Radar Outage Costs and the Value of Alternate Datasets

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ABSTRACT: Quantifying the costs of radar outages allows value to be attributed to the alternate datasets that help mitigate outages. When radars are offline, forecasters rely more heavily on nearby radars, surface reports, numerical weather prediction models, and satellite observations. Monetized radar benefit models allow value to be attributed to individual radars for mitigating the threat to life from tornadoes, flash floods, and severe winds. Eighteen radars exceed $20 million in annual benefits for mitigating the threat to life from these convective hazards. The Jackson, Mississippi, radar (KDGX) provides the most value ($41.4 million), with the vast majority related to tornado risk mitigation ($29.4 million). During 2020–23, the average radar is offline for 2.57% of minutes or 9.27 days per year and experiences an average of 58.9 outages per year lasting 4.32 h on average. Radar outage cost estimates vary by location and convective hazard. Outage cost estimates concentrate at the top, with 8, 2, 4, and 5 radars exceeding $1 million in outage costs during 2020, 2021, 2022, and 2023, respectively. The KDGX radar experiences outage frequencies of 4.92% and 5.50% during 2020 and 2023, resulting in outage cost estimates > $2 million in both years. Combining outage cost estimates for all radars suggests that approximately $29.1 million in annual radar outage costs may be attributable as value to alternative datasets for helping mitigate radar outage impacts.

SIGNIFICANCE STATEMENT: This study combines information on radar status and monetized radar benefit models to attribute value to individual radars, estimate radar outage costs, and quantify the potential value of alternative datasets during outage-induced gaps in coverage. Eighteen radars exceed $20 million in annual benefits for mitigating the combined threat to life from tornadoes, flash floods, and severe winds. The first and third most valuable radars, both in Mississippi, experience outage frequencies twice the national average, accounting for a disproportionate share of the overall outage costs. Our findings suggest that characterizing and mitigating these outages might provide a near-term solution to better protect these communities from convective hazards. Combining outage cost estimates for all radars suggests that approximately $29.1 million in annual radar outage costs may be attributable as value to alternative datasets for helping mitigate the impacts of radar outages.

KEYWORDS: Thunderstorms; Radars/Radar observations; Satellite observations; Decision support; Economic value

1. Introduction

Quantifying the costs of radar outages allows value to be attributed to the alternate datasets that help mitigate these outages. Monetized geospatial benefit models quantify the value radars provide for mitigating the threat to life from tornadoes, flash floods, and severe winds (Cho and Kurdzo 2019, 2020a,b). These benefits are realized annually despite some level of radar loss. Our premise is that preventing all radar outages would marginally increase the radar value above the Cho and Kurdzo estimates. Our assumption is that the radar values estimated by Cho and Kurdzo would be lesser without alternative datasets filling the outage-induced gaps. Our goal is to quantify the cost of outage-induced radar coverage gaps to attribute value to the alternate datasets that cover these outages. When radars are offline, forecasters rely more heavily on nearby radars, surface reports, numerical weather prediction (NWP) models, and Geostationary Operational Environmental Satellite R series (GOES-R) observations for their warning decision-making process. The GOES-R Advanced Baseline Imager (ABI; Schmit et al. 2017) and Geostationary Lightning Mapper (GLM; Rudlosky et al. 2019) provide broad spatial coverage and rapid temporal updates that complement radar observations and become even more important during convective warning operations and radar outages.

The paper first summarizes the value radars provide for mitigating the risk associated with convective hazards (section 2a) and then presents operational examples demonstrating how alternate datasets help mitigate radar outages (section 2b). Section 3 describes the data and methods used to estimate the value of individual radars and the costs associated with outages. Section 4a illustrates the spatial distribution of radar value, section 4b describes the radar outage cost estimates during 2020–23, and section 4c discusses limitations to our approach. Section 5 summarizes alternate dataset use during outages and our findings on the radar value and outage cost distributions.

2. Background

a. Radar value

Weather radars support forecast and warning decisions that save lives, reduce injuries, and protect property. The U.S. National Weather Service (NWS) maintains 160 Next Generation Weather Radar (NEXRAD) high-resolution S-band Doppler

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weather radars in the United States and overseas. In the contiguous United States (CONUS), a network of 143 operational Weather Surveillance Radar-1988 Doppler (WSR-88D) radars facilitate public alerts for dangerous weather including the precise location and timing of impacts. Weather radar data and severe weather warnings significantly reduce the impacts of severe weather, generating measurable benefit to society (e.g., Wolfson and Clark 2006; Regnier 2008; Crum et al. 2013; Gultepe et al. 2019).

While weather radars benefit society, they are complicated to install, operate, and maintain. The NEXRAD network, initially deployed in 1991, became operational in 1992 and deployed the final WSR-88D in 1997 (Crum and Alberty 1993). The network has undergone continuous improvements to extend its service life beyond the estimated 20-yr life cycle (Zrnić et al. 2007). The nearly complete Service Life Extension Program (SLEP) will extend their life cycle beyond 2030 while NOAA continues research on the next generation of weather radars (Boettcher et al. 2022). The SLEP includes a pedestal replacement program (NWS 2020) that requires each radar to be offline for ~2 weeks while improvements are made (Crum et al. 1998; Radar Operations Center 2022; National Weather Service 2020). Additional upgrades and modifications aim to improve the data utility (e.g., upgrade to dual polarization technology).

To understand the benefits following the nationwide deployment of the NEXRAD network, Bieringer and Ray (1996) employed tornado warning statistics to evaluate improvements in warning lead times and tornado detection. Their early analysis suggested improvements in tornado warning performance at select locations (Bieringer and Ray 1996). Simmons and Sutter (2005) further examined the CONUS radar network and found that expected casualties and fatalities were ~40% lower after the installation of WSR-88D radars. Brotzge and Donner (2013) presented an end-to-end examination of the tornado warning process, highlighting the integral role of weather radars in tornado probability of detection and mean warning lead times.

Cho and Kurdzo (2019, 2020a,b) constructed and applied a monetized geospatial benefit model to calculate and attribute economic benefits to various radar network configurations. Variability in radar coverage was quantified using the fraction of volume observed below 20 000 ft and the cross-range horizontal resolution. The monetized benefit model derives value from a reduction in casualties resulting from severe weather warnings (Cho and Kurdzo 2019). The Cho and Kurdzo (2019) model further confirmed a positive correlation between radar coverage and tornado warning performance shown earlier by Simmons and Sutter (2005) and Brotzge et al. (2011). Using the value of a statistical life (VSL) for casualties and value of personal time lost to sheltering on false alarms, Cho and Kurdzo (2019) were able to monetize the benefits associated with better radar coverage. Relative to a CONUS without weather radars, they found that the current radar configuration provides ~$575 million in tornado benefits annually (for 2020 dollars, VSL, and personal time value; Cho and Kurdzo 2020b).

Cho and Kurdzo (2020a,b) next applied the geospatial benefit model to evaluate casualty reductions as a result of improved warning performance for flash floods and nontornadic thunderstorm winds. Their model results for the current radar configuration yielded ~$341 million in annual flash flood benefits and ~$207 million in annual nontornadic thunderstorm wind benefits (for 2020 dollars and VSL; Cho and Kurdzo 2020b). In the United States, operational flash flood warning decisions rely primarily on the concept of flash flood guidance (FFG; Ostrowski et al. 2003). Forecasters look for accumulated quantitative precipitation estimation (QPE) to exceed the FFG rain accumulation threshold in a given catchment basin when issuing a flash flood warning (Clark et al. 2014). Thus, radar value for flash floods stems from observations of rainfall in the upstream catchment areas, not the actual flash flood occurrence locations. The aggregate annual benefit from the three models is ~$1.12 billion (for 2020 dollars, VSL, and personal time value) for the present CONUS weather radar configuration.

