front [MUCAPE]
3. The potential for organization for any possible ensuing convection [0-6 km shear]
4. Enough flow in the ambient environment to favor development along a downstream portion of the gust front [0-6 km mean wind].

The DCP was utilized for this project owing to its global depiction of derecho-prone environments. Tremendous variability in DCP values is likely associated with uncertainty in the DCP forecast, which can be directly assessed by lead time using the above described methodology.

2c. Simulation Analysis

Once the simulations were completed, the resulting model runs were analyzed by assessing gridpoint variability along the 9 initial conditions. That is, moment statistics (mean, variance, skewness, and kurtosis) of DCP were computed at each gridpoint using the 9 stochastic perturbations for each case and each lead time. However, many points which yielded zero DCP values were excluded, as their moment statistics did not provide meaningful insight into variability structures within the simulations. Once non-zero DCP gridpoint variability was computed, 1000 bootstrap-resampled moment statistics on those non-zero points were formulated, allowing for the generation of confidence intervals for each moment statistic by lead time. These confidence intervals allowed the primary research hypothesis regarding lead time and forecast variability to be assessed. Results from these analyses are provided below.

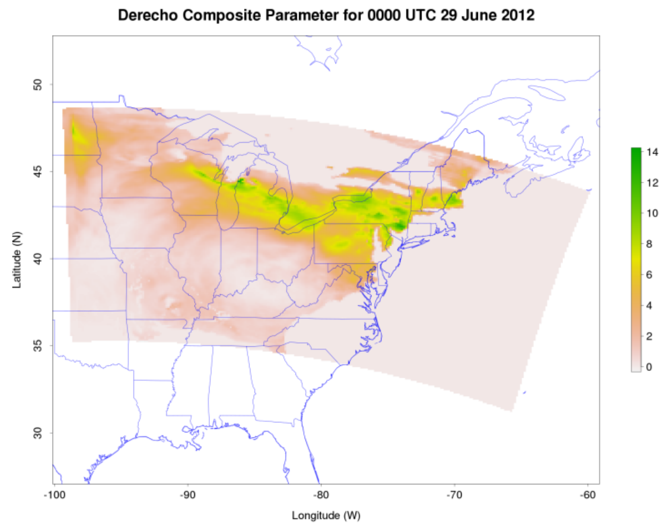

Fig. 1 Derecho Composite Parameter (DCP) for 0000 UTC 29 June 2012. Note the area shaded in gray represents the outbreak domain used for all simulations of the 29 June 2012 derecho event. Higher DCP values support derecho formation maintenance.

All cases showed considerable increases in DCP variability as the event valid time approached, and their resulting variability measures were widely dispersed, with an interesting pattern emerging. In general, 24-48 hour simulations tended to cluster fairly closely with all cases, while 72 to 120 hour simulations tended to cluster with each other and away from the 24-48 hour simulation groups. As an example, the 29 June 2012 derecho event is provided in Fig. 2. In this case, variance statistics at 24 and 48 hours (second panel orange and green lines) tended to cluster very closely together, while the remaining observations tended to group together and away from the 24-48 hour pairing. The gridpoint distribution tended to become more positively skewed as the outbreak progressed, and the skewness values were particularly enhanced at longer lead times, suggesting the tendency for larger DCP outliers with longer lead times. Kurtosis results were similar, as all distributions were platykurtic but longer-lead time simulations revealed more peaked results. Note that similar results were present for the other 4 cases as well (not shown here). Interestingly, 96 and 120 hour results tended to correlate strongly, suggesting that DCP forecasts at 96 and 120 hours offer similar performance, a previously undocumented result.

