HIGH-WIND ALERTS:

A System Created With Observations
From the X-band Teaching and Research Radar

Student Author

Lauren Warner graduated from high school in Summit, Illinois, in 2016 and earned her BS in atmospheric science from Purdue University in 2020. During her junior and senior years she worked with Dr. Robin Tanamachi on this project.

Warner also participated in fieldwork during this period, helping Tanamachi's research group deploy a mobile Doppler radar near severe storms. Warner plans to pursue her master's degree in geography with a focus on meteorology at Ohio University starting in the fall of 2020.

Mentor

Robin Tanamachi is an assistant professor in the Department of Earth, Atmospheric, and Planetary Science. Her research interests include severe convective storms, tornadoes, meteorology, and atmospheric science education

research. Tanamachi earned her BS in atmospheric and oceanic science from the University of Wisconsin–Madison in 2001 and her MS and PhD in meteorology from the University of Oklahoma in 2004 and 2011, respectively. Prior to coming to Purdue, she was a research scientist at the Cooperative Institute for Mesoscale Meteorological Studies in Norman, Oklahoma. Tanamachi has led the Weather Radar Research Laboratory at Purdue since 2015.

Abstract

Following the August 13, 2011, Indiana State Fair stage collapse tragedy, caused by a wind gust from an approaching thunderstorm, Purdue University enforced a wind speed restriction of 30 mph (13 m s^{-1}) for tents at outdoor events. During these events, volunteers stand outside with handheld anemometers, measuring and reporting when the wind speeds exceed this limit. In this study, we report testing of a new system to automate high-wind alerts based on observations from a Doppler radar, the X-band Teaching and Research Radar (XTRRA), near Purdue's campus. XTRRA scans over campus at low elevations approximately every 5 minutes. Using XTRRA data collected over its first eight months of operation, we developed an algorithm that generates high-wind alerts whenever observed winds at altitudes below 240 m (the height of Ross-Ade Stadium) exceed the 13 m s^{-1} threshold. We describe how a combination of median filtering, clutter filtering, and statistical outlier removal mitigated false alarms caused by noise and ground clutter. The high-wind alerts are validated against wind gust observations from a nearby Automated Surface Observing System at Purdue University Airport, known as KLAF. Results indicate that the alerts work well in high-wind events associated with precipitation but less well in high-wind events not associated with precipitation (e.g., frontal passages). This is likely because XTRRA, which has a wavelength of 3 cm, is less sensitive to clear-air echoes than an operational WSR-88D. Following further testing, we envision that these automated high-wind alerts will be distributed to interested parties such as campus event coordinators and safety officials.

Warner, L. (2020). High-wind alerts: A system created with observations from the X-band Teaching and Research Radar. *Journal of Purdue Undergraduate Research*, 10, 78–86.

Keywords

atmosphere, radar, severe weather, wind, safety, remote sensing

INTRODUCTION

Severe wind gusts can pose serious threats to life and property. On August 13, 2011, the Indiana State Fair stage collapsed as fans gathered for a musical performance, resulting in multiple fatalities and injuries. The event was caused by a high-wind gust from an approaching severe thunderstorm (Witt Associates, 2012). In light of this tragedy, Purdue University established new wind speed limits of 30 mph (13 m s^{-1}) for tents at outdoor events (Purdue University Athletics Department, 2019). During these events volunteers stand outside with handheld anemometers, measuring and reporting to event officials when the wind speeds exceed the limit.

The recent installation of the X-band Teaching and Research Radar (XTRRA) near Purdue offered an opportunity to explore automation of these alerts. We report on the development of a prototype high-wind alert system using velocity observations from XTRRA. A high-wind alert is generated when the wind speed limit is surpassed. We reduce false alarms by limiting the observations used to those collected at low altitudes and reducing the effects of ground clutter. We verify these alerts by retrospectively comparing them to data from a surface-wind observing station.