The tornado and nontornadic thunderstorm wind benefit estimates given above include the combined NEXRAD and Terminal Doppler Weather Radar (TDWR) networks because forecasters use TDWR data for making the associated warning decisions. Quantitative precipitation estimates are not generated from TDWR data, so the flash flood analysis only includes NEXRAD. Since the present study deals solely with NEXRAD-associated benefits and gives results in 2023 dollars and values, for consistency, we also provide the NEXRAD-only annual benefit estimates in 2023 dollars and values as follows: $596 million (tornadoes), $363 million (flash floods), and $217 million (severe winds), for a total of $1.176 billion.

Nonuniformity in weather radar coverage, severe weather occurrence, and population density suggest that some radars provide more value than others. Radars are located to cover as much population and severe weather as possible, but neither dense population nor frequent severe weather guarantee robust radar coverage. Tornadoes, severe winds, and flash floods occur in preferred seasons and regions. For example, tornadoes occur most often in Dixie Alley during early spring (Gagan et al. 2010), Tornado Alley in late spring (Gagan et al. 2010), and along the southeast U.S. coast during hurricane season (i.e., late summer and fall; Brooks et al. 2003; Long et al. 2018). The Cho and Kurdzo (2019) models operate on a spatial grid over CONUS that can reveal regional variances in the benefits of radar coverage. They found that mapping tornado cost density could be used to identify radar coverage gaps.

The WSR-88D weather radars are subject to outages, both planned routine maintenance and unplanned outages resulting from mechanical failure or weather impacts. Although radar outages for planned routine maintenance are scheduled for when severe weather is less likely climatologically, impactful weather events can occur during these planned outages. For example, the KLIX radar in New Orleans, Louisiana, was scheduled to be offline 8–15 December 2022 to replace the generator. A high-impact severe weather event on 14 December motivated technicians to quickly restore the radar back to service while tornadoes were already occurring. Despite tornadoes being least likely during mid-December in New Orleans, an enhanced Fujita scale (EF)-2 tornado produced many millions of dollars in damages and injured multiple people in the New Orleans metro. This case highlights how routine maintenance outside peak severe weather season can impact radar outage costs. Weather impacts can take radars offline when it is least convenient [e.g., see section 2b(4)], and these outages can be long term. For example, Hurricane Laura destroyed the WSR-88D in Lake Charles, Louisiana, which remained offline for nearly 5 months in 2020/21 (National Weather Service 2021).

b. Alternate data use during outages

This section describes four examples of severe weather warning operations during radar outages to demonstrate how alternate datasets help mitigate outages. Although NWS forecast and warning operations vary from region to region and office to office, these direct forecaster insights reveal the broad use of alternative datasets to mitigate radar loss during convective warning operations.

1) SBC session 39—Radar Down panel discussion

Satellite Book Club (SBC) Session 39—Radar Down panel discussion (SBCSS 2021a)—describes loss of radar scenarios during both convective and winter weather. Presenters first discuss three cases where nearby radars and satellite products help cover temporary outages of the KHTX radar in Huntsville, Alabama. The first outage occurs as a line of convection crosses northern Alabama during the morning of 11 January 2020, with anticipation of more storms that afternoon. Forecasters switch to backup radars and rely heavily on the GLM observations, especially east of the Interstate 65 corridor where the KGWX radar (Columbus Air Force Base, Mississippi) fails to observe the lowest levels. Forecasters continue issuing warnings without their primary radar as three tornadoes occur before the radar comes back online. Another loss of radar event occurs on 22 June 2018 with severe thunderstorm warnings ongoing. This second case illustrates the limitations of using backup radars to view the lowest parts of the storm that are most closely associated with tornadoes and wind damage. With both the KHTX and Advanced Radar for Meteorological and Operational Research (ARMOR) radars offline during the super outbreak on 27 April 2011, forecasters quickly switch to backup radars. With such large supercells, indications of strong rotation aloft, and a relatively homogeneous boundary layer, these backup radars adequately portray the events unfolding. During the radar outage, satellite products continue showing supercell structures and overshooting tops that aid the warning decision process.

Presenters next discuss a winter storm case near Amarillo, Texas, on 9–10 January 2021. In this case, the KAMA radar in Amarillo is down for scheduled maintenance and the KFDX radar at Cannon Air Force Base, New Mexico, is unexpectedly offline. Satellite imagery is the primary analysis tool, along with water vapor imagery to monitor an upper-level low pressure system and the associated moist and dry features. Frequent review of real-time surface observations allows forecasters to locate and communicate the snowfall onset and intensity. Real-time communication with the public provides critical ground truth throughout the event. Overnight forecasters share a social media post illustrating the midlevel water vapor analysis showing darker colors indicating deeper moisture and moderate snowfall. This messaging informs the public on the location of the heavier snowfall rates in the absence of radar. By 0600 LT, the midlevel water vapor imagery reveals a secondary low pressure system preventing moisture from reaching much of the area. Despite the lack of radar, this reduction in snowfall and impacts is effectively communicated to the public. The midlevel water vapor analysis proved most useful for showing the overall scale of this winter weather event, depicting its evolution, and conveying this information to the public.

2) SBC session 70—Radar Down, Severe Risk Up

Radar Down, Severe Risk Up (SBCSS 2021b) reviews satellite best practices, operational philosophies, and mesoanalysis strategies during an outage of the Duluth, Minnesota, radar on 26–27 July 2021. Forecasters lose the KDLH radar (Duluth, Minnesota) around 1400 LT 26 July, a day ahead of warning operations, which is advantageous to losing the radar during an event. On 27 July, forecasters adapt their morning operations' preparation, AWIPS setups, and staffing position assignments to prepare for having no radar during warning operations. Management clearly communicates to the forecast and warning teams that warnings should be larger and longer lasting because of the terrain storms will traverse and the lack of radar. The 45-min default severe warning duration works better in populated areas with more frequent reports than in regions where no new information can be expected 40 min later. Forecasters simplify the warning process by drawing the warning boxes slightly larger and longer lasting, decreasing their coverage as certainty increases. Reducing the number of warning decisions ultimately improves the warning decisions by increasing decision-making capacity. The event results in 8 hours of continuous warning operations with a total of 25 convective warnings, three-inch hail, and significant wind damage in Grand Rapids, Minnesota.

Without the primary radar, forecasters emphasize the environment and reports and substitute satellites for radar as much as possible. In such a favorable environment, satellite products portray the convective trends well enough to continue issuing warnings with only distant radar observations. Presenters stress keeping it simple by reviewing upstream observations and basic satellite products. Upstream soundings indicate a very favorable storm environment already producing severe storms. Long loops of water vapor and visible imagery provide the necessary context to monitor the elevated mixed layer responsible for triggering convection. Early on the satellite and distant radar help recalibrate expectations on further development of a supercell storm not well handled by the weather models. In this highly sheared, unstable environment, forecasters simply observe an impressive supercell and issue a warning. Even without radar, satellite tendencies or the lack thereof are enough to warrant continuation or cancellation of warnings. GOES mesoscale sector visible and IR imagery provide environmental knowledge and storm top analysis that are key to decision-making. Lightning trends also help diagnose the convective evolution. Forecasters adjust the GLM flash extent density (FED) color map from a maximum of 256 flashes per 5 min to 128 and 64 to better emphasize the lightning flash rate tendencies. This emphasizes the lightning jumps in the GLM data (i.e., rapid increases in flash rate), helping forecasters use the lightning data as essentially a pseudoradar.

The presenters note the advantage of advanced notice and suggested forecast offices to consider how quickly forecasters can adapt to using neighboring radars and other methods when losing a radar midway through an event. Forecasters making warning decisions rely so heavily on radar for severe weather warning operations that they commonly only focus on satellites to assess the preconvective environment. This limits forecaster experience using satellite products for warning operations and leaves them less prepared for loss of the primary radar. Presenters recommend working some satellite products into routine convective warning operations to increase familiarity and improve warnings. Procedures should be in place for every forecaster in the event of a primary radar outage.

