EXPLORING TORNADO VULNERABILITY IN THE APPALACHIAN REGION

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ABSTRACT

The Appalachian region extends from northeastern Mississippi to southern New York, which is outside of the zone traditionally known as "tornado alley." As seen by the EF4 tornado in London, KY on 16 May 2025, however, the region does still experience devastating tornadoes. With influences such as high rates of poverty and mobile/ manufactured home ownership, Appalachia bears an adverse socioeconomic state that has unknown impacts on large-scale tornado vulnerability. Leveraging data from the Center for Disease Control's Social Vulnerability Index (CDC SVI), this study employed GIS software to explore the relationships between various social vulnerability indices and tornado death rates. A similar exploration was conducted for multiple forecast performance indices using data from a National Weather Service (NWS) Stats on Demand Interface. Ultimately, no significant linear correlations were found between tornado deaths and any of the indices examined at the County Warning Area (CWA) level. This information could hold implications for both disaster planning and Impact-Based Decision Support Services (IDSS).

1. INTRODUCTION

On May 16, 2025, a violent tornado traveled almost 60 miles across southeastern Kentucky. In its wake, the small city of London, KY was left with piles of rubble, having sustained EF-4 damage from the storm (Blackford et al. 2025). According to Honeycutt and Starkey, the tornado caused 16 fatalities and numerous injuries in London. The majority of those who died were over the age of 60, and many were long-term London residents who were very active within their community, leaving behind spouses, parents, children, siblings, and friends (Honeycutt and Starkey 2025). Survivors emerged from shelter to see their neighborhoods destroyed, and their neighbors dead or severely injured. In the aftermath, the London community came together to assist those in need. From handing out supplies to aiding in the search for survivors, many residents who were not directly impacted volunteered their time and resources to help their neighbors (Witz et al. 2025). In all, the tornado killed 19 people and caused a total of $60 million to 1,500 homes that were damaged or destroyed while it was on the ground (Blackford et al. 2025).

This project was inspired by a NOAA VORTEX USA grant referred to as Rural Region Readiness (RRR). RRR works with National Weather Service (NWS) weather forecast offices (WFOs) in the Appalachian region to target rural members of the integrated warning team (IWT) through tornado readiness workshops. These workshops include members of the WFO, traditional members of the IWT, such as emergency managers, as well as local community leaders and members of emergency preparedness and response teams. Central to the RRR project is understanding *who* is most vulnerable to tornadoes in the rural Appalachian region. Targeting communities similar to London, KY, the IWT workshops hosted by RRR aim to help build Impact Based Support Services (IDSS) frameworks for rural communities, which exist across the nation (Hurst et al. 2024).

London is located in the heart of Appalachia, a region which according to the Appalachian Regional Commission (ARC), extends from northern Mississippi to southern New York (ARC 2022). Appalachia is outside of the zone traditionally known as the "tornado alley," a tornado-prone region in the central and southern

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plains (Long and Stoy 2014). However, as seen by London, KY, the region is still impacted by tornadic storms. A background on the state of Appalachia and on tornado vulnerability will be provided next in section 2, followed by information about the data and methods used for this study in section 3. The results, a discussion, and a conclusion will then be presented in sections 4, 5, and 6 respectively.

2. BACKGROUND

2.1 *State of Appalachia*

The Appalachian region bears a unique, adverse socioeconomic state. Within Appalachia, educational attainment, internet access, mean household income, and the majority of health indicators perform below their respective national averages, while poverty and mortality rates stand above the national average (Srygley et al. 2024; Marshall et al. 2017; Heffernan et al. 2024). Between 2013–2017 and 2018–2022, the region experienced improvements: racial and ethnic diversity, the percentage of adults with a diploma, and the percentage of households with a computer and internet all increased (Srygley et al. 2024). Regionally, there was an increase in adults with Associate's degrees in central Appalachia, and an increase in adults with Bachelor's degrees in southern and urban Appalachia (Srygley et al. 2024). The portion of adults with a diploma increased between 2013–2017 and 2018–2022 at a greater rate in Appalachia than the rest of the nation, however, it still trails behind the rest of the nation. Additionally, a digital divide between Appalachia and the rest of the nation is present, meaning there is a notable gap in home computer and internet access between Appalachia and the rest of the nation. Income in Appalachia also continues to lag behind the rest of the nation, increasing at a slower rate in Appalachia than outside of the region (Srygley et al. 2024).