XTRRA DATA

XTRRA is a 3-cm-wavelength weather radar with a maximum range of 60 km installed on top of Wang Hall, a four-story 147,000-square-foot facility, located near Purdue University, that includes academic, research, and retail spaces. Energy transmitted by the radar backscatters off meteorological (raindrops, snowflakes) and nonmeteorological scatterers (ground clutter targets, dust, birds, and insects). For comparison, the National Weather Service's operational radar—Weather Surveillance Radar-1988 Doppler (WSR-88D)—uses a 10-cm wavelength and has a range of 230 km (Crum & Alberty, 1993). XTRRA was designed to fill a lower atmospheric observing gap between the nearest three WSR-88Ds (installed at Indianapolis, Indiana; North Webster, Indiana; and Chicago, Illinois). These radars do not detect near-surface winds at Purdue because their beam height (1.2 km) is too high.

The microwave pulses transmitted by XTRRA are dual-polarized, meaning they are transmitted in both vertical and horizontal polarizations (e.g., Doviak & Zrnić, 1993). The dual-polarized signals allow for better discrimination of nonmeteorological scatterers (e.g., Kumjian, 2013a). Additionally, the shape

(spherical, oblate, or prolate) and phase (liquid, frozen, or a mixture) of hydrometeors in the radar beam can also be inferred (e.g., Kumjian, 2013b).

XTRRA was installed on top of Wang Hall in June 2018 and began collecting volume scans in September 2018. Since then the radar has operated continuously, collecting observations of weather conditions ranging from quiescent clear skies to severe thunderstorms. During the period covered by this study, XTRRA scanned the volume of atmosphere around it in one of two modes: clear-air mode, covering 9 elevation angles ranging from 0.5°C to 6.4°C , and precipitation mode, covering 15 elevation angles ranging from 0.5°C to 19.5°C . The data are stored in radar-centered spherical coordinates (azimuth angle, elevation angle, and range) binned into “gates” (voxels). Observations include logarithmic reflectivity factor, or reflectivity, in standard meteorological units of dBZ (Doviak & Zrnić, 1993), Doppler radial velocity (in m s^{-1}), spectrum width (in m s^{-1}), signal-to-noise ratio (SNR, in dB), differential reflectivity (in dB), differential phase (in degrees), and copolar correlation coefficient (unitless), among other variables. In this study we focus almost exclusively on the Doppler radial velocity observations (i.e., measurements of radial motion toward or away from the radar), since they are most closely related to surface wind speeds. Reflectivity and SNR are used for quality control, as detailed in the next section.

METHODS

Data Preprocessing

To ensure accuracy of the high-wind alerts and minimize false alarms, we applied the high-wind alert algorithm (described in the next section) to an eight-month subset of the data (September 1, 2018, to April 30, 2019). The raw Doppler velocity data were preprocessed to reduce the size of the data structures, improve data quality, and minimize false alarms (Figure 1). Initial testing indicated that velocity readings from nonmeteorological clutter targets often caused false alarms. For weather radar, clutter echoes can be caused by things such as planes, buildings, insects, and birds that can reflect the beam back to the radar with a different velocity than the air or hydrometeors around them. This is demonstrated in Figure 1a, where multiple patches of dark blue and red (indicating high velocities) are associated with nonmeteorological scatterers. These nonmeteorological velocity readings could potentially trigger an alert when there is no threat (i.e., a false alarm).

Figure 1. Doppler radial velocity observations (in m s^{-1}) collected during a precipitation event.

Note: The panels show different stages in the decluttering process at a single elevation angle (0.5°C): (a) raw data, (b) after texture and SNR restrictions, (c) after applying height restriction and median filtering, and (d) after removal of statistical outliers.

First, an SNR threshold of 3 dB was applied. If the SNR at a gate was less than 3 dB the signal was considered unreliable, and the data were masked. Next, the resulting SNR mask was dilated by one point to eliminate edge effects.

Second, texture filtering (Gourley, Tabary, & Parent du Chatelet, 2007) was applied in two dimensions. Areas of clutter-contaminated velocity tend to have higher texture than areas of meteorological echo, which tend to vary smoothly. If the texture at a point was greater than or equal to 10 m s^{-1} , the optimal value we found in testing, then the point was masked (see Figure 1b).

