A Multidisciplinary Method to Support the Evolution of NWS Weather Radar Technology

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ABSTRACT: The highly successful fleet of Weather Surveillance Radar-1988 Doppler (WSR-88D) radars is approaching its end of service, and research efforts are under way to inform a decision toward a possible WSR-88D replacement. A methodology to link radar design characteristics to impacts on how radar data are used to diagnose hazardous weather was developed through a unique partnership between radar-engineering innovations in radar simulations and National Weather Service (NWS) radar data interpretation expertise. Deep commitment to two-way learning across disciplines resulted in a methodology that is both efficient and highly relevant to the NWS hazardous weather warning program. The methodology presented in this paper is a model for revealing complex trade-offs between weather radar characteristics and their resultant impact on NWS data interpretation for threat identification. This qualitative methodology is presented in the context of a broader proof-of-concept study from which it was developed. Adapted for further research, it can support the crucial role of deriving quantitative radar design criteria that balance the trade-offs among radar capabilities, cost, and impact to users. That is, the proposed methodology supports the evaluation of candidates for a potential WSR-88D replacement and any necessary major system upgrades in the interim.

SIGNIFICANCE STATEMENT: Defining the requirements for an operational weather radar system is ideally achieved with clearly identified trade-offs among cost, radar design characteristics, and impacts on user data interpretation. This work is an advancement of the historic evolution of weather radar development to support the U.S. National Weather Service (NWS) mission, based on collaboration among researchers, radar engineers, and NWS forecasters. The methodology presented here is an adaptable tool for revealing these essential, but complex trade-offs, providing a roadmap for further studies toward the next-generation NWS weather radar fleet.

KEYWORDS: Data quality control; Radars/Radar observations; Decision making; Experimental design

1. Introduction

The Weather Surveillance Radar-1988 Doppler (WSR-88D) fleet is overseen by the Next Generation Weather Radar (NEXRAD) program and has served the needs of the National Weather Service (NWS) and other agencies since its deployment starting in 1991 (Crum and Alberty 1993). A Service Life Extension Program is expected to meet NWS operational needs until 2040 (Radar Operations Center 2019), while research is underway toward an eventual WSR-88D replacement. For any operational weather radar system, there are inevitable trade-offs between cost and capabilities to support user needs. For a potential WSR-88D replacement, decisions are best informed when based on a deep understanding of these complex trade-offs. This work describes a methodology developed from close collaboration between radar engineers and an NWS-proficient meteorologist that can be adapted for future radar design studies to make fully informed decisions in support of the NWS' critical public safety mission to the American public (Uccellini and Ten Hoeve 2019).

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Radar base data quality is foundational for NWS warning decision making (Andra et al. 2002; Brotzge and Donner 2013) and is a crucial input for downstream algorithms. In this work, radar base data refers to the fields of data used by NWS forecasters: reflectivity (Z), Doppler radial velocity (V), spectrum width (SW), differential reflectivity (Z_{DR}), correlation coefficient (CC), and specific differential phase (K_{DP}). Another commonly used field included in our analysis is storm-relative velocity (SRV), which is the Doppler radial velocity after subtracting the estimated storm motion. All these fields are used as base radar products by forecasters and are input to a variety of algorithms, such as the mesocyclone detection algorithm (MDA) and applications such as the Multi-Radar Multi-Sensor System (MRMS). Since our analysis methodology focused on single-radar base data quality in the context of qualitative interpretation for identifying weather hazards by NWS forecasters, algorithm performance was not included.

The history of the NEXRAD program provides a model for a path toward an eventual replacement with crucial collaborations since the earliest days. For example, a coupling of research and operations was noted as a driving force for the development of the NEXRAD program (Brown and Lewis 2005). Collaborations among researchers, engineers, and

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TABLE 1. Radar design characteristics tested for each weather hazard stressor.

Primary weather hazard stressor	Radar design characteristics				
	Antenna pattern sidelobes	Range sidelobes	Sensitivity	Beamwidth	Azimuthal sampling
Hail core	X	X		X	X
Supercell	X				
Bow echo				X	X
Circulation				X	X
Lake-effect snow			X		
Mesoscale snowband			X		
Dendritic growth layer			X		
Refreezing			X		
Convective outflow boundaries			X		

meteorologists have also been crucial for the major WSR-88D upgrades throughout the NEXRAD program's life-span thus far. An example of such collaborations comes from the WSR-88D upgrade to dual-polarization, which investigated the trade-off of a loss of sensitivity against data-interpretation benefits such as greater confidence in winter precipitation type, location and characteristics of hail, and identification of tornadic debris. A series of studies involving radar engineers and operational meteorologists was conducted to fully explore this trade-off, ultimately contributing to the dual-polarization deployment decision (Radar Operations Center 2010).

In this paper, we present the methodology from a similar interdisciplinary collaboration that was conducted as part of the multiagency Spectrum Efficient National Surveillance Radar (SENSR) program. The SENSR program was established to evaluate the feasibility of consolidating several government radar networks into a single frequency allocation (FAA 2019). Weber et al. (2021) provide an overview of the research activities under the SENSR program that are relevant to NOAA's next-generation operational weather radar (National Oceanic and Atmospheric Administration (NOAA) 2020). One of the research projects under the SENSR program, the SENSR Data Quality (DQ) study, explored the systematic evaluation of complex trade-offs between cost-driving radar design characteristics and impacts on user interpretation. In that proof-of-concept study, a team of engineers and an NWS-proficient meteorologist developed a methodology that relies on simulations and qualitative analysis tools. The methodology was tested by exploring how key cost-driving radar design characteristics (Table 1) impact the quality of the base data and how this impact is connected to a forecaster's ability to interpret the radar data. The SENSR DQ study is referred to as a proof-of-concept study because it was limited to a subset of radar design characteristics and did not involve all of the appropriate stakeholders. As a result of these limitations, it was not intended to be used directly as a basis for developing future radar requirements. Nevertheless, the SENSR DQ study demonstrated that, through a proper combination of simulation and analysis tools, we can obtain meaningful quantitative information about complex tradeoffs between radar design and impacts on forecaster interpretation. The results of the SENSR DQ study are documented in a technical report (Nai et al. 2020b). The unique methodology that was developed to produce these results is the focus of this paper.

The methodology developed for the SENSR DQ study and documented in this work provides a direct linkage between specific cost-driving radar design characteristics (e.g., antenna sidelobe levels) and the resultant impacts on data interpretation by NWS meteorologists (e.g., antenna sidelobe contamination of the base data in critical locations, such as near the hook echo of a supercell). In section 2, based on our deep, shared understanding of the engineering and meteorology perspectives, we define radar base data quality, which inevitably involves radar design trade-offs. We then discuss the dual-polarization upgrade of the WSR-88D network, which provides an example of how these trade-offs were addressed through interdisciplinary collaborations and served as inspiration for the methodology presented in this work. Base data quality must be holistically measured by closely coordinated engineering-based quantitative and user-based qualitative analyses. Engineers understand the tension among competing elements of radar design, while meteorologists understand which aspects of radar performance (e.g., sensitivity) are a priority for a particular weather hazard (e.g., lake effect snow). Section 3 describes two key tools that we developed in support of the proposed methodology: high-fidelity engineering simulations and NWS forecaster analyses. The methodology that directly links data produced by different simulated radar designs to forecasters' data-interpretation process is presented in section 4. The first step in this methodology is the identification of the particular weather threats that are expected to be most impacted by performance changes associated with specific cost-driving radar characteristics. After the relevant weather threats are identified and multiple weather cases of that threat are chosen, the next step is the use of high-fidelity engineering simulations to produce realistic base data as observed by radars with systematically varying characteristics. These simulated data are then qualitatively analyzed by the meteorologist as an NWS representative using tailored approaches, which must be designed to effectively reveal the impacts of a given radar characteristic to radar data interpretation. Considered separately, these two areas of engineering and meteorological expertise may not be unique, but their combination is, which resulted in the novel methodology presented in this paper. Whereas the methodology is described in the context of the proof-of-concept SENSR DQ study, it can be adapted and generalized to future studies.

2. Our holistic approach to base data quality and historical precedent

As we embarked on the SENSR DQ study, we quickly realized that the meaning of "data quality" was significantly different for the radar meteorologist compared to the radar engineers on the team. Our ability to find direct relationships between specific radar design characteristics and resultant impacts on NWS forecasters' data interpretation required bridging the gap between our somewhat disparate concepts of data quality. In the past, overcoming these differences and combining them often led to meaningful improvements to the WSR-88D's performance and contributions to radar meteorology (e.g., Schuur et al. 2003; Saxion and Ice 2012). Historic precedent therefore highlights the benefit of reconciling differing perspectives of data quality to improve weather radar systems, which is what our team strived to accomplish with the SENSR DQ study.

a. Radar engineer's perspective of base data quality

From the radar engineer's perspective, "data quality" encompasses three aspects of weather radar data: update rate, spatial coverage (hereafter referred to simply as coverage), and the accuracy and precision of the radar variable estimates (hereafter referred to simply as accuracy and precision). With any given radar system's characteristics (e.g., transmit power, antenna size, and frequency), improving the performance of one aspect (e.g., update rate) often leads to degradation in the performance of one or both other aspects. Figure 1 shows the "data-quality triangle," where the three vertices correspond to update rate, coverage, and accuracy and precision. The area of the triangle represents the total available radar resources; that is, for a given radar system, the area of the triangle is fixed. Thus, moving one of the vertices (to change the performance of the radar) requires adjusting one or both of the other vertices. In this sense, the data-quality triangle represents the domain of trade-offs that can be achieved with a particular radar system. For context, the illustration includes the qualities of two commonly used WSR-88D Volume Coverage Patterns (VCP): 212 for convective precipitation observations, and 32 for weak precipitation or clear-air observations. For this example, both triangles have the same area; however, one has a higher update rate (VCP 212), while the other one has better accuracy and precision (VCP 32). This illustrates the trade-offs between different aspects of data quality that must be considered when designing a VCP.