While differences among moment statistic distributions were a useful component of this research, the primary research objectives dealt with output variability by lead time over all cases, not just individual example case studies. To demonstrate overall performance, individual lead time data for all 5 cases were averaged, yielding average moment statistics by lead time for the selected events. These analyses revealed several interesting patterns (Fig. 3). First, as expected, variance by lead time increased with increasing lead time, with a notable jump observed at 96 and 120-hour lead times. Also, note that the 96 and 120-hour results are not significantly different based on the confidence intervals, supporting the previous conclusion regarding 96-120 hour day predictability essentially remaining equal. Another notable result was the sharp increase in positive skewness at 96 and 120-hour lead times in contrast with the relatively unskewed 72 and earlier lead time forecasts. This result supports the previous conclusions regarding the similarities among the 24-48 hour forecasts and their stark contrasts with 96 to 120 hour predictions. Additionally, kurtosis values showed an unusual drop off in mean kurtosis value at the 72-hour forecast, likely owing to outlier results due to periods of relatively low DCP values (e.g. the green dip in Fig. 2's bottom panel). Outside of that individual outlier, the kurtosis behavior was in line with skewness behavior, with a relatively platykurtic distribution observed at 24-48 hours lead time and a more peaked (but still non-Gaussian) distribution observed at lead times in excess of 72-hours. These results further support the existence of a few outlier points that are driving up the kurtosis values and increasing the skew of the distributions.

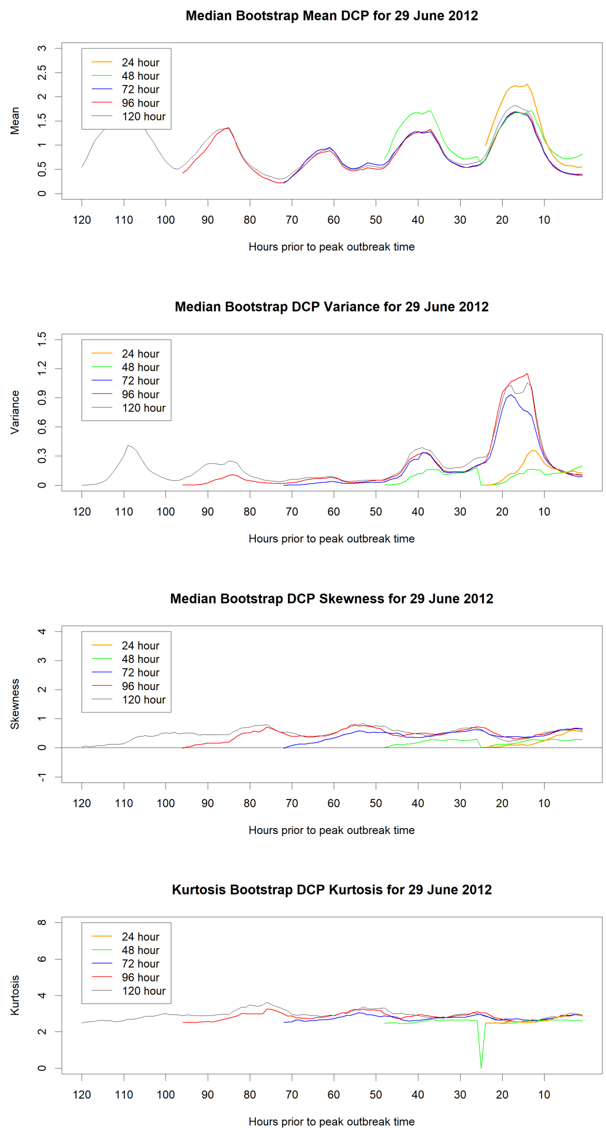

Fig 2. Moment statistics for the 29 June 2012 derecho. The top panel shows median bootstrap mean DCP values, while the second panel shows variance statistics, the third panel skewness, and the fourth kurtosis. Note that for this event outbreak valid time is roughly 12 hours prior to the end of the simulation.

3. DISCUSSION AND LESSONS LEARNED (EDUCATIONAL IMPACT)

The primary objective of this research was to ascertain WRF model uncertainty by lead time for five major non-tornadic severe weather events. Outbreak severity was assessed using DCP as a proxy measure for the derecho environment. Overall, the major findings included the consistency among 96 and 120-hour lead time runs, the outlier and relatively unpredictable nature of 72-hour simulations, and the similarities among 24-48 hour runs. These results are very useful to forecasters for a variety of reasons. First, forecast confidence in a 120-hour forecast is unlikely to change for a 96-hour forecast, a result that has not been quantified previously. Second, similar behavior exists at 24 and 48-hours lead time as their DCP mean and variability structure was quite similar. While this study does not measure accuracy of the DCP forecasts, all events selected were major derecho events, and as such higher values of DCP (e.g. the 24-72 hour runs for 29 June 2012 – Fig. 2) are more supportive of an environment conducive for derecho formation. Mean DCP values were generally higher in the shorter lead-time runs, which should increase forecaster confidence in derecho occurrence as well.