3) WDTD SOTM—Using GLM in the convective warning process

Using GLM in the convective warning process, presented in the Warning Decision Training Division Storm of the Month (WDTD SOTM 2020), further describes the first outage case presented by SBCSS (2021a). Recall that KHTX is offline just as severe weather begins on the morning of 11 January 2020. Forecasters have access to the ARMOR research radar, but they only receive scans once the entire volume scan is complete (i.e., ~5 min). The nearest radars [KGWX, KBMX (Birmingham, Alabama), and KOHX (Nashville, Tennessee)] are unable to observe the lowest levels, and a lack of real-time severe weather reports also obscures what if any damage is occurring.

The GLM plays an integral role in the warning decisions on 11 January 2020. Forecasters first note a significant lightning jump with the Pickens County storm in NWS Birmingham's area of responsibility, which relates to a deadly EF-2 tornado. Knowing that instability is more favorable to the south, forecasters adjust their warning thresholds accordingly. They begin observing increased GLM flash rates over Cullman County corresponding with a surge in the line of storms. They issue the first tornado warning primarily based on the three-ingredient method (Schaumann and Przybylinski 2012) and continue monitoring the GLM for lightning increases. The GLM provides an added layer of confidence for both the second and third warnings downstream, with a clear lightning jump preceding the EF-2 tornado that stuck the Brindlee Mountain School. The presenters conclude that 1) the GLM is an essential tool that should be used during every convective warning situation and 2) GLM can aid in detection, increase warning lead times, and improve messaging during severe weather events.

4) Data Fusion Exercise for Flash Flood Warnings: 26 July 2021 flash flood event

Data Fusion Exercise for Flash Flood Warnings (WDTD 2023) is an NWS training module that provides an example of flash flood warning operations during an outage of the primary radar. In their second scenario, lightning strikes the Las Vegas, Nevada, radar (KESX) on 0423 UTC 26 July 2021, taking it offline until 0112 UTC 27 July. On 26 July, the near-storm environment information indicates atmospheric conditions conducive to flash flooding. The *GOES-17* ABI Day Cloud Phase Distinction product illustrates rapidly growing convection just west of Las Vegas between 1600 and 1700 UTC. The *GOES-17* GLM indicates increasing flash extent density coincident with low minimum flash areas, suggesting increasing updraft strength and severe potential. The *GOES-17* ABI also indicates decreasing brightness temperatures and precipitation estimates of ~1/3 of an inch per hour. Forecasters issue a flash flood warning at 1720 UTC citing radar observed thunderstorms and a precipitation observation of 1 in. in 30 min at Red Rock Canyon. An additional report of 1.18 in. in an hour arrives at 1734 UTC, increasing confidence in the warning. Flash flood reports arrive at 1830 and 1936 UTC.

As part of this training exercise, forecasters rate their level of confidence (1–5) in assessing the flash flood threat using five main tools/products, 1) KEYX (Edwards Air Force Base, California) radar data, 2) Multi-Radar Multi-Sensor (MRMS) products, 3) satellite imagery and products, 4) lightning data, and 5) near-storm environment information. An expert walk through then suggests the relative value of these datasets during this flash flood scenario. Near-storm environment information rates highest (5) since the atmospheric conditions are ripe for flash flooding associated with any storm that develops. With the KESX radar offline, the KEYX radar rates lowest (1) due to its distance from the storms (~130 miles away). The MRMS products rate 2 since they carry some weight but have reduced confidence due to the missing primary radar. Satellite imagery and products rate 3 because the data are useful in observing the convective initiation and subsequent growth but underestimate the rainfall rates. Surface precipitation reports are arguably the most important tool for forecasting these flash floods, rating 4 despite the desire for more observation sites with more frequent updates. Lightning data rate 4 because they help identify convective initiation and storm intensity trends, plus the ground-based observations help precisely locate the updraft cores which helps draw the warning polygons.

The training module concludes by stressing that forecasters should focus on the available datasets. It is important to consider which other datasets increase in priority when a key dataset is no longer available. In this case, trends in satellite imagery and lightning products are in good agreement and fit within a favorable near-storm environment. This increases confidence in the flash flood warning decisions. Forecasters must rely on the strengths of the combined datasets to help overcome any challenges that may arise.

3. Data and methods

This section describes the data and methods used to estimate the value of individual radars and the costs associated

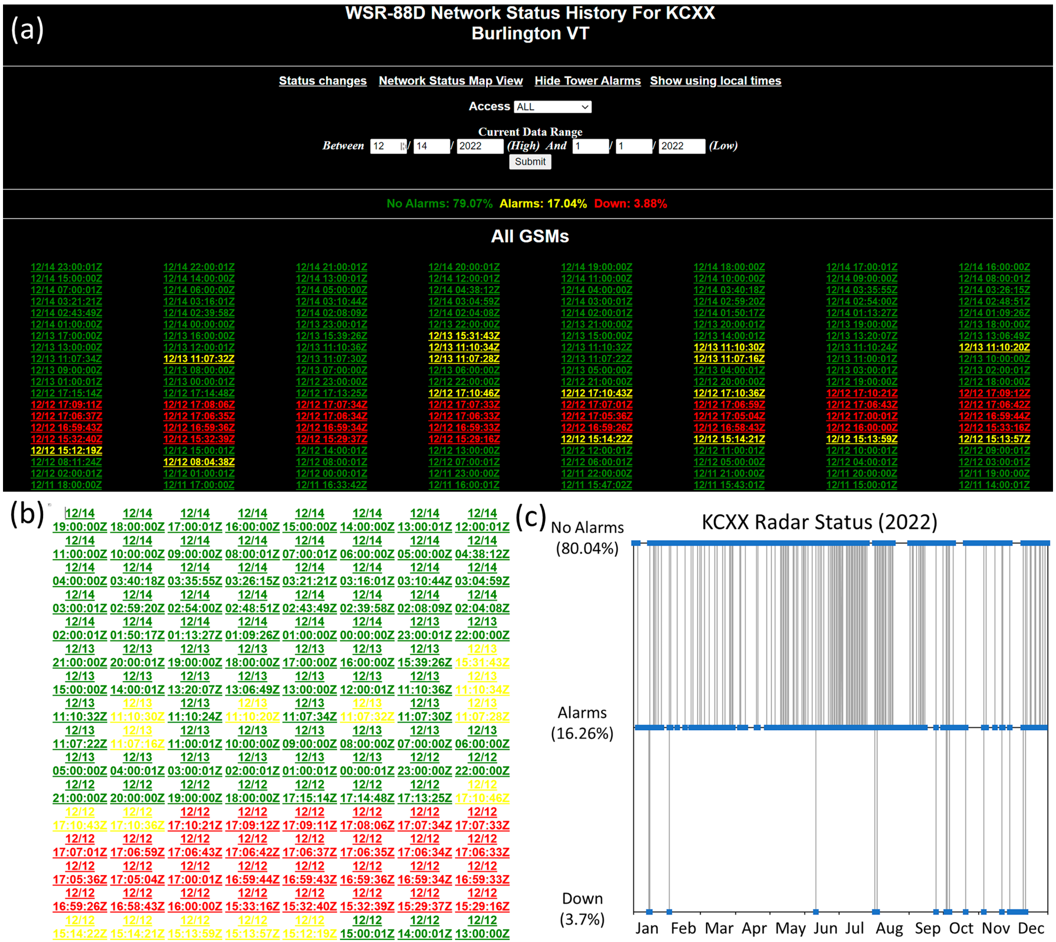

FIG. 1. This example illustrates the process for creating an annual radar status time series for the KCXX radar in Burlington, VT, during 2022. (a) A screenshot from an internal ROC website that provides color-coded links to publicly available radar status reports (green is "no alarm," yellow is "alarm," and red is "down"), (b) the result of converting the HTML file to a Microsoft word document, and (c) the result of combining the intermittent radar status updates into 1-min status time series.

with outages. Value estimates separated by severe weather types are computed for each radar, and intermittent radar status updates are converted into 1-min radar status time series. The radar-specific value estimates are combined with their corresponding outage frequencies to estimate the annual outage costs for each radar.