The "update rate" vertex of the data-quality triangle represents the time it takes for the radar to revisit a volume of space. For example, VCP 212 has an update time of about 4.5 min, which is the fastest available among the VCPs used operationally. In contrast, VCP 32's update time is about 10 min. For all VCPs, key factors that determine the update rate are the pulse repetition frequency (PRF), the number of pulses per radial (M), and the number of elevation cuts defined in the VCP.

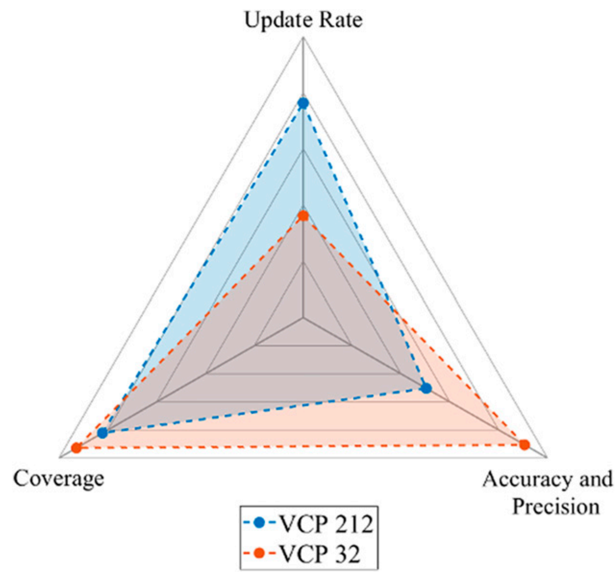

FIG. 1. Weather radar data-quality trade-off triangle. The vertices represent the update rate, coverage, and accuracy and precision, while the area of the triangle represents the available radar resources. Movement away from the triangle centroid toward each vertex represents an improvement in the data-quality aspect corresponding to that vertex.

The second vertex of the data quality triangle is coverage, which describes the ability of the radar to observe the surrounding atmosphere. The elements that define coverage are the radar spatial resolution and sampling (in azimuth, elevation, and range), and the sensitivity. The spatial resolution is determined by the size of the radar resolution volume in azimuth, elevation, and range to which the radar estimates are assigned. For the WSR-88D, the size of the resolution volume is determined by the pulse width in range (250 m with its short pulse of 1.57 μs), the antenna beamwidth in elevation (~1°), and the effective beamwidth in azimuth (~1° for super resolution and ~1.4° for legacy resolution). The spatial sampling determines the location of the radar resolution volumes. For example, in azimuth, the WSR-88D forms radials every 0.5° for super resolution and every 1° for legacy resolution. In range, the WSR-88D uses 250-m sampling, which matches the range resolution of its short pulse. It should be noted that spatial resolution and sampling are independent of one another and may be controlled separately (Torres and Curtis 2007). For weather radars, sampling is typically matched to resolution; so, WSR-88D users may not be familiar with the fact that these are independent radar characteristics. The final ingredient for radar coverage is the sensitivity of the radar. For radar engineers, the radar sensitivity determines the weakest echo a radar can observe at a given range while maintaining acceptable signal-to-noise ratio (SNR). For operational meteorologists, sensitivity relates directly to the footprint of radar echoes, which engineers define as detectability, a term that combines radar sensitivity and the results of signal processing. For meteorologists, "sensitivity" is most relevant in the presence of weak returns such as those from freezing drizzle or convective boundaries. For the WSR-

88D, VCP 32 uses more pulses per radial (64 for surveillance mode at 0.5°) than VCP 212 (15 for surveillance mode at 0.5°). This results in higher detectability for VCP 32, which is perceived as improved coverage.

The last vertex of the data quality triangle is accuracy and precision, which are equivalent to the bias and standard deviation of the radar-variable estimates. For meteorologists, this relates to the reliability of the data; that is, how well the data can be trusted to effectively inform their conceptual models. The bias of a radar variable represents the average difference between the estimated value and the true intrinsic value. While zero bias would be ideal, in practice, factors such as the radar-variable estimation technique, the SNR, and the presence of unwanted signals, such as those from ground clutter, can lead to nonzero biases. Sidelobe contamination is another example of unwanted contamination that can increase the bias of radar-variable estimates (Boettcher and Bentley 2022). In addition to a radar variable's bias, the estimate's spread around its mean is measured by the standard deviation. A large standard deviation implies a larger uncertainty in the estimate and a smaller likelihood that it actually represents physical reality. Factors such as the scanning strategy and signal processing techniques can affect the accuracy and precision of all radar-variable estimates. For example, as mentioned above, VCP 32 uses more pulses per radial than VCP 212; this results in estimates with smaller standard deviation for VCP 32, which is perceived as less noisy, smoother fields of radar data.

While all aspects of base data quality are important, a given radar design may not be sufficient to always maintain acceptable data quality for all weather hazards. Specific weather threats put different demands on different aspects of the trade-off triangle. The most common ways radar engineers focus their efforts on improving a given aspect of data quality are via modifications to the scanning strategies (e.g., increasing the number of pulses at the cost of a slower update rate) and improvements to the signal processing techniques (e.g., clutter filtering and radar-variable estimators). However, the utility of the base data is ultimately judged by the users.

b. Radar meteorologist's perspective of base data quality

At the most basic level, operational meteorologists desire radar base data that facilitate interpretation. Differing weather hazards are analyzed by NWS forecasters relying on radar base data and conceptual models for sensemaking (Klein et al. 2006). For example, patterns of radar features define supercells, and the foundational conceptual models for supercells were developed from and are revealed by radar base data (Browning 1964; Lemon and Doswell 1979; Doswell and Burgess 1993). When forecasters analyze multiple base data fields, pattern recognition is used to build a mental model to compare with known conceptual models. In the crucial domain of NWS warning decision making, radar base data are the primary source (Andra et al. 2002; Brotzge and Donner 2013). Base data quality is also important because meaningful data cues can be subtle or of small scale. A particularly subtle example from winter hazards is a ring of slightly enhanced Z_{DR} below the melting layer and close to the surface that suggests refreezing and thus a likelihood of sleet at the surface. Small-scale examples include short-lived tornadoes, such as those that occur along a quasi-linear convective system (QLCS).

With respect to Fig. 1, operational meteorologists regard "data quality" as the combination of the three aspects described previously, though they may not be aware of the individual contributors represented by the vertices in Fig. 1 (Torres et al. 2014). That is, operational meteorologists do not typically think about the inherent trade-offs represented by the data-quality triangle and how they define the associated limitations on the overall possible data quality for a given radar system. For example, rotating the WSR-88D antenna faster on a given VCP would increase the update rate, but would also reduce the number of radar pulses per radial, thus increasing the standard deviation of the radar-variable estimates. The gap between the SENSR DQ team's radar meteorologist and the engineers' concept of data quality was an initial barrier that had to be overcome.

c. The historical precedent of engineer/meteorologist studies addressing trade-offs for NWS forecasters

To overcome this gap in understanding, we first looked at the NEXRAD program's rich history of meteorology and engineering collaborations, which inspired the SENSR DQ study. Addressing the trade-offs associated with the WSR-88D dual-polarization upgrade provides an excellent example. The benefits of dual-polarization base data, such as revealing complexities of the height and depth of the melting layer in winter, had to be assessed against the loss of sensitivity primarily due to splitting the transmit power into horizontal and vertical channels. A series of trade-off studies of the sensitivity loss against the benefits to operations occurred from 2009 to 2010 (Radar Operations Center 2010).

Initially, there were two sequential groups of subject-matter experts investigating this trade-off, composed of experts from the National Severe Storms Laboratory (NSSL) and NWS operations in coordination with the Radar Operations Center (ROC). Based on research conducted by the ROC Engineering Branch, the sensitivity loss was expected to be between 3.5 and 4 dB (Ice et al. 2011). By mimicking differing levels of sensitivity loss for a variety of weather hazards, the subject-matter experts were able to observe the impacts on hazard identification. They found that a loss of 4 dB or less was operationally acceptable, while also recommending a follow-on operational assessment with multiple forecasters. The resulting Operational Assessment of Predeployment WSR-88D Dual-polarization Data took place 17–19 August 2010, with 20 forecasters (18 NWS, 2 U.S. Air Force) meeting in Norman, Oklahoma. The operational benefits related to specific weather hazards (e.g., winter, hail, and heavy rain) were identified by the forecasters, concluding that the benefits provided by the dual-polarization upgrade were much greater than the loss in data coverage due to the maximum expected 4-dB decrease in sensitivity. Though there were other factors, these conclusions contributed to the final decision to go forward with the deployment of dual-polarization to the WSR-88D fleet.

Other collaborative research activities involving NWS forecasters inspired the SENSR DQ study. Since a phased array radar (PAR) system is one promising candidate for a future WSR-88D replacement, a major effort toward NWS forecasters' exposure to PAR rapid-scan data was conducted from 2010 to 2015 using data collected from the National Weather Radar Testbed (NWRT) PAR at NSSL in Norman, Oklahoma. The Phased Array Radar Innovative Sensing Experiment (PARISE) project exposed NWS forecasters to severe weather events scanned by the NWRT PAR with update rates of about 1 min (Heinselman et al. 2012; Heinselman et al. 2015; Bowden et al. 2015; Bowden and Heinselman 2016; Wilson et al. 2017). In addition to warning performance improvement, the cognitive benefits of rapid-scan data included an increase in confidence, lowering of ambiguity, better discernment of the threat, and observed patterns better matching conceptual models. Cognitive challenges due to the faster updates and potential data overload were also investigated, with forecasters finding ways to modify their workflow processes to compensate. This history of PAR exposure to NWS forecasters and the associated cognitive trade-offs revealed from the PARISE experiments motivated the inclusion of PAR antenna systems in the SENSR DQ study. All of these studies illustrate the differing ways collaborative research among engineers and meteorologists provide major contributions to the evolution of the NWS radar network.

After review of these historical collaborations, we realized that the differing data-quality perspectives required the interdisciplinary team to first understand one another and build a holistic view of its meaning. The radar meteorologist on the team came to better understand the array of engineering contributors to data quality for a given radar system, as presented in Fig. 1. The radar engineers on the team came to understand how the base data are used by NWS forecasters to support the hazardous weather warning mission. Our shared understanding allowed for a novel methodology that links specific radar characteristics to the resultant impacts on NWS forecasters' interpretation of specific threats. The following sections describe this methodology.