Third, the radar height equation (e.g., Doviak & Zrnić, 1993; Rinehart, 1997) was used to calculate the height of each gate above the radar. Observations from heights 240 m above radar level (the height of Purdue's Ross-Ade Stadium) and those taken at elevation angles of greater than 2.0° were ignored, as they were not considered representative of surface conditions that could affect Purdue's campus. This height restriction corresponded to a range limit of approximately 6 km from XTRRA (see Figure 1c).

The remaining nonmeteorological echoes generally consisted of isolated single gates, so to despeckle these points, a median filter with a 3-point square kernel was applied to the data. This technique replaces the value at a gate with the median value of those at the eight gates surrounding it, thereby eliminating outliers (see Figure 1c).

Finally, some more persistent clutter that resisted all the previous filtering efforts were eliminated via statistical outlier removal. Values that were more than five standard deviations away from the mean of all the filtered data were masked (see Figure 1d). These three preprocessing steps eliminated most false alarms associated with noise and nonmeteorological targets such as clutter; remaining false alarms are considered to be due to circumstances beyond the user's control.

High-Wind Alert Algorithm

The high-wind alert algorithm was applied to the resulting filtered Doppler velocity field. Initially, a Doppler velocity threshold of 30 mph (13 m s^{-1}) was applied (Purdue University Athletics Department, 2019). Because Doppler velocity observations by XTRRA are radar-relative, the measured Doppler velocity can be considered a lower bound on the actual wind speed that an observer located at a given gate would experience. By convention, velocities directed toward the radar are negative, while velocities directed away are positive, so the absolute value (magnitude) of the wind field is checked against the threshold wind speed. If the magnitude of the wind speed was above this 13 m s^{-1} threshold, an alert trigger text product was generated but not issued (disseminated); this alert is plotted as either green or orange boxes with a default duration of 30 minutes in Figure 2. The text product contained the alert start time; the maximum, minimum, mean, and standard deviation of the Doppler velocity; and the number of gates that exceeded the threshold.

An areal coverage constraint was then applied. An alert generated as a result of measurements at only a small number of gates was deemed likely to be a false alarm (i.e., resulting from noise or nonmeteorological targets). Alerts were not issued if fewer than at least 250 gates (covering an area of

Figure 2. XTRRA low-level winds, KLAf wind gusts, and high-wind alerts.

Note: Red dots, in m s^{-1} , indicate low-level winds, and blue dots, in m s^{-1} , indicate KLAf wind gusts. The high-wind alerts are color-coded to show whether they were classified as hits (green) or false alarms (orange). Misses are plotted as 30-minute segments following the detection by KLAf of winds exceeding the 13 m s^{-1} threshold; these are color-coded as low-reflectivity misses (pink) or all other misses (blue). For clarity, correct negatives are not plotted.

approximately 0.5 km^2) exhibited Doppler velocity magnitude at or above 13 m s^{-1} .

Owing to the 6-minute volume update time of XTRRA, there is the potential for a high-wind alert to be triggered every 6 minutes. The eventual intent is to send automated high-wind alerts to interested parties in the form of an e-mail or text message but spaced out in 30-minute intervals to avoid “spamming” the recipients. Therefore, each new alert text was checked to see if it was generated within 30 minutes of a previously issued alert. If it happened less than 30 minutes after a previous alert, no new alert was issued.

Alert Verification

A common forecast verification framework for binary (yes/no) forecasts in meteorology is the contingency table (Wilks, 2006; WWRP/WGNE Joint Working Group on Forecast Verification Research, 2015). To generate this table, a forecast product is compared to a validation data source (such as an independently collected observation), and issued forecast products are separated into four categories: hits, in which the forecast condition is observed to occur; misses, in which no forecast is issued and the condition occurs; false alarms, in which a forecast condition does not occur; and correct negatives, in which no forecast is issued and the condition does not occur. Specific metrics calculated based on these values are discussed in the “Results” section.