The Cho and Kurdzo (2019, 2020a,b) monetized geospatial benefit models allow value to be attributed to individual radars for mitigating the threat to life from convective hazards. Voronoi polygons (Boots et al. 1999) identifying the nearest radar to each model grid cell are joined with spatial grids of the radar benefit for mitigating the tornado, flash flood, and severe wind threats. The value of each radar for mitigating each hazard represents an accumulation of all gridcell values within the corresponding radar polygons.

Routinely generated radar status notifications describe the frequency and timing of radar outages. An internal radar operations center (ROC) website provides color-coded links to publicly available radar status reports (Fig. 1—green is "no alarm," yellow is "alarm," and red is "down"). Internal users can select date and time ranges for individual radars to display an HTML web page with links to all status updates (Fig. 1a). We first save these HTML pages locally and then convert them to Microsoft word documents (Fig. 1b). Python codes including the re module (https://docs.python.org/3/library/re.html) then parse these files into lists of times and statuses. The intermittent radar status updates are combined into 1-min status time series (Fig. 1c), with the present status repeated until a different status is detected.

The status time series allow calculation of the total outage time per year for each radar, along with composite outage statistics for all 143 WSR-88D radars. The average annual outage frequency averages the annual outage frequency (i.e., outage minutes/total minutes) from each radar. The average annual outage period averages the total outage duration from each radar. The average outage duration reports the average of the average outage duration per radar. Composite statistics also include the mean and median number of outages per radar.

Individual radar value estimates are multiplied by their corresponding outage frequencies to estimate the annual outage costs for each radar. For each radar, the estimated annual benefit is multiplied by the fraction of minutes the radar was offline during the year to estimate the total outage cost for each radar. The total outage costs are summed to estimate the annual benefit provided by alternate datasets covering these outage-induced radar gaps.

4. Analysis and results

a. Radar value estimates

The Cho and Kurdzo (2019, 2020a,b) monetized geospatial benefit models quantify the spatial distribution of value provided by the present WSR-88D radar network. Figure 2 illustrates the spatial value distribution, with the left column showing the benefits per grid cell (30 arc s in latitude and longitude) and the right column depicting the accumulated benefits per radar. For 2023 dollars, VSL, and personal time value, the WSR-88D network provides $1,176,082,930 in value annually for mitigating the combined casualty threat from tornadoes ($596,120,019), flash floods ($362,890,910), and severe winds ($217,072,001). The tornado benefit includes reduction of time lost to sheltering on false alarms through false alarm rate improvement. Table 1 reveals that 18 radars exceed $20 million in annual benefits for mitigating these combined convective threats. Value is concentrated in the eastern half of the United States due to relatively dense population experiencing more frequent convective weather (Fig. 2). Since casualty reduction by radar-informed warnings forms the basis of the benefit models and radar value estimates, more valuable radars should be located in more populous regions.

Radars contribute much greater value for tornado risk mitigation than for flash floods and severe winds. Radar values for mitigating the tornado threat exceed $100 per grid cell over large parts of the central and eastern United States (Fig. 2c). Maxima associated with the well-known Tornado and Dixie Alleys extend well north into the Midwest and Great Lakes regions and eastward into the Carolinas. Figure 2d more clearly indicates where radars provide the most value for mitigating the tornado threat. The much greater value attributed to tornado risk mitigation (Fig. 2d) requires a different color scale than the flash flood (Fig. 2f) and severe wind (Fig. 2h) distributions. Five radars exceed $20 million in annual value for mitigating the tornado threat (Fig. 2d, Table 2). Tornado risk mitigation represents >50% of the value for 51 of 143 radars (35.7%, not shown) including eight of the top ten most valuable radars. The KDGX radar provides the most combined value ($41.0 million), with much greater value for tornado risk mitigation ($28.8 million) than for flash flood ($8.2 million) and wind ($4.1 million) risk mitigation.

The flash flood value distribution reveals considerable overlap with the tornado and severe wind distributions, with some notable differences (Fig. 2). Flash flood mitigation accounts for more than half of the value for 50 of 143 radars (35.0%, not shown), including KSGF (Springfield, Missouri), KLWX (Sterling, Virginia), KDIX (Philadelphia, Pennsylvania), and KFCX (Roanoke, Virginia) from the top 20 most valuable radars (Table 1). The more localized nature of flash flood impacts presents a less uniform spatial distribution than the other hazards (Fig. 2e). The greatest flash flood benefits coincide with population centers and river basins, most apparent in the central and southwest United States. Figure 2f indicates a broad distribution of value attributed to flash flood risk mitigation, with values exceeding $5 million per radar concentrated over the Mississippi River basin, the Appalachian Mountains, and the Mid-Atlantic region. Table 2 reveals that five radars exceed $10 million in annual value for mitigating the flood threat, including KDIX, KFCX, KSGF, KLWX, and KLSX (Saint Louis, Missouri).

Only 13 of 143 radars (9.1%) generated more than half of their value by mitigating the severe wind risk (none of the top 20). Casualty rates for nontornadic thunderstorm wind events are much lower than those for tornadoes and flash floods, so the available benefit pool is correspondingly smaller. Most maxima in severe wind benefit distribution coincide with population centers (Fig. 2g). The Mid-Atlantic region presents the broadest and most pronounced local maxima in the severe wind benefit distribution. Four radars exceed $5 million in annual value for mitigating the severe wind threat (Table 2), including KLWX, KILN (Cincinnati, Ohio), KGSP (Greer, South Carolina), and KFCX.

b. Outage cost estimates

Radar status varies considerably between radars and years. The number of operational radars varies minute to minute (Fig. 3), with an average of 139 of 143 radars online each minute. During 2020–23, 54.6%, 95.4%, and 99.5% of minutes have 140+, 135+, and 130+ radars online, respectively (not shown). Only 0.06% of minutes have less than 125 radars online. Annual composite statistics summarize the outage characteristics of individual radars (Table 3). The average radar is offline for 2.57% of minutes or 9.27 days per year. Each radar experiences an average of 58.9 outages per year lasting 4.32 h on average. The average annual outage percentage during 2020 (2.71%) and 2023 (2.74%) exceeds the 2021 (2.37%) and 2022 (2.45%) values. The greater outage percentage during 2020 results from fewer outages with longer durations, while 2023 exhibits more frequent outages with shorter average durations (Table 3). These annual composite values provide context for the outage frequencies attributed to individual radars.

Figure 4 illustrates variability in both the outage frequency and outage cost estimates for individual radars during 2020–23. Outage cost estimates (right panels) are computed by multiplying the annual outage frequencies (left panels) by the total estimated benefit for mitigating all three convective hazards (Fig. 2b). The darkest blue shades in Fig. 4 indicate >5.0% outage frequency (left panels) and >$1 million in annual outage costs (right panels). The annual outage frequency distributions reveal no clear spatial or temporal patterns, while the annual outage costs concentrate in the eastern half of the United States. Radars with annual outage costs > $125,000 exhibit similarly broad spread each year. The more frequent outages during 2020 and 2023 (Table 3) are most evident in the