3. The expertise partnership: High-fidelity radar engineering simulations with NWS forecaster analysis

As mentioned before, the SENSR DQ study relied on a novel combination of radar engineering and meteorological expertise. The engineering team members developed tools to simulate radar base data for a given weather event as though sampled by radars with differing characteristics and thus differing performance. These radar-characteristic variations represented a variety of dual-polarization radars, including those with dish antennas and planar PARs. This simulation capability was of sufficient quality to produce radar data with the same "look and feel" of real weather radar data (i.e., high-fidelity). The simulation contribution also provided flexibility for case selection and simulation of any weather scenario as though observed by weather radars with differing characteristics. For both case selection and simulation analysis, the meteorologist provided expertise for radar data interpretation from the perspective of the NWS hazardous weather warning mission. Weather cases for the simulations were chosen from the National Centers for Environmental Information (NCEI) database, which contains base data from any WSR-88D in the fleet, making this approach highly flexible and cost effective.

a. Radar simulations

The Signal Processing and Radar Characteristics (SPARC) simulator is a versatile weather radar in-phase and quadrature (IQ), time series simulator able to ingest archived fields of dual-polarization radar data and produce IQ data as it would be observed by a specified radar system (Schvartzman and Curtis 2019). The IQ data produced by the SPARC simulator are processed to generate the base data using a weather radar digital-signal-processing simulator (herein referred to as the Signal Processor). The Signal Processor was developed in house to support NSSL's weather radar engineering research and development activities; it implements a collection of techniques including ground-clutter mitigation, range-and-velocity ambiguity mitigation, and radar-variable estimation, similarly to what the WSR-88D signal processor does. Thus, the coupling of the SPARC simulator with the Signal Processor allows for end-to-end radar design, emulating different subsystems (e.g., antenna and receiver), scanning strategies (e.g., PRF and number of samples), and signal processing techniques. From the selected WSR-88D cases, six fields of radar variables are ingested into the SPARC simulator: Z, V, SW, Z_{DR}, differential phase (PHI), and CC. For the modeled radar design (characterized by the antenna pattern, spatial sampling grid, transmitted waveform, etc.), simulated returns are calculated through multiple steps to emulate the time series signals that would be received by the radar. These data are then processed using the Signal Processor to produce radar-variable fields as would be observed by the modeled radar. This makes the combination of the SPARC simulator and the Signal Processor ideal to study and better understand the data-quality implications of adopting different technologies (e.g., PAR) and/or radar designs on the quality of radar-variable estimates. Figure 2 presents a simplified block diagram of the simulation process with the WSR-88D input data on the left. The SPARC output is processed with the Signal Processor and shown on the right. For this example, the simulated radar characteristics are that of the WSR-88D to validate the simulation quality. Though the images are not identical, the simulated fields are nearly indistinguishable from the WSR-88D input in terms of how they convey the threat to an NWS forecaster. This high level of data quality produced by the SPARC simulator is independent of any chosen weather event.

The SPARC simulator was initially designed for simulations of data corresponding to a single radar plan position indicator (PPI), which was sufficient for all the aspects of the SENSR DQ study except for elevation sidelobe contamination. To address this limitation, the engineering team enhanced the SPARC simulator to include the effects of the full volumetric antenna pattern (i.e., azimuth and elevation) to evaluate the impact of elevation sidelobe contamination on data interpretation (Nai et al. 2020a). The design of the SPARC simulator is such that the modeled radar's sidelobe levels cannot be lower than those of the observing system that

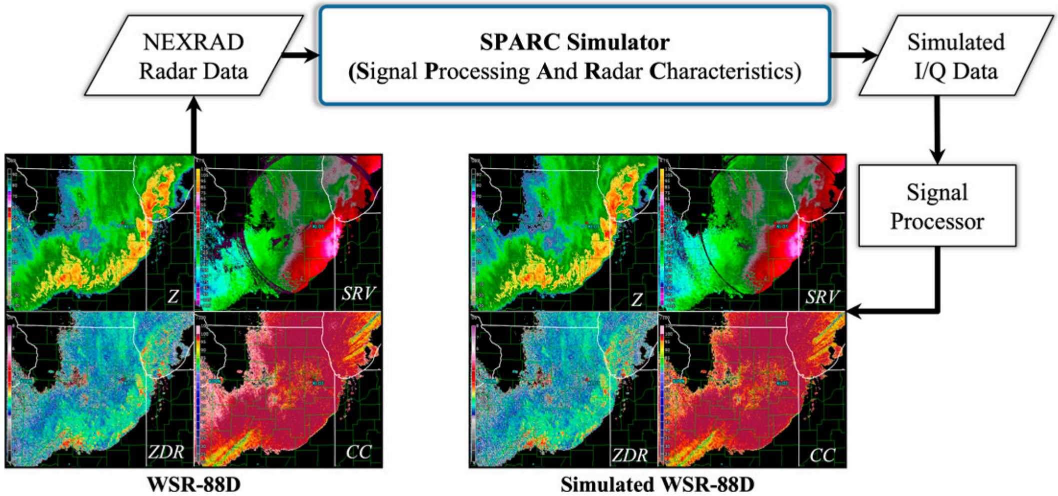

FIG. 2. Simplified block diagram of the engineering simulation method. (left) The four-panel image corresponds to the WSR-88D input data. The SPARC simulator produces simulated time series (IQ) data. (right) The Signal Processor ingests the simulated time series data and produces simulated fields of radar variables as would be observed by the modeled radar system. In this case, the characteristics of the WSR-88D were chosen for the modeled radar to demonstrate the high fidelity of the simulation capability.

created the input data (the WSR-88D for the SENSR DQ study). For the purposes of the SENSR DQ study, using radar design characteristics (such as sidelobe levels) that result in the same or worse performance than the WSR-88D was desirable. That is, the performance of the WSR-88D is well understood and currently serves as the standard by which potential replacement radar systems should be evaluated (NOAA 2015). However, given that affordability is a major challenge, it is prudent to explore how the mission of the NWS would be impacted by the adoption of replacement radar systems with slightly degraded performance. This information would be important either to substantiate the investment in a more expensive design or to justify the relaxation of one or more cost-driving requirements to improve affordability while keeping the impacts to data quality at minimal levels. Because of this, the SENSR DQ study's goal of exploring the complex trade-offs between cost and impacts on user data interpretation included simulating characteristics that were the same or slightly degraded with respect to the WSR-88D.

This engineering simulation capability is a key element of the unique methodology presented here, providing the flexibility to ingest weather events diverse in both hazard type and geography. The fidelity of the simulations is sufficient for expert-forecaster analyses in terms of identifying key mission-critical meteorological features. As the specific radar characteristic (e.g., sensitivity) is varied, the direct impact on data interpretation (e.g., changes to the footprint of low Z echoes) can be analyzed and documented.

b. NWS forecaster perspective

The SENSR DQ project funded a radar meteorologist on the team to provide expertise for both selecting appropriate weather cases for the simulations and qualitatively assessing the impact on data interpretation from changes in radar characteristics. With over 20 years of experience in WSR-88D training for NWS forecasters and 10 years in NWS operations, Boettcher had vast experience interacting with NWS forecasters from novices to experts. Throughout the process of case selection and simulation analysis, she had numerous discussions with operational NWS forecasters to support her goal of representing the NWS forecaster population as a whole. While this was sufficient for our proof-of-concept study, an extension of our methodology to support decisions toward either upgrades to the existing system or a WSR-88D replacement should include more NWS forecasters and a broader collection of stakeholders. Boettcher's NWS training focus areas were the WSR-88D hardware and software upgrades, and the human-centered domain of NWS warning decision making, the latter of which provided expert judgement for the analysis phase of the SENSR DQ study. Initially, the base data produced from the engineering simulations with a WSR-88D-like radar were qualitatively analyzed by Boettcher with the goal of increasing simulation fidelity (i.e., the goal was for the simulated weather features to be consistent with those observed with the WSR-88D). This iterative simulation refinement process continued until Boettcher could not identify which image was from the actual WSR-88D versus which was simulated with the WSR-88D as the modeled radar (Fig. 2).

For each of the cost-driving radar design characteristics studied, cases were chosen that stressed the specific characteristic (Table 1). For example, events with relatively weak signal returns were selected for the sensitivity study since a reduction in radar sensitivity could result in the loss of important weather features. The specific weather threats included winter events, such as lake-effect snow, and warm season events, such as convective outflow boundaries. Similarly, cases of severe convection with large reflectivity gradients were selected for the study on antenna sidelobe levels since increasing sidelobe levels result in increasing sidelobe contamination. All the cases were chosen from the WSR-88D archive of base data from 2013 to 2018 that include dual-polarization variables. All radar images presented in this paper were captured from the Gibson-Ridge Analyst–Level 2 (GRLevel2) radar data viewer, which was used to display and evaluate radar data.

4. Methodology for determining trade-offs between cost driving radar characteristics and user impacts

To explore the complex trade-offs between radar design and user impacts, it was crucial to devise a methodology that could directly link data produced by different simulated radar designs to forecasters' data interpretation process. It was necessary to systematically adjust radar design characteristics, such as antenna sidelobe levels, and produce realistic base data simulations that isolated the effects of the specific characteristic. This section describes the method that evolved from our symbiotic, two-way learning commitment to reach our goals.

a. Pre-analysis feedback loop for each of the radar characteristics studied

The three-step pre-analysis phase required the greatest time commitment. The first step was to refine the simulator settings such that the simulated base data met the baseline data-quality expectations of forecasters. That is, the simulated data should be free of artifacts that could hinder interpretation. The next step was to ensure that any data-quality changes in the simulations were the direct result of changing specific radar characteristics. The third step was to develop an analysis method that could be applied to these differing characteristics with sufficient granularity to capture the data-quality impact on data interpretation as precisely as possible.

1) STEP 1: DO THE DATA LOOK REAL?