To verify the high-wind alerts, four months’ worth of alerts were compared with wind gust data from the Automated Surface Observing System (ASOS; National Oceanic and Atmospheric Administration, Department of Defense, Federal Aviation Administration, and United States Navy et al., 1998) station located at the Purdue University Airport, also known as KLAF (Figure 3). The ASOS measures wind using an in situ sonic anemometer mounted on a 10-m tower. Because of their use in assessing safe conditions for aircraft takeoff and landing, ASOS wind speeds are calibrated to within 1 m s^{-1} or 5% of the measured wind speed, whichever is greater (National Oceanic and Atmospheric Administration, Department of Defense, Federal Aviation Administration, and United States Navy, 1998).

An obvious method for verifying the high-wind alerts would have been to directly compare the KLAF wind speed observations to the XTRRA Doppler velocity observations at the lowest elevation angle (0.5°C) at the gate closest to KLAF. However,

Figure 3. XTRRA and KLAF locations, major roads, and radar range rings.

Note: Major roads are in red; radar range rings are in gray.

this method has several shortcomings. First, KLAF wind gust observations and XTRRA Doppler velocity observations often do not coincide in time. While XTRRA collects a 0.5°C sweep every 6 minutes, KLAF produces 10-minute averaged observations and also generates special observation messages if high-wind gusts occur (National Oceanic and Atmospheric Administration, Department of Defense, Federal Aviation Administration, and United States Navy, 1998). Second, the XTRRA Doppler velocity observations are radar-relative, meaning that the Doppler velocities measured at the gate closest to KLAF are dependent upon the direction of the motion as well as the speed. For example, if the winds at KLAF are blowing directly toward or away from XTRRA, then the winds measured by KLAF should agree well with XTRRA’s Doppler velocity measurements at that location. However, if the winds are blowing perpendicular to the 3.6-km baseline connecting XTRRA to KLAF, XTRRA will record a Doppler velocity observation of 0 m s^{-1} . As previously mentioned, the XTRRA Doppler velocity observations are at best a lower bound on the actual wind speeds.

XTRRA is located 3.6 km from KLAF (see Figure 3). If a wind event completely covers the circular area inside this radius (a reasonable assumption for most high-wind events), we can estimate the winds that would be observed at KLAF by taking the maximum magnitude of Doppler velocity observed along the ring of constant 3.6-km range from XTRRA. This concept is borrowed from the velocity-azimuth display technique for determining wind profiles over a Doppler radar site (Browning & Wexler, 1968; Doviak & Zrnić, 1993).

This maximum wind speed at a radius 3.6 km is compared to the 10-m winds observed at the KLAF site within a 5-minute window.

During this verification process, many of the misses (i.e., KLAF observed high-winds, while XTRRA did not) were found to be attributable to situations in which little to no precipitation occurred. An example of this kind of scenario is widespread high winds observed in the precipitation-free air behind an advancing cold front; this would result in high-wind observations at KLAF but possibly no high-wind alert from XTRRA owing to a scarcity of meteorological scatterers at the 3.6-km radius. Accordingly, we investigated the impact of reflectivity on the alerts. The mean reflectivity around the 3.54–3.60-km annulus was recorded. A histogram of these annular mean reflectivity values associated with the four months' worth of high-wind alerts revealed a bimodal distribution with an inflection point around 7 dBZ (Figure 4). This reflectivity threshold was used to separate the miss category into low-reflectivity (low-Z) misses and other misses. By accounting for these different miss classifications, we hoped to discern the effects that low-precipitation, high-wind events have on the performance of the alerts.

Figure 4. Logarithmic normalized kernel density of reflectivity (in dBZ) for all miss events.

Note: This density was used to determine the reflectivity threshold of 7 dBZ (orange) for delineating low-Z misses from other misses. Miss events are indicated by the blue curve.