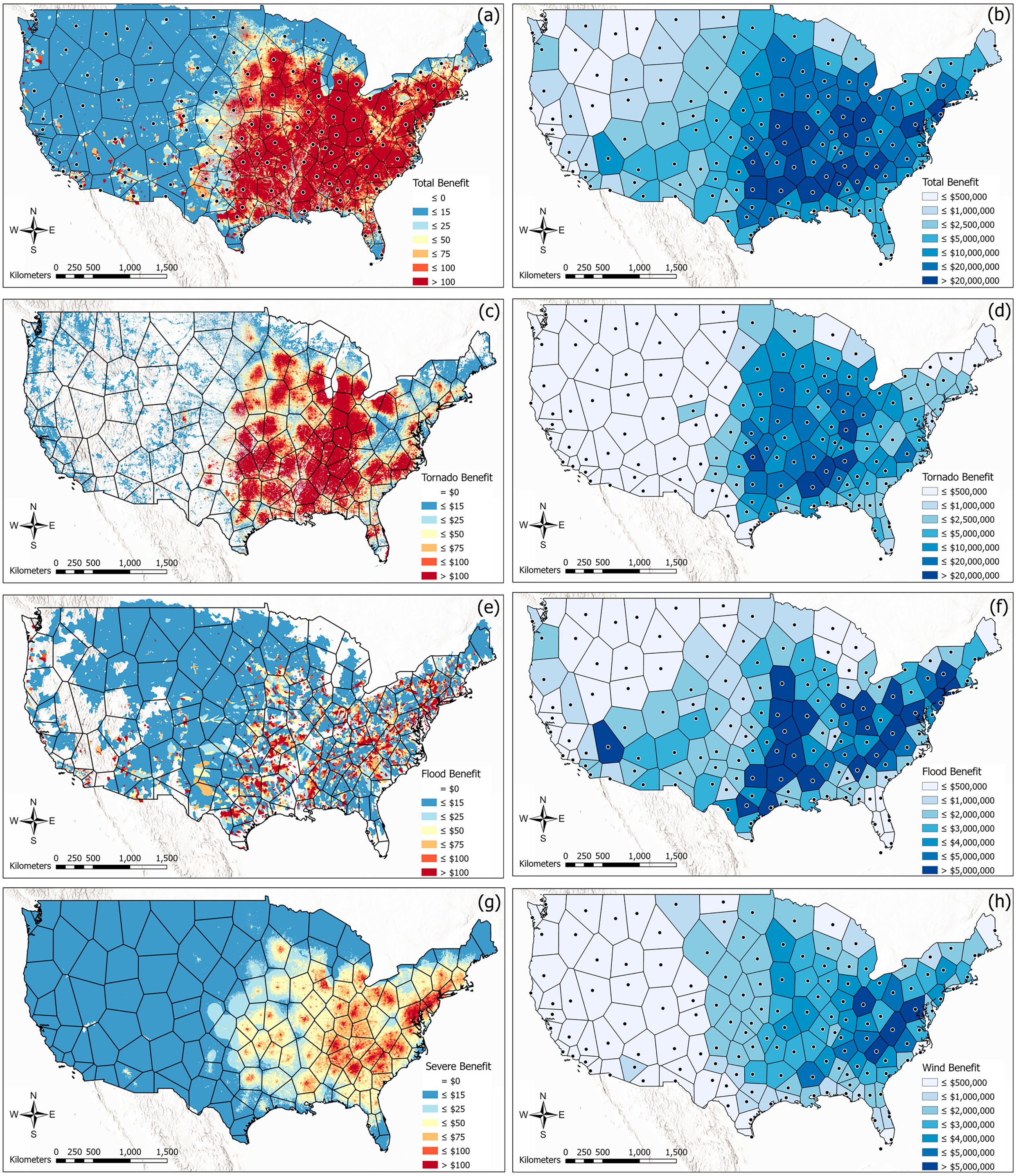

FIG. 2. Spatial distribution of the radar value derived from the Cho and Kurdzo models. (a),(c),(e),(g) The radar value per grid cell and (b),(d),(f),(h) the accumulated value per radar. Note the different color scales for (b) and (d) vs (f) and (h).

number of radars with outage costs > \$500,000 (Figs. 4b,h) versus 2021 and 2022 (Figs. 4d,f).

Outage cost estimates concentrate at the top, especially during 2020 and 2023. Table 4 lists the top five radar outage cost estimates for each year 2020–23 including the outage costs associated with each convective hazard. Eight (five) radars exceeded \$1 million in outage cost estimates during 2020 (2023), versus two and four during 2021 and 2022, respectively. The most valuable radar (KDGX) experiences outage frequencies of 4.92% and 5.50% during 2020 and

TABLE 1. Top 20 most valuable radars for mitigating the combined tornado, flash flood, and severe wind threats along with the benefit attributed to mitigating each convective hazard.

Radar	Location	Combined benefit	Tornado benefit	Flash flood benefit	Wind benefit
KDGX	Jackson, MS	$41,776,546	$29,349,583	$8,222,902	$4,204,061
KHTX	Huntsville, AL	$34,311,248	$25,145,381	$4,626,307	$4,539,560
KGWX	Columbus Air Force Base, MS	$33,933,141	$26,587,563	$4,237,758	$3,107,820
KILN	Cincinnati, OH	$30,607,519	$19,310,946	$6,214,406	$5,082,167
KLVX	Louisville, KY	$29,921,566	$22,125,126	$4,289,633	$3,506,807
KTLX	Oklahoma City, OK	$29,870,501	$25,468,440	$2,450,086	$1,951,975
KIND	Indianapolis, IN	$28,659,865	$15,923,233	$9,448,965	$3,287,668
KFWS	Dallas/Ft. Worth, TX	$26,264,482	$14,605,135	$9,132,429	$2,526,918
KLSX	Saint Louis, MO	$24,364,127	$10,077,855	$10,852,953	$3,433,319
KSGF	Springfield, MO	$23,560,927	$8,322,255	$11,936,732	$3,301,940
KSHV	Shreveport, LA	$23,307,023	$13,152,074	$7,381,871	$2,773,079
KBMX	Birmingham, AL	$22,717,475	$19,049,831	$1,711,040	$1,956,603
KLZK	Little Rock, AR	$22,522,378	$13,902,861	$5,769,774	$2,849,742
KEAX	Kansas City, MO	$22,227,152	$11,677,577	$7,956,292	$2,593,283
KFFC	Atlanta, GA	$21,973,823	$9,720,755	$8,297,934	$3,955,133
KLWX	Sterling, VA	$21,457,219	$3,725,715	$10,896,012	$6,835,492
KGSP	Greer, SC	$21,120,359	$6,831,228	$9,211,660	$5,077,471
KDIX	Philadelphia, PA	$20,324,213	$1,679,546	$14,771,474	$3,873,193
KDMX	Des Moines, IA	$19,926,187	$10,788,473	$5,984,084	$3,153,631
KFCX	Roanoke, VA	$19,675,139	$1,876,969	$12,789,687	$5,008,484

2023, resulting in outage cost estimates > $2 million both years. The third most valuable radar (KGWX) experiences outage frequencies of 5.56% and 5.76% during 2022 and 2023, resulting in outage cost estimates of ~$1.9 million each year. The tremendous value attributed to the Mississippi radars reveals the risk and vulnerability experienced by the communities they serve, making these outage frequencies and cost estimates particularly concerning. Our findings suggest that characterizing and mitigating these outages might provide a near-term solution to better protect these communities from convective hazards.

The greatest outage cost estimates typically result from either 1) above average outage frequency of a moderately valuable radar, 2) very high outage frequency of an average value radar, or 3) below average outage frequency of a very valuable radar. Although KDGX is online more frequently than the average radar during 2021 (1.9% vs 2.37%), it ranks third in outage costs for the year ($793,754). Relocation of the KLIX radar in late 2023 results in an outage frequency of 12.84%. This combines with an estimated annual benefit of $9,511,262 to rank KLIX fifth in outage costs for 2023 ($1.2 million). Most of the remaining radars on the annual top five lists demonstrate the first scenario listed above (i.e., above average outage frequency of a moderately valuable radar).

Combining outage costs for all radars totals $31.5 million, $23.8 million, $27.5 million, and $33.7 million during 2020, 2021, 2022, and 2023, respectively (Table 5). The Cho and Kurdzo models attribute 50.7%, 30.9%, and 18.5% of the present WSR-88D network value to mitigating the casualty threat from tornadoes, flash floods, and severe winds, respectively. The 2022 distribution of outage costs by hazard most closely matches the overall radar value distribution. Of the 2022 outage costs, $13.9 (50.5%), $8.4 (30.7%), and $5.2 (18.8%) million are attributed to mitigating the tornado, flash flood, and severe wind threats, respectively. The greatest relative proportion of outage costs attributed to flash floods occurs during 2021 (33.8%), while this value is greatest for severe winds during 2020 and 2021 (19.1%). Our findings suggest that approximately $29.1 million in annual radar outage

TABLE 2. Top 10 most valuable radars for mitigating the tornado, flash flood, and severe wind threats.