As illustrated in Fig. 3, the first step was refining the initial engineering simulations to determine if the simulated data met forecasters' (represented by Boettcher) baseline expectations

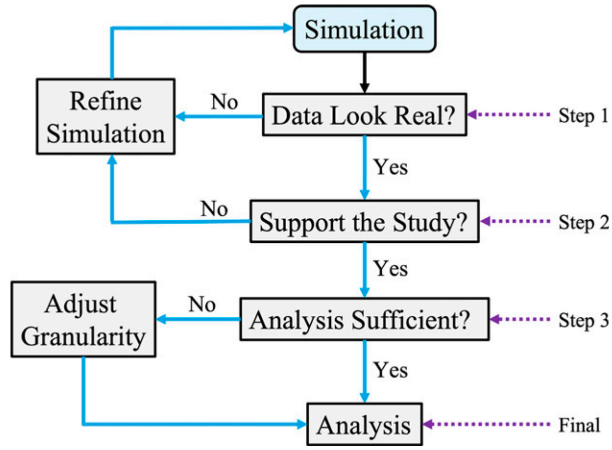

FIG. 3. An overview of the methodology for each of the radar characteristics studied.

for data quality (i.e., do the data look real?). The quality of each simulated dataset depends on an extensive number of engineering "settings." Initial attempts resulted in data containing artifacts that would hinder an NWS forecaster's interpretation process. A feedback loop to refine the simulations was established as illustrated in Step 1 of Fig. 3. Figure 4a shows simulated Z, SRV, Z_{DR}, and CC for an unsatisfactory early simulation that produced data with apparent smoothing, though none was applied with GRLevel2. Figure 4b shows the results from a subsequent simulation with much more realistic, improved fidelity of the radar data. This apparent smoothing was an artifact produced by the simulation and not the intended data quality effect of a given radar characteristic. By providing forecaster-perspective feedback to the engineers, the simulations were refined to remove artifacts not readily apparent to the engineers. This process (Step 1 in Fig. 3) was repeated until the fidelity of the simulation was sufficient to meet forecaster expectations of data quality, as discussed in section 3b.

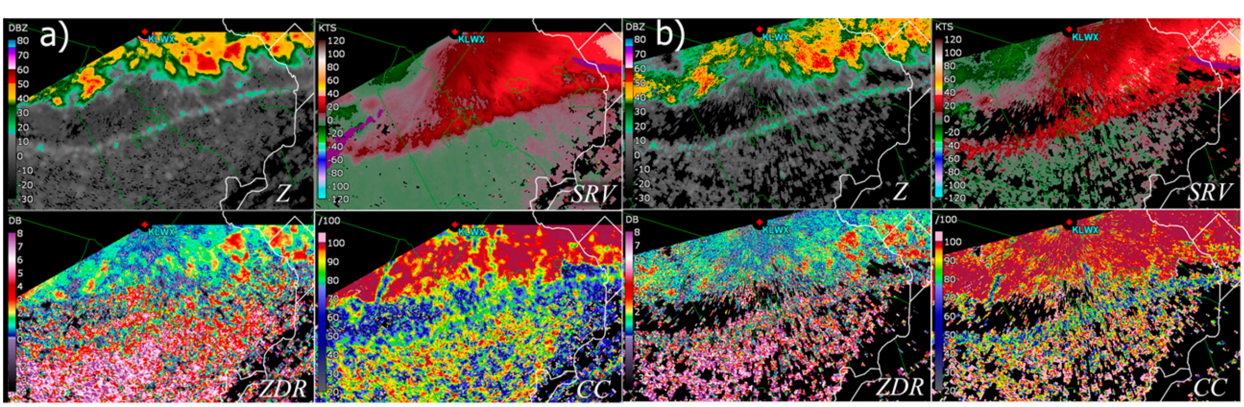

FIG. 4. A convective outflow boundary event. (a) A low fidelity simulation showing (top left) Z, (top right) SRV, (bottom left) Z_{DR}, and (bottom right) CC. (b) The smoothness of the fields indicates that further simulation refinement was required, with the resultant high-fidelity version shown.

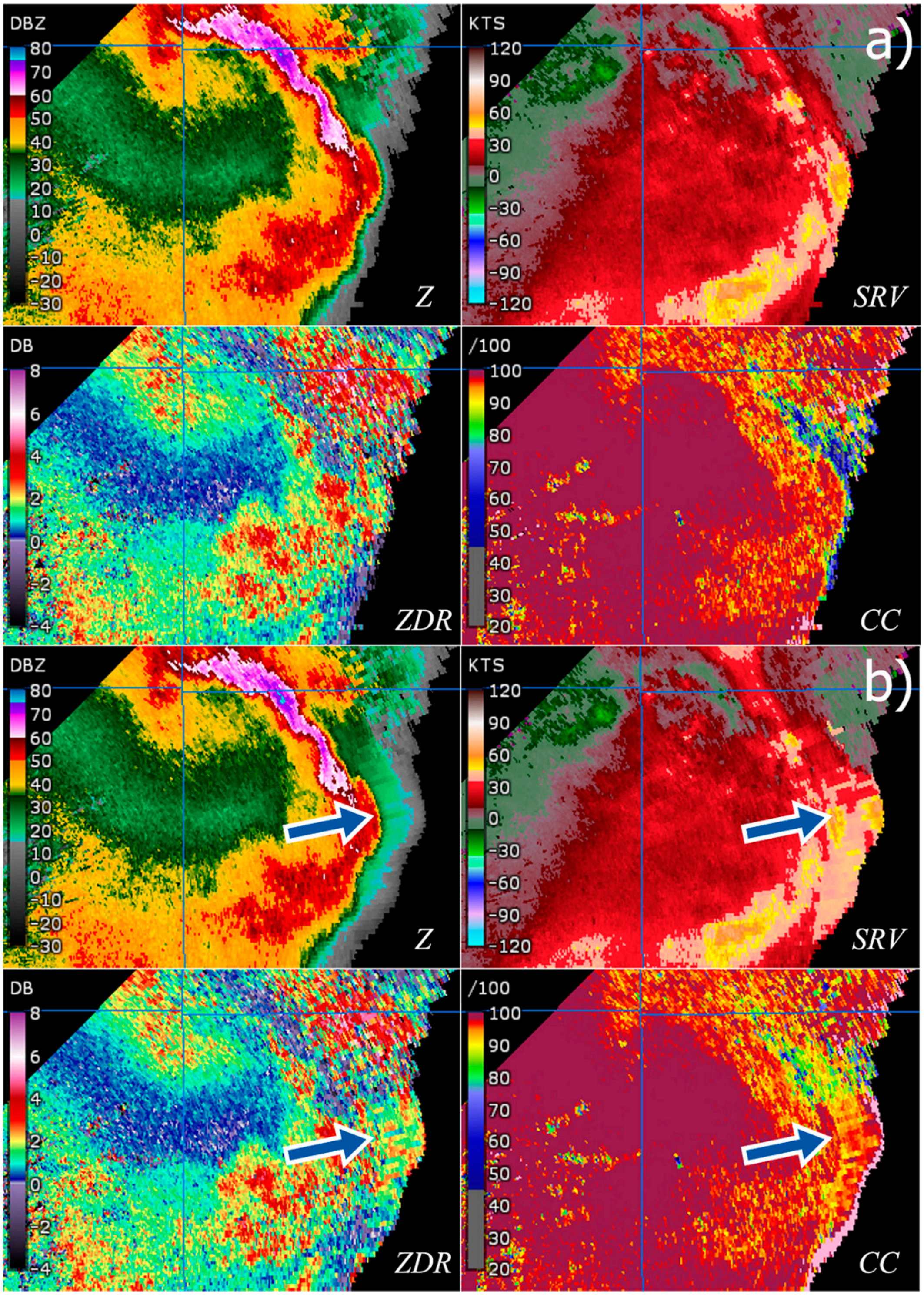

FIG. 5. A hail core within a bow echo event. (a) One simulation for a radar with very low range sidelobes and (b) a second simulation of the same case but for a radar with much higher range sidelobes. As expected, the simulations for the radar with higher range sidelobe levels result in greater range-sidelobe contamination.

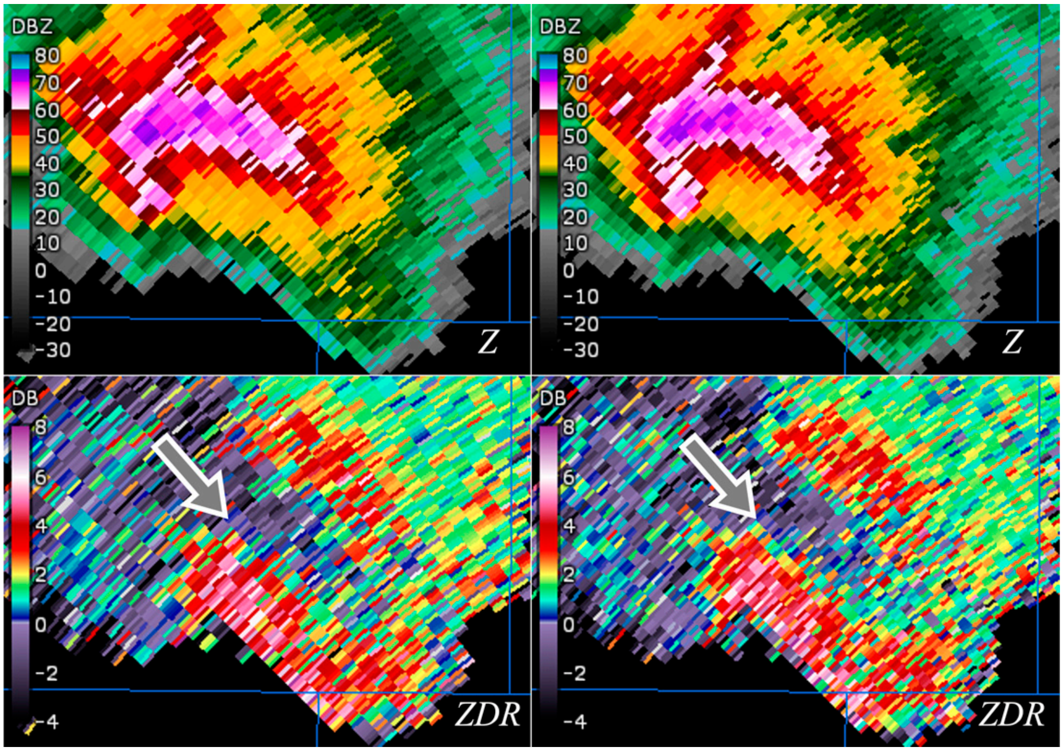

FIG. 6. A hail core event. (top) Z and (bottom) Z_{DR} with (left) 0.7° azimuthal sampling and (right) 0.5° azimuthal sampling using a PAR. For both columns, the angle perpendicular to the array is in the direction of the interface between areas of big drops and hail (marked by arrow).