This project was completed using Blue Waters supercomputing resources as a part of the Blue Waters Undergraduate Internship program. The educational component of the research for the undergraduate student fell in two key areas. First, the student was exposed to the challenges of dynamic atmospheric modeling within a high-performance computing environment, including the temporal and physical constraints of simulations and configuring parallel processing jobs. The student also gained valuable experience working with big datasets (the project generated nearly 1 TB of data) and the computational challenges associated with such big data interactions.

In addition to the general education experiences for the undergraduate student, they learned key lessons regarding supercomputing research. These are listed below.

1. Simulation data were lost due to typical file system cleaning and the undergraduate student not storing the data properly. The student learned the importance of file backups as the cases were rerun.
2. The student gained valuable insight into the challenges of forecasting non-tornadic severe weather events, including the forecasting metrics that are used to evaluate the likelihood of these outbreaks.
3. The student learned data organization and the challenges of large data transfers, as the 225 simulations needed to be moved between machines prior to running the model.
4. The student discovered an issue with an initial condition, which forced the original 10 initial condition ensemble members to be reduced to 9. This helped the student learn the importance of data quality and close interaction with the project to limit the risks of future issues.

One important computational challenge was encountered as well, which required the use of an external machine to post-process the results. The Blue Waters Cray system was not compatible with the Unified Post Processor software used to post-process the WRF simulations due to compilation issues, which the student struggled with for a long period in the internship. Despite this small setback, the student felt the experience was largely successful and the mentor was satisfied that the student gained important supercomputing skills that are essential for successful research meteorologists.

The work would not have been possible without access to the resources offered by the Blue Waters Supercomputing Center, particularly the quantity of simulations in the required 1-year study period. The computing time utilized by the project exceeded 1000 computational hours, which is difficult for an undergraduate student to finish in a traditional computing environment, particularly given the limited timeline. Additionally, the quantity of data produced by the project (nearly 1 TB) and quantity of forecast hour files (16,425) are unwieldy for even a modest supercomputing center, requiring the robust resources offered by Blue Waters.

4. REFLECTIONS

Undergraduate research projects are typically fraught with challenges simply owing to the student's inexperience working in research. While this internship had its share of challenges, the student gained valuable experience working in supercomputing, which is becoming more important in operational meteorology as National Weather Service offices begin to maintain their own small supercomputing clusters for regional modeling. Additionally, with the introduction of high resolution imaging provided by new data platforms such as the GOES-R satellite, big data experience is an essential part of any successful research meteorologist's repertoire. Finally, the student's participation in the project prepared them for graduate study, which they are now engaged in, and that experience, combined with the Blue Waters Summer Internship Program experience, will help set the student apart from their peers when they begin searching for jobs.

5. SUMMARY AND CONCLUSIONS

The primary objectives of this research were to obtain measures of forecast precision and variability at lead times from 1 to 5 days. It is well established in meteorology that short-term forecasts are more precise and accurate than longer-term predictions, but few studies have formally quantified these differences. The research objectives herein addressed these concerns in the context of derecho forecasts, with interesting results.

To address this variability, five derecho events spanning 1979 to 2012 were selected. Outbreak-centric domains were retained from WRF simulations of each event, where WRF simulations were run with 24, 48, 72, 96, and 120 hours lead time. Each lead time's simulations were perturbed stochastically nine times, introducing forecast uncertainty from which lead time precision could be obtained. Resulting gridpoint precision for non-zero gridpoints of DCP were retained using bootstrap-resample moment statistics for each case and global values for all cases.

Overall, several key findings resulted from this analysis. First, model precision (and predictions) tended to remain very similar with both 24 and 48-hour lead times and with 96 and 120-hour lead times. This suggests only minimal drop-offs in forecast skill between 24 and 48 hours lead time and between 96 and 120 hours.