Radar	State	Tornado benefit	Radar	State	Flash flood benefit	Radar	State	Severe wind benefit
KDGX	MS	$29,349,583	KDIX	PA	$14,771,474	KLWX	VA	$6,835,492
KGWX	MS	$26,587,563	KFCX	VA	$12,789,687	KILN	OH	$5,082,167
KTLX	OK	$25,468,440	KSGF	MO	$11,936,732	KGSP	SC	$5,077,471
KHTX	AL	$25,145,381	KLWX	VA	$10,896,012	KFCX	VA	$5,008,484
KLVX	KY	$22,125,126	KLSX	MO	$10,852,953	KPBZ	PA	$4,702,815
KILN	OH	$19,310,946	KIND	IN	$9,448,965	KHTX	AL	$4,539,560
KBMX	AL	$19,049,831	KGSP	SC	$9,211,660	KMRX	TN	$4,361,989
KIND	IN	$15,923,233	KFWS	TX	$9,132,429	KDGX	MS	$4,204,061
KFWS	TX	$14,605,135	KFFC	GA	$8,297,934	KRAX	NC	$4,002,917
KLZK	AR	$13,902,861	KDGX	MS	$8,222,902	KFFC	GA	$3,955,133

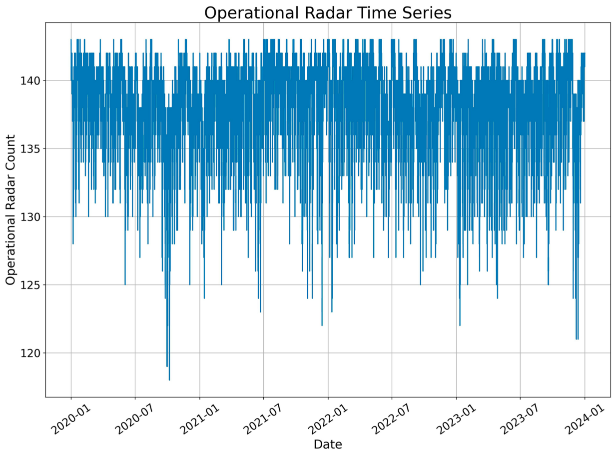

FIG. 3. Time series of the cumulative number of the 143 WSR-88D radars online during each minute (i.e., those listed as "no alarm" or "alarm").

costs may be attributable to alternative datasets as value for helping mitigate radar outages.

c. Limitations

Quantifying the costs of radar outages and attributing value to alternate datasets relies on economic benefit transfer and other assumptions. We assume that preventing all radar outages would marginally increase the radar value above the Cho and Kurdzo (2019, 2020a,b) estimates and that these radar value estimates would be lesser without alternative datasets filling the outage-induced gaps. Limited formal documentation exists on the use of alternate datasets by NWS forecasters during radar outages, requiring the use of recorded training presentations as references. These direct forecaster insights reveal the broad use of alternative datasets to mitigate radar loss during convective warning operations but do not fully characterize this application.

Use of weather radar benefit models also includes a few caveats. The warning performance modeling is based on historical averages across CONUS, but variability exists between weather forecast offices and storm types that influences the radar value in particular situations. Severe weather event records are imperfect (e.g., tendency for higher reporting rates near population centers), which could bias the benefits toward dense population. Climate change is driving shifts in severe weather occurrence rate, strength, and locations, which can impact the magnitude and spatial distribution of weather radar benefit projections.

Although differentiating between planned and unplanned outages remains outside the scope of the present analysis, doing so could help better understand the costs of upgrades and unplanned outages. Future work should seek to determine whether the existing schedules and logs documenting planned outages could be used to make this distinction with enough confidence to generate meaningful results. If so, differentiating between unplanned outages caused by weather versus those caused by nonweather factors also could prove beneficial.

5. Summary and conclusions

The WSR-88D weather radars support forecast and warning decisions that save lives, reduce injuries, and protect property. Weather radars are subject to outages, both planned routine maintenance and unplanned outages resulting from mechanical failure or weather impacts. Weather impacts often take radars offline when it is least convenient (e.g., during forecast and warning operations). Although radar outages for planned routine maintenance are scheduled for when severe weather is less likely climatologically, impactful weather events can occur during these planned outages.

Examples of severe weather warning operations during radar outages demonstrate how alternate datasets help mitigate outages. When radars are offline, forecasters rely more heavily on nearby radars, surface reports, numerical weather prediction (NWP) models, and satellite observations. Although NWS forecast and warning operations vary from region to region and office to office, direct forecaster insights reveal the broad use of alternative datasets to mitigate radar loss during convective warning operations.

Without the primary radar, forecasters emphasize the environment and reports and substitute satellites for radar as much as possible. In favorable storm environments, satellite products can portray the convective trends well enough to continue issuing warnings with only distant radar observations. Even without radar, in a favorable environment, satellite tendencies or the lack thereof often are enough to warrant continuation or cancellation of warnings. Lightning trends also help diagnose convective tendencies, and in some

TABLE 3. Composite outage statistics for all 143 WSR-88D radars, including the average annual outage frequency (outage minutes/total minutes), average annual outage period in days (average of the total outage duration per radar in minutes/60 × 24), the mean and median number of outages per radar, and the average outage duration in hours (average of the average outage duration per radar).

	Average annual outage frequency (%)	Average annual outage period (days)	Mean outage count	Median outage count	Average outage duration (h)
2020	2.71	9.92	50.4	45	4.72
2021	2.37	8.66	52.8	49	3.94
2022	2.45	8.95	57.8	51	3.72
2023	2.74	9.54	74.6	49	3.60
2020–23	2.57	9.27	58.9	50	4.32