2) STEP 2: DO THE SIMULATIONS SUPPORT THE STUDY?

Once the fidelity of the simulated base data was sufficient, the next step in our feedback loop was to ensure that the radar characteristics we wished to study were the independent variables that caused the data quality to change from one simulation to another (Step 2 of Fig. 3). We use an example from the range-sidelobe study to depict this process. Due to its klystron amplifier, the WSR-88D is capable of transmitting a short, high-power pulse, which does not produce range sidelobes. Most WSR-88D users are unlikely to be familiar with potential data-quality issues arising from waveforms with range sidelobes. Unlike the WSR-88D, other radar designs, such as a relatively low-powered PAR, may require the use of pulse compression associated with long waveforms (to improve sensitivity), which results in range sidelobes. However, techniques described in Torres et al. (2017) and in Schvartzman and Torres (2019) can be used for mitigation of potential range-sidelobe contamination, which is apparent in the base data as a radial enhancement of Z on either side of large gradients aligned along the range dimension. As with azimuthal sidelobe contamination from the antenna pattern, the extension of weak echoes into clear-air regions is the most obvious effect of range-sidelobe contamination. Figure 5 provides two examples of simulated data with differing range-sidelobe levels, where Fig. 5b has higher levels than Fig. 5a. Comparing these two images, note the greater extension of Z in the clear air in the highlighted region (see arrows) for Fig. 5b as well as that of the other radar variables. These two simulations corresponding to radar systems with different range-sidelobe levels (and others not shown) demonstrate that, as required, the extent of range sidelobe contamination is only a function of the modeled range-sidelobe level, which was the independent variable from one simulation to the next. If needed, this process (Step 2 in Fig. 3) was repeated until the variable was isolated.

3) STEP 3: IS THE ANALYSIS APPROACH SUFFICIENT?

Unlike the previous two steps, which focused on refining the engineering simulations, Step 3 in Fig. 3 is focused on developing and refining the data analysis methods. It is obviously important to extract as much meaning as possible from the data analyses; therefore, we focused on developing analysis methods that were tailored to each of the radar characteristics studied. This was needed because changes in a given radar characteristic result in data-quality impacts specific to that characteristic. That is, as a radar characteristic gradually changed in our simulations, so did the resulting radar data. For the different radar characteristics that we studied, the impacts to the radar data manifested in different ways, from the extent of contamination in the data to subtle differences in how a signature was revealed. Further, given the complexity of the human data-analysis process, these distinct manifestations led to different interpretation impacts. The qualitative data interpretation process for meteorologists is inherently subjective, as the cognitive goal is supporting or refuting conceptual models and revealing processes (Hoffman et al. 2017). Due to this underlying human cognitive processing, an analysis method that uses an arbitrary number of levels of discernment may not be reliable or even feasible. For this study, the resultant analyses ranged from a binary comparison (e.g., are signatures from two different sampling grids revealed similarly or is one more apparent?) to a five-level ranking based on specific data-quality impacts (e.g., to what extent is contamination from different antenna sidelobe levels distracting from the interpretation of supercell features?). Though future studies may use different analysis granularity, the overall methodology is general and adaptable. The following examples are specific to our study and are shown here to illustrate the complex connection between cost-driving radar design characteristics and impacts on radar base data interpretation from the NWS perspective.

(i) Two-level analysis

An example of a binary comparison analysis comes from studying different azimuthal sampling grids with a PAR antenna. The data-quality impacts from changes in the azimuthal sampling grid manifested as either "very subtle differences" or "no differences" in the interpretation of the data. Our analysis focused on comparing data from two different sampling grids and determining if one of the grids resulted in better or the same data quality in support of data interpretation. For example, one of the cases presented a radially oriented interface (arrows in Fig. 6) between the areas of big drops (~3–6 dB) and hail (~0 dB) in Z_{DR}. The first sampling grid on the left panels is uniformly spaced with a 0.7° azimuthal sampling interval between adjacent radials (hereafter referred to as 0.7° sampling). The second sampling grid on the right panels is uniformly spaced with a 0.5° azimuthal sampling interval between adjacent radials (hereafter referred to as 0.5° sampling). In these two simulations, the direction perpendicular to the array (i.e., broadside of the array) is pointed directly at the interface between the areas of big drops and hail. Comparing the bottom panels in Fig. 6, the 0.7° sampling results in a less sharp and less apparent boundary in azimuth between the big drops and hail in Z_{DR}. Because of these subtle differences, the 0.5° sampling was rated better in this case. Depending on the case and the sampling grids applied, the comparison sometimes resulted in no difference in the interpretation of the hazard.

(ii) Three-level analysis

An example of a three-level analysis comes from the study of azimuthal sidelobe contamination as the antenna pattern sidelobe levels were varied. For trained forecasters, this type of contamination is usually straightforward to identify in real time because the large Z gradient that produces the contamination (Boettcher and Bentley 2022) is evident on the same radar image. Thus, the extent of the footprint of the contamination is sufficient to judge the data-interpretation impact, and the three categories defined were "acceptable," "marginal," and "unacceptable." For the simulations in Fig. 7, there is a large Z gradient due to the hail core. The top four-panel image (Fig. 7a) is an example of a simulation rated as "acceptable." That is, the azimuthal contamination in Z, SRV, Z_{DR}, and CC is minimal and thus, does not impact data interpretation. The middle four-panel image (Fig. 7b) is an example of a simulation rated as "marginal." That is, the azimuthal contamination is more extensive and somewhat detracts from data interpretation. The bottom four-panel image (Fig. 7c) is an example of a simulation rated as "unacceptable." In this case, the azimuthal contamination

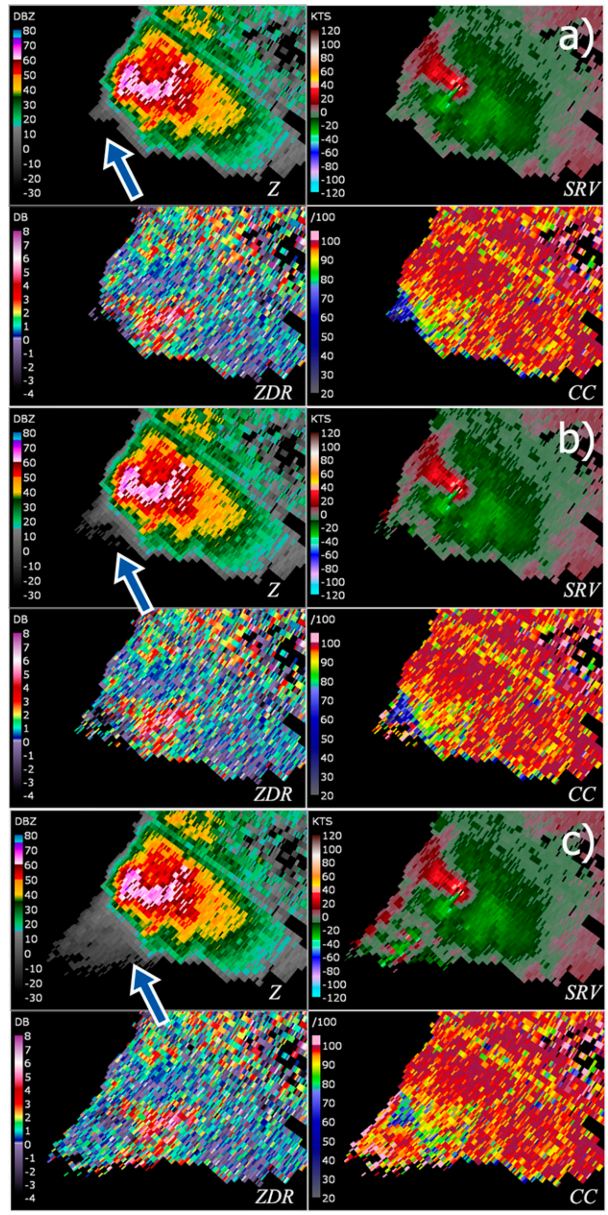

FIG. 7. A hail core event. Each four-panel group shows (top left) Z, (top right) SRV, (bottom left) Z_{DR}, and (bottom right) CC for a series of simulations for azimuthal sidelobe contamination for images rated as (a) "acceptable," (b) "marginal," and (c) "unacceptable." The narrow data loss on the northern portion of the storm is due to beam blockage.

TABLE 2. Five-level rating system for the elevation sidelobe contamination study.

Numeric level	Definition	Description
1	Fully acceptable	No distractions
2	Acceptable	Minimal distractions
3	Ambiguous	Impact of distractions would vary significantly among individuals
4	Unacceptable	Sufficient distractions to affect nearly all individuals
5	Completely unacceptable	Dramatic distractions for decision makers or features obscured

footprint is extensive and more significantly detracts from data interpretation.

(iii) Five-level analysis

The first example of a five-level analysis is the elevation sidelobe contamination study (Nai et al. 2020a). Engineers understand that, in reality, sidelobes are an ever-present characteristic of a radar's antenna radiation pattern, and sidelobe contamination includes unwanted signals from all directions other than the direction of interest. Operational meteorologists have a different perspective: the word "sidelobes" typically refers to the data contamination on the radar images.