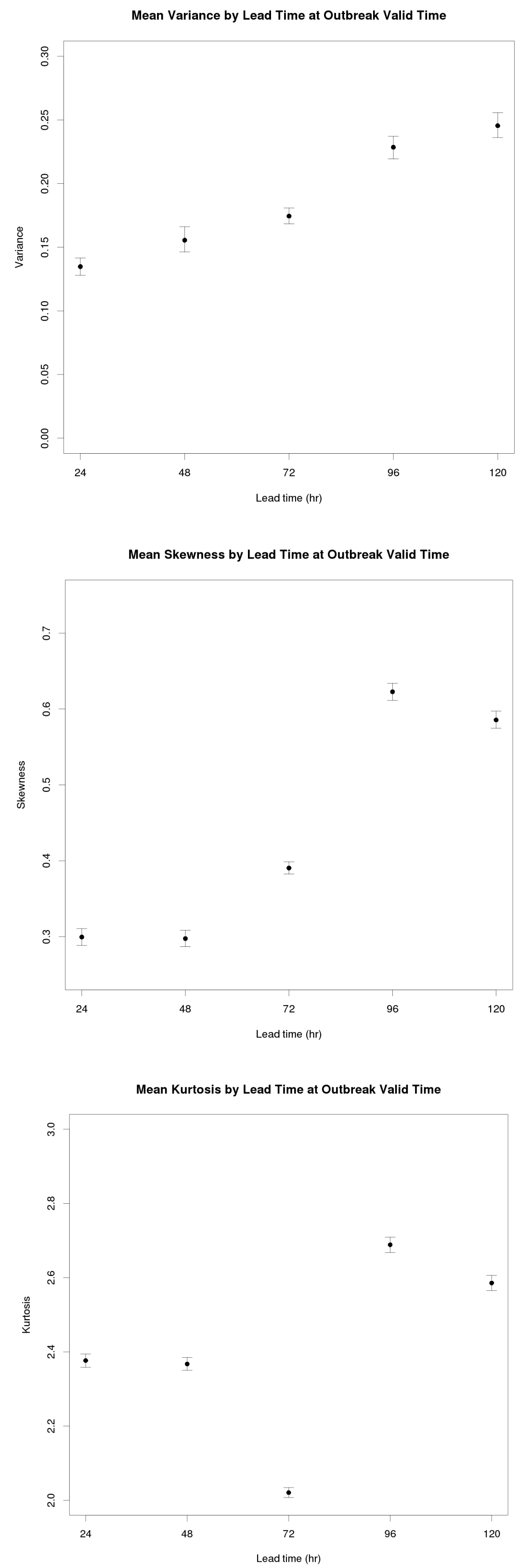

Fig. 3. Average moment statistics by lead time for all derecho events at all forecast times. The top panel represents variance by lead time, while the middle panel is skewness and the bottom panel is kurtosis.

The 72-hour simulations were inconsistent, with some producing lower variability than either 24 or 48 hours lead time and others higher. This suggests the existence of a forecast confidence change point around 72 hours lead time, which is a likely good demarcation between short-term high skill forecasts and medium-term modest skill forecasts. These results are in line with Mercer et al. (2009) who noticed some skill drop-off at 72 hours but did not consider longer lead times, which would have likely revealed these patterns as well.

These results have significant forecast implications, as they allow forecasters to have prior knowledge of anticipated WRF forecast skill, which is useful for prediction purposes. The results also help reveal a cutoff point in terms of lead times; that is, what defines a "short term" and a "medium term" derecho forecast. Future work will address this issue with additional non-tornadic derecho events and add tornado outbreaks as well. It is expected that similar behavior in tornado outbreaks will exist, though tornado outbreaks are less predictable than their non-tornadic counterparts. Overall, this study reveals important insight into non-tornadic outbreak predictability, which will be useful for future outbreak forecasts.

6. ACKNOWLEDGEMENTS

This research is part of the Blue Waters sustained-petascale computing project, which is supported by the National Science Foundation (awards OCI-0725070 and ACI-1238993) and the state of Illinois. This work resulted from a Blue Waters undergraduate internship opportunity, and we are thankful for their financial and technical support throughout the project. We are also grateful for feedback during the peer-review process.

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