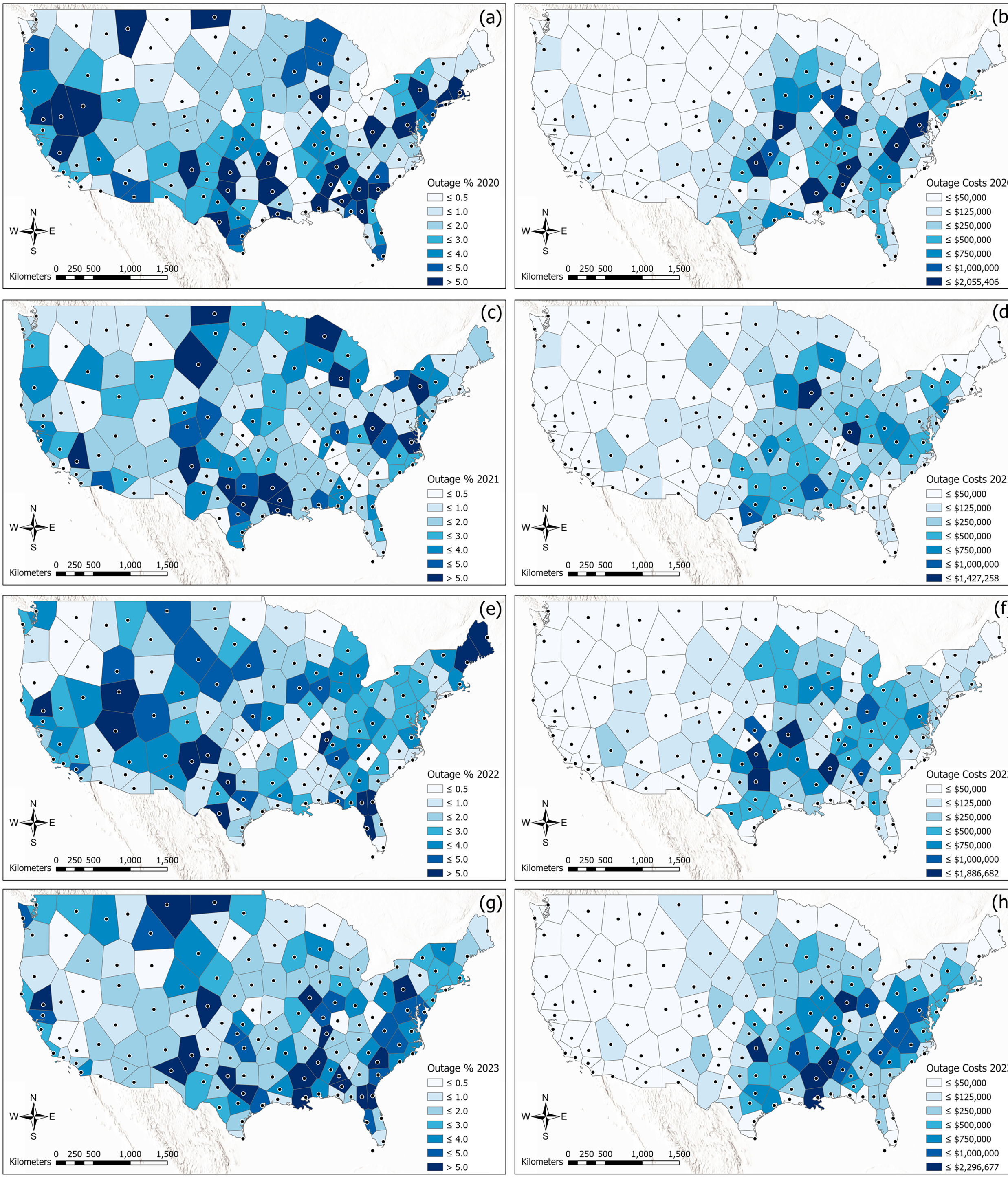

FIG. 4. Radar outage frequency for each radar during (a) 2020, (c) 2021, (e) 2022, and (g) 2023, along with radar outage cost estimates for (b) 2020, (d) 2021, (f) 2022, and (h) 2023.

cases, forecasters use the lightning data as essentially a pseudoradar.

Monetized geospatial benefit models quantify the spatial distribution of value provided by the present WSR-88D radar network and allow attribution of value to individual radars. Eighteen radars exceed $20 million in annual benefits for mitigating the combined tornado, flash flood, and severe wind threats. Value is concentrated in the eastern half of the United States due to relatively dense population experiencing more frequent convective weather. The KDGX radar provides the most

TABLE 4. Top five radar outage cost estimates for each year 2020–23. The radar outage cost estimates result from multiplying the outage frequency by the estimated value each radar provides for mitigating each hazard.

Radar	Location	Outage frequency (%)	Combined cost	Tornado cost	Flash flood cost	Severe wind cost
		2020				
KDGX	Jackson, MS	4.92	$2,055,406	$1,443,999	$404,567	$206,840
KBMX	Birmingham, AL	5.69	$1,292,624	$1,083,935	$97,358	$111,331
KTLX	Oklahoma City, OK	4.07	$1,215,729	$1,036,565	$99,719	$79,445
KLWX	Sterling, VA	5.64	$1,210,187	$210,130	$614,535	$385,522
KHTX	Huntsville, AL	3.27	$1,121,978	$822,254	$151,280	$148,444
		2021				
KLVX	Louisville, KY	4.77	$1,427,259	$1,055,369	$204,615	$167,275
KDVN	Davenport, IA	9.65	$1,038,672	$516,731	$249,928	$272,014
KDGX	Jackson, MS	1.9	$793,754	$557,642	$156,235	$79,877
KEWX	San Antonio, TX	7.08	$759,683	$177,668	$541,903	$40,111
KFCX	Roanoke, VA	3.62	$712,240	$67,946	$462,987	$181,307
		2022				
KGWX	Columbus Air Force Base, MS	5.56	$1,886,683	$1,478,268	$235,619	$172,795
KTLX	Oklahoma City, OK	3.79	$1,132,092	$965,254	$92,858	$73,980
KFWS	Ft. Worth, TX	4.14	$1,087,350	$604,653	$378,083	$104,614
KSGF	Springfield, MO	4.43	$1,043,749	$368,676	$528,797	$146,276
KFFC	Atlanta, GA	4.09	$898,729	$397,579	$339,386	$161,765
		2023				
KDGX	Jackson, MS	5.50	$2,296,677	$1,613,501	$452,056	$231,119
KGWX	Columbus Air Force Base, MS	5.76	$1,952,899	$1,530,151	$243,889	$178,859
KTLX	Oklahoma City, OK	4.68	$1,397,196	$1,191,289	$114,603	$91,304
KIND	Indianapolis, IN	4.58	$1,312,050	$728,967	$432,574	$150,510
KLIX	New Orleans, LA	12.84	$1,221,318	$696,272	$339,053	$185,993

combined value ($41.0 million), with much greater value for tornado risk mitigation ($28.8 million) than for flash flood ($8.2 million) and wind ($4.1 million) risk mitigation.

Radars contribute much greater value for tornado risk mitigation than for flash floods and severe winds. Radar values for mitigating the tornado threat exceed $100 per grid cell over large parts of the central and eastern United States. Maxima associated with the well-known Tornado and Dixie Alleys extend well north into the Midwest and Great Lakes regions and eastward into the Carolinas. Five radars exceed $20 million in annual value for mitigating the tornado threat. Tornado risk mitigation represents >50% of the value for 51 of 143 radars (35.7%), including 8 of the top 10 most valuable radars. Flash flood mitigation accounts for more than half of the value for 50 of 143 radars (35.0%), while only 13 of 143 radars (9.1%) generated more than half of their value by mitigating the severe wind risk.

The number of operational radars varies minute-to-minute (Fig. 3), with an average of 139 of 143 radars online each minute. During 2020–23, 54.6%, 95.4%, and 99.5% of minutes have 140+, 135+, and 130+ radars online, respectively. Annual composite statistics summarize the outage characteristics of individual radars and provide context for the outage frequencies attributed to individual radars. The average radar is offline for 2.57% of minutes or 9.27 days per year, and each radar has an average of 58.9 outages per year lasting 4.32 h on average. The average annual outage percentage during 2020 (2.71%) and 2023 (2.74%) exceed the 2021 (2.37%) and 2022 (2.45%) values. The greater outage percentage during 2020 results from fewer outages with longer durations, while 2023 exhibited more frequent outages with shorter average durations.

Radar outage cost estimates vary considerably by location and convective hazard. Outage cost estimates concentrate at

TABLE 5. Accumulated outage costs by hazard and total, along with the relative percentage of the combined value associated with each hazard during each year.

	Tornado outage costs	Flash flood outage costs	Wind outage costs	Total outage costs
2020	$15,614,298	$9,875,658	$6,007,601	$31,497,557
2021	$11,213,853	$8,065,698	$4,552,739	$23,832,290
2022	$13,891,860	$8,427,510	$5,174,852	$27,494,222
2023	$17,616,289	$9,930,467	$6,171,337	$33,718,093
2020	49.6%	31.4%	19.1%	100.0%
2021	47.1%	33.8%	19.1%	100.0%
2022	50.5%	30.7%	18.8%	100.0%
2023	52.2%	29.5%	18.3%	100.0%

the top, with 8, 2, 4, and 5 radars exceeding $1 million in outage costs during 2020, 2021, 2022, and 2023, respectively. The KDGX radar experiences outage frequencies of 4.92% and 5.50% during 2020 and 2023, resulting in outage cost estimates > $2 million both years. The KGWX radar at Columbus Air Force Base, Mississippi, experiences outage frequencies of 5.56% and 5.76% during 2022 and 2023, resulting in outage cost estimates of ~$1.9 million each year. The tremendous value attributed to the Mississippi radars reveals their importance, making these outage frequencies and cost estimates concerning. Our findings suggest that characterizing and mitigating these outages might provide a near-term solution to better protect these communities from convective hazards.

Combining outage costs for all radars totals $31.5 million, $23.8 million, $27.5 million, and $33.7 million per year during 2020, 2021, 2022, and 2023, respectively. This suggests that approximately $29.1 million in annual radar outage costs may be attributable as value to alternate datasets for helping mitigate the impacts of radar outages.