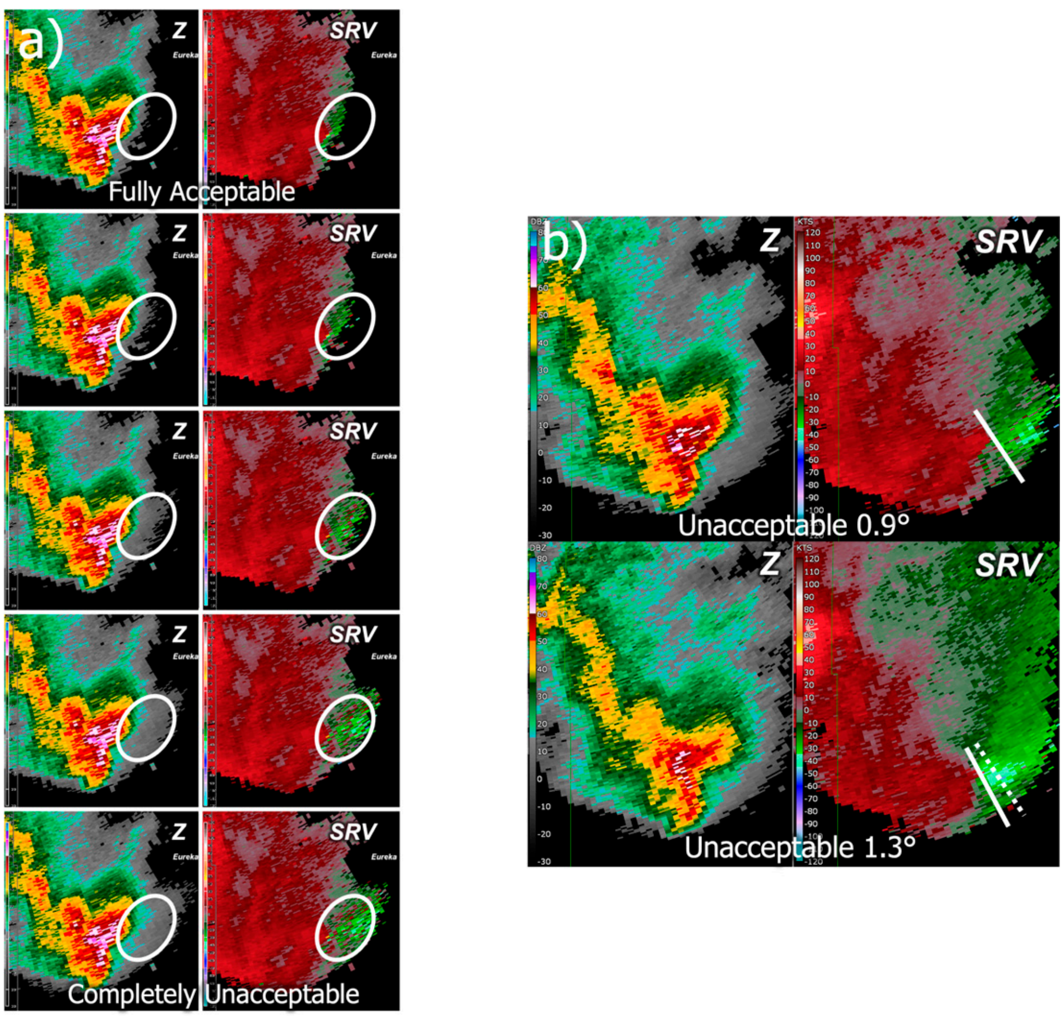

FIG. 8. A supercell event. (a) Z (left column) and SRV (right column) at 0.5° elevation with ascending levels of elevation sidelobe contamination from top (rating of 1, "fully acceptable") to bottom (rating of 5, "completely unacceptable"). The data-quality impacts caused by increasing sidelobe levels can be seen in the SRV field in the circled area (adapted from Nai et al. 2020a). (b) For the simulation rated unacceptable, a closer look at the transition in azimuth from the apparent circulation midline (solid line) at 0.9° and 0.5° to the midlevel mesocyclone midline at 1.3° (solid line). The midline position of the low-level apparent circulation is indicated at 1.3° by the dashed line.

TABLE 3. Five-level rating system for the sensitivity study.

Numeric level	Definition	Description
1	Fully acceptable	No or trivial data loss
2	Acceptable	Minimal data loss
3	Ambiguous	Marginal impact on the presentation of significant features
4	Unacceptable	Data loss partially erodes the presentation of important weather features
5	Completely unacceptable	Data loss significantly erodes the presentation of important weather features

Initially, this fundamental difference in perspective between the engineers and the meteorologist on our team made it difficult to fully understand one another in our conversations. As we began to understand each other better, we came together on a naming convention based on the Z gradient source of the sidelobe contamination. As described in the previous example, when azimuthal sidelobe contamination is evident, the Z gradient source is also apparent on the same radar image. However, elevation sidelobe contamination presents itself without a source on the same radar image and, unfortunately, it is most likely to occur in one of the most cognitively demanding NWS domains: severe and potentially tornadic supercells. Depending on the storm geometry with respect to the radar, elevation sidelobe contamination can appear as an apparent circulation (Piltz and Burgess 2009; Boettcher and Bentley 2022), requiring additional cognitive resources to diagnose in real-time. A five-level analysis was used for the elevation sidelobe contamination study based on the level of "distraction" to the data-interpretation process generated by the nature and extent of the sidelobe contamination on the low-level radar images. The analysis process mirrored the NWS forecaster storm interrogation process of examining multiple elevations to determine storm structure and salient features. Distraction in this context is defined as a hindrance to the forecaster's data interpretation process due to the contamination. Table 2 describes the differing levels used, which reflect our estimation of how the NWS population as a whole could respond to the level of elevation sidelobe contamination.

Elevation sidelobe contamination was often present on one or more of the simulated lower-elevation radar images. Figure 8a shows Z and SRV corresponding to five simulations with gradually larger antenna sidelobe levels. These were rated from "fully acceptable" to "completely unacceptable." The case in Fig. 8a (adapted from Nai et al. 2020a) demonstrates a noisy SRV field with an expanding footprint. Given the need to monitor the supercell for tornadic circulations, the size of the footprint was not the sole contribution to the rated level of distraction. For each simulation, while progressively examining the data from the lowest to the highest elevations, there was an apparent circulation at the lowest two elevations resulting from the contamination. However, above the lowest two elevations, the midlevel mesocyclone was seen with no contamination, and this true midlevel circulation was slightly shifted in position relative to the low-level apparent circulation, suggesting that the low-level circulation was not valid. This shift is demonstrated in Fig. 8b, with a closer look at the transition from 0.9° to 1.3° and the associated circulation midlines depicted. As the simulated antenna sidelobe levels progressively increased, the low-level contamination became more salient and thus more likely to detract from the shift in position described above. The example simulations shown in Fig. 8 illustrate the full range of data-interpretation impacts used in this analysis.

The second example of a five-level analysis is the sensitivity study. Sensitivity is the radar characteristic that determines the strength of the weakest signals that are revealed in base data displays. The impacts of sensitivity on data interpretation are very different from elevation sidelobe contamination, as the effect of sensitivity is limited to the availability (or footprint) of weak but important weather features for a single elevation. Ratings were based on the footprint of very low Z and other radar variables, which are directly related to the simulated sensitivity. Table 3 describes the data-loss conditions for each of the five levels. Figure 9 shows Z, Z_{DR}, and K_{DP} corresponding to five simulations with gradually decreasing sensitivity. These were rated from "fully acceptable" to "completely unacceptable" due to the gradually shrinking footprint of echoes, specifically a dendritic growth layer at 6.0° during a heavy snow event. Though the analysis for elevation sidelobe contamination and sensitivity both employed five levels, the judgement was based on very different elements: distraction to the severe convection interrogation process versus the areal extent of data loss.

b. *Analyze all the cases for the radar characteristic*

As illustrated in Fig. 3, once the analysis method was defined for a given radar characteristic, the final step was the analysis for all the relevant cases, which was relatively straightforward (the appendix lists all the cases used for each radar characteristic studied). The simulations for all the cases with a systematically varied radar characteristic were analyzed by Boettcher as a proxy for the perspective of the NWS forecaster population as a whole. This population includes a wide range of interpretation expertise, spanning from novices to routine experts to adaptive experts (Hunter et al. 2017), where routine experts function well performing procedure-driven tasks, while adaptive experts have the capacity to modify task processes as needed to meet overall goals. Thus, viewing the data solely from the perspective of Boettcher (an expert) was not sufficient. To gain the perspective of the NWS forecaster population, numerous discussions with NWS forecasters took place supporting Boettcher's goal of performing the analyses from the perspectives of a continuum of levels of expertise. For example, some sidelobe contamination simulations had sufficient data-quality distractions to interfere