The flow chart in Figure 5 depicts the categorization of high-wind alerts into the classifications needed for a contingency table (Table 1). The XTRRA-based high-wind alert would be a hit if a KLAF wind gust equal to or greater than 13 m s^{-1} was observed within 30 minutes of the alert start time (green box in Figure 2). If KLAF did not observe winds equal

to or greater than 13 m s^{-1} during the 30-minute alert period, the alert was classified as a false alarm (orange box in Figure 2). For the other two categories, 30-minute KLAF-based faux alerts were created that started at times when KLAF detected winds greater than or equal to 13 m s^{-1} . A miss was cataloged if XTRRA did not detect Doppler velocity above the 13 m s^{-1} threshold along its 3.6-km-range ring in the 30 minutes before a KLAF alert period. As previously discussed, it was found that many misses were attributable to low-precipitation scenarios. Therefore, the misses were further split depending on reflectivity to account for situations such as those depicted in Figure 2. If the XTRRA mean reflectivity in the 3.54–3.60 km annulus during the KLAF alert fell below the reflectivity threshold, the miss would become a low-Z miss. During those periods when no high-wind alert was present based on either KLAF or XTRRA observations (e.g., white spaces in Figure 2), these intervals were split into 30-minute periods (for consistency with the 30-minute alert duration), each of which was classified as a correct negative.

RESULTS

The contingency table generated is shown in Table 1. From this table, six commonly used verification metrics were calculated (Table 2). Interested readers are referred to Wilks (2006) and WWRP/WGNE Joint Working Group on Forecast Verification Research (2015) for more comprehensive overviews of these six metrics, their precise formulation, significance, and limitations. Only a brief review will be given here. Specifically, we calculated accuracy, bias, probability of detection (POD), false alarm ratio (FAR), probability of false detection (POFD), and critical success index (CSI).

1. *Accuracy.* The accuracy is the fraction of all forecasts that were correct but can be heavily influenced by the number of correct negatives (Equation 1). Values of accuracy range from 0% (no skill) to 100% (perfect).

$$\text{Accuracy} = \frac{\text{hits} + \text{correct negatives}}{\text{total}} \quad (1)$$

2. *Bias.* Bias shows the frequency comparison between forecasted and observed “yes” events, determining whether the condition is overforecast (bias > 1) or underforecast (bias < 1) (Equation 2).

$$\text{BIAS} = \frac{\text{hits} + \text{false alarms}}{\text{hits} + \text{misses}} \quad (2)$$

Figure 5. Flowchart for contingency table categorizations.

Note: Misses are split into those associated with low-reflectivity conditions and those that are not.

	KLAF Observed Gust $\geq 13 \text{ m s}^{-1}$	KLAF Observed Gust $< 13 \text{ m s}^{-1}$
XTRRA high-wind alert	31 hits	14 false alarms
No XTRRA high-wind alert	5 misses, 110 low-Z misses	4251 correct negatives

Table 1. Contingency table for comparison of XTRRA data with KLAF gusts .

	All Misses	Excluding Low-Z Misses
Accuracy	97.1%	99.6%
CSI	0.19	0.62
Bias	0.31	1.25
POD	21.2%	86.1%
POFD	0.33%	0.33%
FAR	31.1%	31.1%

Table 2. Calculated forecast verification values for the high-wind alert system

3. *Probability of detection.* POD provides the fraction of observed “yes” events that were correctly predicted (Equation 3). Values of POD range from 0% (no chance of correct prediction) to 100% (perfect prediction).

$$POD = \frac{\text{hits}}{\text{hits} + \text{misses}} \quad (3)$$

4. *False alarm ratio.* FAR demonstrates what fraction of predicted “yes” events did not actually occur (Equation 4). Values of FAR range from 0% (no false alarms) to 100% (all false alarms).

$$FAR = \frac{\text{false alarms}}{\text{hits} + \text{false alarms}} \quad (4)$$

5. *Probability of false detection.* POFD gives the fraction of the observed “no” events that were incorrectly forecasted as “yes” events (Equation 5). Values of POFD range from 0% (no false detections) to 100% (all false detections).

$$POFD = \frac{\text{false alarms}}{\text{correct negatives} + \text{false alarms}} \quad (5)$$

6. *Critical success index.* The CSI seeks to remedy the heavy influence of the correct negatives in the accuracy metric (see Equation 1) and shows how well the forecasted “yes” events correspond to the observed “yes” events, ignoring correct negatives (Equation 6). Values of CSI range from 0 (no skill) to 1 (perfect skill).