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Data availability statement. Due to access limitations, only NOAA employees can view the radar status summary pages from which the radar outage time series were computed. The current status of all WSR-88D radars can be found at https://radar2pub.ncep.noaa.gov/ and https://radar3pub.ncep.noaa.gov/. The economic analysis data needed for the VSL and personal time value calculations are available through the U.S. Bureau of Labor Statistics online database at https://www.bls.gov/data/inflation_calculator.htm (consumer price index), https://www.bls.gov/cps/cpswktabs.htm (median usual weekly earnings), and https://www.bls.gov/ces/data/employment-situation-table-download.htm (average earnings, employment rate, average weekly hours). Equations used for these calculations are given in Cho and Kurdzo (2019).

REFERENCES

Bieringer, P., and P. S. Ray, 1996: A comparison of tornado warning lead times with and without the NEXRAD Doppler radar. *Wea. Forecasting*, **11**, 47–52, https://doi.org/10.1175/1520-0434(1996)011<0047:ACOTWL>2.0.CO;2.

Boettcher, J., S. Torres, F. Nai, C. Curtis, and D. Schvartzman, 2022: A multidisciplinary method to support the evolution of NWS weather radar technology. *Wea. Forecasting*, **37**, 429–444, https://doi.org/10.1175/WAF-D-21-0159.1.

Boots, B., A. Okabe, and K. Sugihara, 1999: Spatial tessellations. *Geogr. Inf. Syst.*, **1**, 503–526.

Brooks, H. E., C. A. Doswell III, and M. P. Kay, 2003: Climatological estimates of local daily tornado probability for the United States. *Wea. Forecasting*, **18**, 626–640, https://doi.org/10.1175/1520-0434(2003)018<0626:CEOLDT>2.0.CO;2.

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.

——, S. Erickson, and H. Brooks, 2011: A 5-yr climatology of tornado false alarms. *Wea. Forecasting*, **26**, 534–544, https://doi.org/10.1175/WAF-D-10-05004.1.

Cho, J. Y. N., and J. M. Kurdzo, 2019: Monetized weather radar network benefits for tornado cost reduction. MIT Lincoln Laboratory Project Rep. NOAA-35, 88 pp., https://www.ll.mit.edu/sites/default/files/publication/doc/monetized-weather-radar-network-benefits-cho-noaa-35.pdf.

——, and ——, 2020a: Weather radar network benefit model for flash flood casualty reduction. *J. Appl. Meteor. Climatol.*, **59**, 589–604, https://doi.org/10.1175/JAMC-D-19-0176.1.

——, and ——, 2020b: Weather radar network benefit model for nontornadic thunderstorm wind casualty cost reduction. *Wea. Climate Soc.*, **12**, 789–804, https://doi.org/10.1175/WCAS-D-20-0063.1.

Clark, R. A., J. J. Gourley, Z. L. Flamig, Y. Hong, and E. Clark, 2014: CONUS-wide evaluation of National Weather Service flash flood guidance products. *Wea. Forecasting*, **29**, 377–392, https://doi.org/10.1175/WAF-D-12-00124.1.

Crum, T. D., and R. L. Alberty, 1993: The WSR-88D and the WSR-88D operational support facility. *Bull. Amer. Meteor. Soc.*, **74**, 1669–1688, https://doi.org/10.1175/1520-0477(1993)074<1669:TWATWO>2.0.CO;2.

——, R. E. Saffle, and J. W. Wilson, 1998: An update on the NEXRAD program and future WSR-88D support to operations. *Wea. Forecasting*, **13**, 253–262, https://doi.org/10.1175/1520-0434(1998)013<0253:AUOTNP>2.0.CO;2.

——, E. J. Ciardi, J. B. Boettcher, M. J. Istok, and A. Stern, 2013: How the WSR-88D and its new dual polarization capability can benefit the wind energy industry. *Fourth Conf. on Weather, Climate, and the New Energy Economy*, Austin, TX, Amer. Meteor. Soc., 794, https://ams.confex.com/ams/93Annual/webprogram/Manuscript/Paper222787/2013_AMS_DP_Wind%20Energy_Paper_Final3.pdf.

Gagan, J. P., A. Gerard, and J. Gordon, 2010: A historical statistical comparison of "Tornado Alley" to "Dixie Alley". *Natl. Wea. Dig.*, **34**, 145–155.

Gultepe, I., and Coauthors, 2019: A review of high impact weather for aviation meteorology. *Pure Appl. Geophys.*, **176**, 1869–1921, https://doi.org/10.1007/s00024-019-02168-6.

Long, J. A., P. C. Stoy, and T. Gerken, 2018: Tornado seasonality in the southeastern United States. *Wea. Climate Extremes*, **20**, 81–91, https://doi.org/10.1016/j.wace.2018.03.002.

National Weather Service, 2020: KOKX WSR-88D radar is down for pedestal refurbishment for approximately 2 weeks. Accessed 23 February 2023, https://www.weather.gov/okx/SLEP-PEDESTAL-KOKX.

——, 2021: Lake Charles weather radar back online after Hurricane Laura damage. Accessed 23 February 2023, https://www.weather.gov/news/012221-lake-charles-radar.

Ostrowski, J., and Coauthors, 2003: Flash flood guidance improvement team. NWS Office of Hydrologic Development Final Rep., 47 pp., https://www.weather.gov/media/owp/oh/rfcdev/docs/ffgitreport.pdf.

Radar Operations Center, 2022: WSR-88D Service Life Extension Program (SLEP); pedestal refurbishment. Accessed 23 February

2023, https://www.roc.noaa.gov/WSR88D/SLEP/pedestalrefurb.aspx.

Regnier, E., 2008: Doing something about the weather. *Omega*, **36**, 22–32, https://doi.org/10.1016/j.omega.2005.07.011.

Rudlosky, S. D., S. J. Goodman, K. S. Virts, and E. C. Bruning, 2019: Initial Geostationary Lightning Mapper observations. *Geophys. Res. Lett.*, **46**, 1097–1104, https://doi.org/10.1029/2018GL081052.

SBCSS, 2021a: SBC Session 39 – Radar down panel discussion. YouTube, accessed 4 March 2021, https://youtu.be/V1JpMob-Hj0?si=Nf6tQoJmf2N4ovDE.

——, 2021b: SBC Session 70 – Radar down, severe risk up. YouTube, accessed 7 October 2021, https://youtu.be/8evb5v4g3Yg?si=hYpMaVEQxmnaUXv6.

Schaumann, J. S., and R. W. Przybylinski, 2012: Operational application of 0-3 km bulk shear vectors in assessing QLCS mesovortex and tornado potential. Preprints, *26th Conf. on Severe Local Storms*, Nashville, TN, Amer. Meteor. Soc., P9.10, https://ams.confex.com/ams/26SLS/webprogram/Manuscript/Paper212008/SchaumannSLS2012_P142.pdf.

Schmit, T. J., P. Griffith, M. M. Gunshor, J. M. Daniels, S. J. Goodman, and W. J. Lebair, 2017: A closer look at the ABI on the GOES-R series. *Bull. Amer. Meteor. Soc.*, **98**, 681–698, https://doi.org/10.1175/BAMS-D-15-00230.1.

Simmons, K. M., and D. Sutter, 2005: WSR-88D radar, tornado warnings, and tornado casualties. *Wea. Forecasting*, **20**, 301–310, https://doi.org/10.1175/WAF857.1.

WDTD, 2023: Data fusion exercise for flash flood warnings: 26 July 2021 Flash Flood Event. Regional and Mesoscale Meteorology Branch, accessed 23 October 2023, https://rammb.cira.colostate.edu/training/visit/training_sessions/data_fusion_20210726/story.html.

WDTD SOTM, 2020: Using GLM in the convective warning process. YouTube, accessed 1 May 2020, https://youtu.be/i0_kfvt0Wck?si=dOHND1zOsgYgszIM.

Wolfson, M. M., and D. A. Clark, 2006: Advanced aviation forecasts. *Lincoln Lab. J.*, **16**, 31–58.

Zrnić, D. S., and Coauthors, 2007: Agile-beam phased array radar for weather observations. *Bull. Amer. Meteor. Soc.*, **88**, 1753–1766, https://doi.org/10.1175/BAMS-88-11-1753.