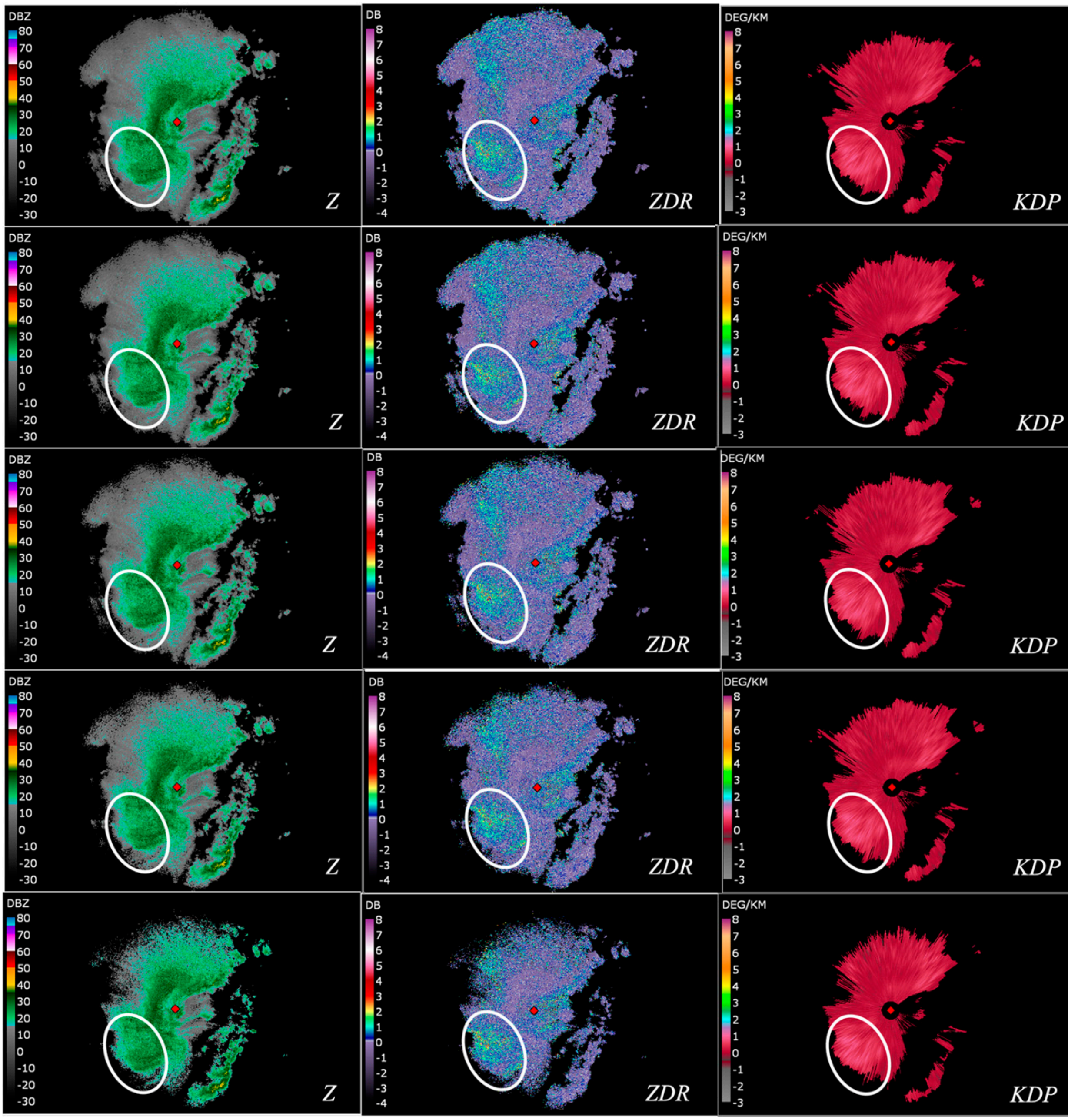

FIG. 9. A winter dendritic growth layer event. (left) Z, (center) Z_{DR}, and (right) K_{DP} simulations at 6.0° elevation with descending sensitivity from top (rating of 1, "fully acceptable") to bottom (rating of 5, "completely unacceptable"). The data-quality impact caused by the decreasing sensitivity is the erosion of a dendritic growth layer aloft during a heavy snow event (circled).

with data interpretation for the entire NWS population, while others presented more subtle contamination that would be missed by all but those with the highest level of adaptive expertise. The analyses were based on how well the feature of interest was revealed in the data to a forecaster viewing that data with the time constraint of warning operations.

For all the cases, the simulations were randomized and presented "blindly" for analysis. For example, the sidelobe levels of the antenna pattern that were used for the azimuthal and elevation sidelobe simulations were unknown to Boettcher. The results of each of these studies linking different radar characteristics to data interpretation are beyond the scope of this paper and are available from the SENSR Data Quality Simulations Final Report (Nai et al. 2020b). Table 4 summarizes the characteristic studied, the analysis type performed, and the number of cases (with associated threats) analyzed, while the appendix provides a case list for each characteristic studied.

TABLE 4. Analysis summary.

Radar design characteristic	Analysis type	No. of cases	Threat
Antenna pattern sidelobes			
Azimuthal	Three level	9	Hail cores
Elevation	Five level	13	Supercells
Range sidelobes	Three level	6	Hail cores
Sensitivity	Five level	8	Winter, convection
Beamwidth	Two level	16	Winter, convection, circulations
Azimuthal sampling	Two level	16	Winter, convection, circulations

5. Summary and recommendations

This paper presented a methodology that serves as a model for understanding linkages between radar design characteristics and the resultant impacts on NWS forecasters' data interpretation to detect hazards. Through examples, we showed that these linkages are complex in ways not initially expected by the authors. For the radar engineers, the diversity of how meteorologists interpret the differing weather threats was not well understood. In contrast, the meteorologist did not have a deep understanding of the relationships between cost-driving radar characteristics and the resultant limitations on data interpretation. This collaboration resulted in a shared understanding of the complexity of relating radar design characteristics to user impacts. Like previous studies supporting the NEXRAD program, this involved a mutually beneficial engineer–meteorologist collaboration, and this work is an advancement of the historic evolution of weather radar development to support the NWS warning mission. The result of our deep commitment to two-way learning is the methodology presented here that is highly efficient and consistently relevant to the NWS hazardous weather warning program.

This methodology is adaptable to future studies and aligned to the precedent studies that supported both the origin of the NEXRAD program and the numerous and mission-supportive follow-on WSR-88D upgrades, such as dual-polarization. The methodology has the unique benefit of closely integrating high-fidelity base data simulations as obtained by radar systems with varying characteristics with NWS forecaster needs for interpreting a range of hazards. Its adaptability provides a roadmap for additional research toward a WSR-88D replacement, addressing the challenge of balancing the trade-offs among radar capabilities, cost, and impact to users. Subsequent interdisciplinary teams can adapt this methodology for refinement of these trade-offs, such as including groups of NWS forecasters in a formal assessment, as was done for the deployment of WSR-88D dual-polarization. The process of deriving quantitative radar design criteria that incorporates these complex trade-offs supports both NOAA decision makers considering a WSR-88D replacement and the NWS forecasters who use the system as they deliver mission-critical hazardous weather warning services.

While the inclusion of NWS meteorologists and radar engineers using an adaptation of this methodology is a necessary component toward a WSR-88D replacement, the authors do not wish to convey that it would be sufficient. All the essential stakeholders, coordinated within a well-defined, closed-loop structure, would bring the necessary diversity of perspectives together. Expanding the number of NWS forecasters for base data interpretation exercises would be an important component as is resourcing appropriate levels of radar-engineering expertise. Beyond these two groups are research meteorologists, including those exploring NWS-focused benefits and limitations of rapid-scan dual-polarization base data, NWS core partners including broadcast meteorologists who present radar data to the general public, and emergency managers who use radar data to make decisions. Finally, NOAA decision makers are crucial stakeholders, as they must balance deployment and operation-and-maintenance (O&M) costs with radar performance to support the NWS mission. Optimizing the decision outcome is most likely with NOAA decision makers, radar engineers, research meteorologists, NWS core partners, and NWS forecasters working together to derive quantitative radar design criteria based on clearly defined trade-offs among cost, capabilities, and user impacts.

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Data availability statement. All the weather cases for this study are publicly available from the National Centers for Environmental Information (NCEI) WSR-88D level-II database, downloaded throughout the study from Amazon Web Services: https://noaa-nexrad-level2.s3.amazonaws.com/index.html.

APPENDIX

Simulated and Analyzed Case Summary

Table A1 lists the weather cases selected, simulated, and analyzed for each of the radar design characteristics studied.

TABLE A1. List of cases simulated and analyzed for each radar characteristic studied.

Radar design characteristic	Case list
Antenna pattern sidelobes	
Azimuthal	2350 UTC 3 May 2012 KBGM 0.9°
	2358 UTC 3 May 2012 KBGM 0.5°
	2212 UTC 30 Jul 2013 KGLD 19.5°
	2140 UTC 30 Jul 2013 KGLD 0.5°
	0036 UTC 7 May 2016 KCBX 0.5°
	0018 UTC 7 May 2016 KCBX 0.5°
	2258 UTC 12 Jun 2017 KAMA 1.2°
	2242 UTC 12 Jun 2017 KAMA 1.2°
	2258 UTC 12 Jun 2017 KAMA 0.8°
Elevation	2055 UTC 27 Jul 2014, KMRX
	0347 UTC 14 Jun 2014, KUDX
	0120 UTC 18 Sep 2015, KTWX
	1905 UTC 4 Aug 2015, KBOX
	0011 UTC 21 Jun 2015, KUDX
	2203 UTC 10 Sep 2015, KUEX
	2343 UTC 26 Apr 2015, KFWS
	2314 UTC 10 Sep 2015, KTWX
	0050 UTC 2 Apr 2014, KDYX
	2258 UTC 25 May 2014, KDFX
	0445 UTC 22 Jul 2014, KLRX
	0039 UTC 23 May 2015, KGLD
	2112 UTC 1 Jun 2015, KSFX
Range sidelobes	2021 UTC 11 Apr 2012, KAMA
	2301 UTC 19 Jul 2017, KARX
	2021 UTC 12 Jun 2017, KCYS
	0305 UTC 23 Jun 2017, KEAX
	1719 UTC 22 Jul 2017, KLWX
	1214 UTC 11 Jun 2017, KMPX
Sensitivity	1833 UTC 22 Jul 2017, KLWX
	2240 UTC 4 Mar 2015, KLVX
	2039 UTC 18 Nov 2014, KBUF (long pulse)
	1211 UTC 19 Nov 2014, KBUF (short pulse)
	1108 UTC 4 Jan 2017, KGRR
	0329 UTC 22 Jan 2015, KAMA
	2219 UTC 23 May 2015, KTLX
	1457 UTC 25 De KGYX
Beamwidth	2037 UTC 2 Mar 2014, KTLX
	2037 UTC 2 Mar 2014, KTLX
	0001 UTC 4 Jan 2015, KENX
	2240 UTC 4 Mar 2015, KLVX
	2349 UTC 3 May 2012, KBGM
	2325 UTC 10 Sep 2015, KTWX
	2006 UTC 30 Jun 2014, KDVN
	1159 UTC 27 Jun 2014, KOAX
	0302 UTC 29 Feb 2012, KTWX
	0709 UTC 29 Feb 2012, KSGF
	0023 UTC 19 May 2013, KDDC
	2251 UTC 27 May 2013, KUEX
	2119 UTC 28 May 2013, KTWX
	0353 UTC 18 Jun 2014, KFSD
	0119 UTC 11 Sep 2015, KTWX
	0028 UTC 26 May 2016, KTWX
Azimuthal sampling	2037 UTC 2 Mar 2014, KTLX
	2037 UTC 2 Mar 2014, KTLX
	0001 UTC 4 Jan 2015, KENX
	2240 UTC 4 Mar 2015, KLVX
	2349 UTC 3 May 2012, KBGM
	2325 UTC 10 Sep 2015, KTWX
	2006 UTC 30 Jun 2014, KDVN
	1159 UTC 27 Jun 2014, KOAX
	0302 UTC 29 Feb 2012, KTWX
	0709 UTC 29 Feb 2012, KSGF
	0023 UTC 19 May 2013, KDDC
	2251 UTC 27 May 2013, KUEX
	2119 UTC 28 May 2013, KTWX
	0353 UTC 18 Jun 2014, KFSD
	0119 UTC 11 Sep 2015, KTWX
	0028 UTC 26 May 2016, KTWX

REFERENCES

Andra, D. L., E. M. Quoetone, and W. F. Bunting, 2002: Warning decision-making: The relative roles of conceptual models, technology, strategy, and forecaster expertise on 3 May 1999. *Wea. Forecasting*, **17**, 559–566, https://doi.org/10.1175/1520-0434(2002)017<0559:WDMTRR>2.0.CO;2.