$$CSI = \frac{\text{hits}}{\text{hits} + \text{misses} + \text{false alarms}} \quad (6)$$

We recomputed these six metrics (see Table 2) both with and without low-Z misses to examine the impact of including them. With metrics that are calculated using misses (i.e., accuracy, the CSI, bias, and POD), the inclusion of low-Z misses significantly lowers the performance of the high-wind alert system. The accuracy is the least changed, as it also accounts for the large number of correct negatives, while the other statistics are lowered more dramatically. Due to these impacts, users of the alert system will be advised that it can only be expected to work for high-wind events accompanied by precipitation and not low-precipitation high-wind events such as nonprecipitating frontal passages.

When low-Z events are excluded, the forecast metrics (see Table 2, left column) look more favorable. The accuracy was 99.6%; however, the correct negatives in the distribution heavily influence the accuracy. Excluding the correct negatives, the CSI shows that 62% of KLAFF-observed high-wind events were correctly forecast by the XTRRA-based high-wind alert system. The alert system slightly overforecasts high-wind events, as shown by the bias of 1.25. The POD demonstrates that 86.1% of the high-wind events observed by KLAFF would have received alerts from our alert system. In conjunction, FAR indicates that about one-third of the alerts generated by the XTRRA-based system were not accompanied by an observed high-wind event. POFD was 0.33%, meaning 0.33% of observed high-wind events were incorrectly forecast by the alert system.

CONCLUSION

We have created a prototype high-wind alert system for Purdue University’s main campus based on observations from a recently installed weather radar, XTRRA. This system performed well with respect to several standard forecast verification metrics. One major failure point of the high-wind alert system was the high number of misses associated with low-Z high-wind events (i.e., high-wind events that were not accompanied by precipitation). This is because XTRRA, being an X-band radar, is not as sensitive to clear-air scatterers and Bragg scatter as its larger operational cousin, the S-band WSR-88D. Accordingly, as we deploy this high-wind alert system, we will advise users that it can only be expected to generate alerts in conditions accompanied by precipitation.

Our POD (FAR) for high-wind events in precipitation is 86% (31%), which compares favorably with a POD (FAR) of approximately 80% (50%) for severe thunderstorm warnings issued by the National Weather Service (Karstens et al., 2015). According to Equations (3) and (4), increasing the number of hits would increase the POD but also increase the FAR. Through personal communication with Jefferson Howells, director of Purdue’s Campus Emergency Preparedness and Planning Office, an emphasis is being put on high POD rather than low FAR. When given a hypothetical choice between a high-wind alert system with a POD of 90% and FAR of 40% versus a system with a POD of 80% and a FAR of 30%, Howells preferred the 90% POD/40% FAR system.

There are multiple steps that still need to be taken to further improve the quality of the data going into the high-wind alert system. We will work to mask data

from gates that frequently exhibit multibody scatter, such as those down radial of tall structures on and off campus.

Another concern is the FAR of 31.1%, which means that approximately one out of every three high-wind alerts issued could be false alarms, and preventative actions might be taken unnecessarily. We speculate that some of these false alarms may be spurious, due to limitations of our verification methodology. KLAF is located on the southwest side of campus, meaning that if an event exclusively impacted the northeast side of campus, KLAF may not detect it. Events such as microbursts, which are only 2–4 km in diameter, would be detected by XTRRA but could be isolated enough that KLAF would not detect the winds, leading to the XTRRA-based high-wind alert being classified as a false alarm. In this study, KLAF wind observations were the only observations used for validation, and thus they were implicitly assumed to represent the true wind conditions for all of campus. This representativeness issue could be resolved by deploying additional wind sensors around campus for use in verification.

Future plans for this system include adding multiple tiers based on the different rated wind speeds for tents and temporary structures (Purdue University Athletics Department, 2019). This policy specifies different high-wind limits for multiple-tent structures rather than the Purdue football tent wind limit of 13 m s⁻¹ that was the focus of this study. We also plan to look into evaluating lead time for the system and generating alerts for other severe weather events on Purdue's campus, such as hail and mesocyclones.