Boettcher, J., and E. Bentley, 2022: WSR-88D sidelobe contamination: From a conceptual model to diagnostic strategies for improving NWS warning performance. *Wea. Forecasting*, https://doi.org/10.1175/WAF-D-21-0155.1, in press.

Bowden, K. A., and P. L. Heinselman, 2016: A qualitative analysis of NWS forecasters' use of phased-array radar data during severe hail and wind events. *Wea. Forecasting*, **31**, 43–55, https://doi.org/10.1175/WAF-D-15-0089.1.

——, ——, D. M. Kingfield, and R. P. Thomas, 2015: Impacts of phased-array radar data on forecaster performance during severe hail and wind events. *Wea. Forecasting*, **30**, 389–404, https://doi.org/10.1175/WAF-D-14-00101.1.

Brotzge, J., and W. Donner, 2013: The tornado warning process. A review of current research, challenges, and opportunities. *Bull. Amer. Meteor. Soc.*, **94**, 1715–1733, https://doi.org/10.1175/BAMS-D-12-00147.1.

Brown, R. A., and J. M. Lewis, 2005: Path to NEXRAD: Doppler radar development at the National Severe Storms Laboratory. *Bull. Amer. Meteor. Soc.*, **86**, 1459–1470, https://doi.org/10.1175/BAMS-86-10-1459.

Browning, K., 1964: Airflow and precipitation trajectories within severe local storms which travel to the right of the winds. *J. Atmos. Sci.*, **21**, 624–639, https://doi.org/10.1175/1520-0469(1964)021<0634:AAPTWS>2.0.CO;2.

Crum, T. D., and R. L. Alberty, 1993: The WSR-88D and the WSR-88D operational support facility. *Bull. Amer. Meteor. Soc.*, **74**, 1669–1687, https://doi.org/10.1175/1520-0477(1993)074<1669:TWATWO>2.0.CO;2.

Doswell, C. A., III, and D. W. Burgess, 1993: Tornadoes and tornadic storms: A review of conceptual models. *The Tornado: Its Structure, Dynamics, Prediction, and Hazards, Geophys. Monogr.*, Vol. 79, Amer. Geophys. Union, 161–172.

FAA, 2019: Fact sheet—Spectrum Efficient National Surveillance Radar (SENSR). Department of Transportation, accessed 29 March 2022, www.faa.gov/news/fact_sheets/news_story.cfm?newsId=22634.

Heinselman, P. L., D. S. LaDue, and H. Lazrus, 2012: Exploring impacts of rapid-scan radar data on NWS warning decisions.

Wea. Forecasting, **27**, 1031–1044, https://doi.org/10.1175/WAF-D-11-00145.1.

——, ——, D. M. Kingfield, and R. Hoffman, 2015: Tornado warning decisions using phased-array radar data. *Wea. Forecasting*, **30**, 57–78, https://doi.org/10.1175/WAF-D-14-00042.1.

Hoffman, R. R., D. S. Ladue, H. M. Mogil, P. J. Roebber, and J. G. Trafton, 2017: *Minding the Weather, How Expert Forecasters Think.* MIT Press, 502 pp.

Hunter, R., P. Ward, J. Gore, P. Turner, R. Hoffman, A. Leggatt, and G. Conway, 2017: Developing adaptive expertise: A synthesis of literature and implications for training. *13th Int. Conf. on Naturalistic Decision Making*, Bath, United Kingdom, University of Bath, 92 pp., http://50years.bath.ac.uk/story/event/international-conference-on-naturalistic-decision-making/.

Ice, R., O. Boydstun, W. D. Zittel, R. Hall, G. Cate, R. Rhoton, R. Maceman, and B. Walker, 2011: Sensitivity of operational weather radars. *27th Conf. on Interactive Information Processing Systems*, Seattle, WA, Amer. Meteor. Soc., 370, https://ams.confex.com/ams/91Annual/webprogram/Paper183654.html.

Klein, G., B. Moon, and R. R. Hoffman, 2006: Making sense of sensemaking 1: Alternative perspectives. *IEEE Intell. Syst.*, **21**, 70–73, https://doi.org/10.1109/MIS.2006.75.

Lemon, L. R., and C. A. Doswell III, 1979: Severe thunderstorm evolution and mesocyclone structure as related to tornadogenesis. *Mon. Wea. Rev.*, **107**, 1184–1197, https://doi.org/10.1175/1520-0493(1979)107<1184:STEAMS>2.0.CO;2.

Nai, F., J. Boettcher, C. Curtis, D. Schvartzman, and S. Torres, 2020a: The impact of elevation sidelobe contamination on radar data quality for operational interpretation. *J. Appl. Meteor. Climatol.*, **59**, 707–724, https://doi.org/10.1175/JAMC-D-19-0092.1.

——, ——, D. Schvartzman, C. Curtis, and S. Torres, 2020b: SENSR data quality simulations final report. NOAA/NSSL and OU CIMMS Rep., 168 pp., https://nssl.noaa.gov/publications/mpar_reports/SENSR%20Data%20Quality%20Simulation%20Final%20Report.pdf.

NOAA, 2015: NOAA/National Weather Service Radar Functional Requirements. National Oceanic and Atmospheric Administration, 58 pp., www.roc.noaa.gov/WSR88D/PublicDocs/NOAA_Radar_Functional_Requirements_Final_Sept%202015.pdf.

——, 2020: Weather radar follow-on plan: Research and risk reduction to inform acquisition decisions. NOAA Rep., 21 pp.

Piltz, S. F., and D. W. Burgess, 2009: The impacts of thunderstorm geometry and WSR-88D beam characteristics on diagnosing supercell tornadoes. *34th Conf. on Radar Meteorology*, Williamsburg, VA, Amer. Meteor. Soc., P6.18, https://ams.confex.com/ams/34Radar/techprogram/paper_155944.htm.

Radar Operations Center, 2010: Operational assessment of pre-deployment WSR-88D dual polarization data. Tech. Rep., 59 pp., https://www.roc.noaa.gov/WSR88D/PublicDocs/AppsDocs/OpsAssessment28Dec2010.pdf.

——, 2019: WSR-88D Service Life Extension Program (SLEP). Accessed 15 February 2021, https://www.roc.noaa.gov/WSR88D/Engineering/NEXRADTechInfo.aspx.

Saxion, D., and R. Ice, 2012: New science for the WSR-88D: Status of the dual-polarization upgrade. *28th Conf. on Interactive Information Processing Systems (IIPS)*, New Orleans, LA, Amer. Meteor. Soc., 5, https://ams.confex.com/ams/92Annual/webprogram/Paper197645.html.

Schuur, T., P. Heinselman, and K. Scharfenberg, 2003: Overview of the Joint Polarization Experiment (JPOLE). NOAA/NSSL Rep., 38 pp., https://www.nssl.noaa.gov/publications/wsr88d_reports/JPOLE_Overview_Report.pdf.

Schvartzman, D., and C. D. Curtis, 2019: Signal Processing and Radar Characteristic (SPARC) simulator: A flexible dual-polarization weather-radar signal simulation framework based on preexisting radar-variable data. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, **12**, 135–150, https://doi.org/10.1109/JSTARS.2018.2885614.

——, and S. M. Torres, 2019: Design of practical pulse compression waveforms for polarimetric phased array radar. *39th Int. Conf. on Radar Meteorology*, Nara, Japan, 15A-02, https://cscenter.co.jp/icrm2019/program/data/abstracts/Session15A-02_2.pdf.

Torres, S., and C. Curtis, 2007: Initial implementation of super-resolution data on the NEXRAD network. *23rd Int. Conf. on Interactive Information and Processing Systems for Meteorology, Oceanography, and Hydrology*, San Antonio, TX, Amer. Meteor. Soc., 5B.10, https://ams.confex.com/ams/87ANNUAL/techprogram/paper_116240.htm.

——, P. Heinselman, and K. Bowden, 2014: Understanding forecasters' needs to improve radar observations using adaptive scanning. *30th Conf. on Environmental Information Processing Technologies*, Atlanta, GA, Amer. Meteor. Soc., 6.4, https://ams.confex.com/ams/94Annual/webprogram/Paper231266.html.

Torres, S. M., C. D. Curtis, and D. Schvartzman, 2017: Requirement-driven design of pulse compression waveforms for weather radars. *J. Atmos. Oceanic Technol.*, **34**, 1351–1369, https://doi.org/10.1175/JTECH-D-16-0231.1.

Uccellini, L. W., and J. E. Ten Hoeve, 2019: Evolving the National Weather Service to build a weather-ready nation. *Bull. Amer. Meteor. Soc.*, **100**, 1923–1942, https://doi.org/10.1175/BAMS-D-18-0159.1.

Weber, M., and Coauthors, 2021: Towards the next generation operational meteorological radar. *Bull. Amer. Meteor. Soc.*, **102**, E1357–E1383, https://doi.org/10.1175/BAMS-D-20-0067.1.

Wilson, K. A., P. L. Heinselman, C. M. Kuster, D. M. Kingfield, and Z. Kang, 2017: Forecaster performance and workload: Does radar update time matter? *Wea. Forecasting*, **32**, 253–274, https://doi.org/10.1175/WAF-D-16-0157.1.