ACKNOWLEDGMENTS

The authors are grateful to Purdue University's College of Science, Earth, Atmospheric, and Planetary Sciences for providing funds that partially supported the first author's travel to the 19th American Meteorological Society Student Conference, where this research was presented. Kyle Banter, superintendent of Purdue's Athletics Facilities, supplied the height of Ross-Ade Stadium. Jefferson Howells, director of Purdue's Campus Emergency Preparedness and Planning Office, provided commentary on the alert system. Py-ART (Helmus & Collis, 2016) was used to read the data and prepare some of the figures.

REFERENCES

- Browning, K. A., & Wexler, R. (1968). The determination of kinematic properties of a wind field using Doppler radar. *Journal of Applied Meteorology*, 7, 105–113.
- Crum, T. D., & Alberty, R. L. (1993). The WSR-88D and the WSR-88D Operational Support Facility. *Bulletin of the American Meteorological Society*, 74, 1669–1687. [https://doi.org/0.1175/1520-0477\(1993\)074<1669:TWA TWO>2.0.CO;2](https://doi.org/0.1175/1520-0477(1993)074<1669:TWA TWO>2.0.CO;2)
- Doviak, R. J., & Zrnić, D. S. (1993). *Doppler weather radar and observations* (2nd ed.). Oxford, UK: Academic Press.
- Gourley, J. J., Tabary, P., & Parent du Chatelet, J. (2007). A fuzzy logic algorithm for the separation of precipitating from nonprecipitating echoes using polarimetric radar observations. *Journal of Atmospheric and Oceanic Technology*, 24, 1439–1451. <https://doi.org/10.1175/JTECH2035.1>
- Helmus, J. J., & Collis, S. (2016). The Python ARM Radar Toolkit (Py-ART), a library for working with weather radar data in the Python programming language. *Journal of Open Research Software*, 4, e25–e25. <https://doi.org/10.5334/jors.119>
- Karstens, C. D., et al. (2015). Evaluation of a probabilistic forecasting methodology for severe convective weather in the 2014 Hazardous Weather Testbed. *Weather and Forecasting*, 30, 1551–1570. <https://doi.org/10.1175/WAF-D-14-00163.1>
- Kumjian, M. R. (2013a). Principles and applications of dual-polarization weather radar: Part I, Description of the polarimetric radar variables. *Journal of Operational Meteorology*, 1, 226–242. <http://dx.doi.org/10.15191/nwajom.2013.0119>
- Kumjian, M. R. (2013b). Principles and applications of dual-polarization weather radar: Part II, Warm- and cold-season applications. *Journal of Operational Meteorology*, 1, 243–264. <http://dx.doi.org/10.15191/nwajom.2013.0120>
- National Oceanic and Atmospheric Administration, Department of Defense, Federal Aviation Administration, and United States Navy. (1998). *Automated Surface Observing System (ASOS) user's guide*. Washington, DC: National Oceanic and Atmospheric Administration. Retrieved from <https://www.weather.gov/media/asos/aum-toc.pdf>
- Purdue University Athletics Department. (2019). Parking and tailgating policies. Retrieved from <https://purduesports.com/sports/2019/6/26/parking-and-tailgating-policies.aspx>
- Rinehart, R. E. (1997). *Radar for meteorologists* (5th ed.). New York: Rinehart Publications.
- Wilks, D. S. (2006). Forecast verification. In *Statistical methods in the atmospheric sciences* (2nd ed., 255–336). Oxford, UK: Elsevier.
- Witt Associates (2012). *An independent assessment of the August 13, 2011 Indiana State Fair collapse incident*. Retrieved from https://www.wittobriens.com/wp-content/uploads/2017/09/171758_1883990_3448726_1_6041423_Witt-Associates-Indiana-State-Fair-Report-April-2012.pdf
- WWRP/WGNE Joint Working Group on Forecast Verification Research (2015). *Forecast verification methods across time and space scales*. Retrieved from <https://www.cawcr.gov.au/projects/verification>