In rural regions specifically, Appalachia also tends to sit behind the rest of the nation. Rural Appalachia tends to have lower incomes and education rates than rural regions outside of Appalachia (Srygley et al. 2024). The digital divide between Appalachia and non-Appalachia is also prevalent between Appalachian and non-Appalachian rural regions (Srygley et al. 2024). Disparities between urban and rural regions are also prevalent within Appalachia, with mortality rates and health indicators both performing worse in rural areas than urban areas (Heffernan et al. 2024; Marshall et al. 2017).

2.2 *Hazard Climatology*

Within the United States, the greatest frequency of tornadoes occurs in the great plains. Although this remains the case, a statistically significant increase in tornadoes has been observed in the southeastern United States, which encompasses southern Appalachia (Gensini and Brooks 2018). Seasonal and diurnal cycles of tornado frequency have been found to vary across the United States (Krocak and Brooks 2018). Unlike the great plains, where tornado frequency peaks in the warm season and dies off in the cold season, tornado frequency in the southeastern United States remains fairly consistent throughout the year (Krocak and Brooks 2018). Similarly, while the great plains have a strong peak in tornado frequency in the afternoon, the southeastern United States has a weaker afternoon peak, and nocturnal tornado frequency remains higher (Krocak and Brooks 2018).

West Virginia, which is located in central and north- central Appalachia, experiences a low frequency of tornadoes. Between 1950–1983 and 1984–2017, there was not a significant change in overall tornado frequency within the state, however, there was a significant increase in June and September tornado frequency, and a significant decrease in April and August tornado frequency (Leonard and Law 2019). The diurnal peak for tornadoes within the state has been trending towards later in the day, with a 139 minute shift being noted between 1950–1983 and 1984–2017 (Leonard and Law 2019).

2.3 *Non-Meteorological Tornado Vulnerability Influences*

Within this study, tornado vulnerability can be defined as a measure of how likely a community is to be impacted by a tornado, and how much potential it has to recover (Kasi and Saha 2023; Deziel et al. 2023). Various socioeconomic indicators have been found to directly influence tornado vulnerability. Housing type has generally been found have the most influence on tornado vulnerability, with 1985–2000 tornado death rates being consistently higher for mobile home residents than for permanent home residents (Brooks and Doswell 2002). In cases such as the 3 March 2019 Beauregard, AL EF4, this disparity was attributed to insufficient anchoring and wind grading that may not have been in accordance with Alabama building codes (Holmes et al. 2021). Income has also been found to have influence in tornado vulnerability, with higher poverty rates tending to coincide with higher tornado vulnerability (Lim et al. 2017). This relationship can be attributed to multiple factors. For one, lower income individuals may be more likely to reside in mobile homes, as mobile homes tend to be lower-cost options that do not require qualification for a mortgage (Holmes et al. 2021). Additionally, lower income individuals may be more severely affected by a tornado's impacts, while also having less means to aid in recovery (Strader et al. 2021).

Household composition has also been found to impact tornado vulnerability, especially population age. In general, children and the elderly are particularly vulnerable during disasters due to their reliance on others when taking action (Flanagan et al. 2011). For similar reasons, disabled individuals and single parents also tend to be more vulnerable during tornadoes (Strader et al. 2021). Education has also been found to impact tornado vulnerability, as higher educational attainment tends to accompany a higher likelihood to take emergency action during an event (Lim et al. 2017).

2.4 *Meteorological Tornado Vulnerability Influences*

Performance of a region's local National Weather Service (NWS) Weather Forecast Office (WFO) has also been found to impact tornado vulnerability. People who experience high rates of unwarned tornadoes or false alarm tornado warnings may have reduced trust in their local forecasters, rendering them less likely to take action during an event (Strader et al. 2021; Lim et al. 2017). Tornado warning lead times have also been found to influence tornado vulnerability, with vulnerability being lower for those who experience higher lead times because they have more time to react to the warning (Strader et al. 2021).

2.5 *Research Questions*

This study is exploratory in nature. With the above literature in mind, this study examines the relationships among social vulnerability and death rates in Appalachia. To guide results and discussion, we pose two broad questions:

1. How are social vulnerability indices related to tornado deaths in the Appalachian region?
2. How does tornado vulnerability in Appalachia compare to tornado vulnerability outside of the region?

3. DATA/ METHODS

3.1 *Social Vulnerability Index*

This study utilizes the Centers for Disease Control and Prevention and Agency for Toxic Substances and Disease Registry's (CDC/ATSDR) Social Vulnerability Index (SVI) as its socioeconomic vulnerability metric. The SVI is a measure of variables that may impact a community's resilience to natural disasters, and is used operationally by emergency managers and public health officials for disaster planning (CDC 2022). Its calculation considers 16 census variables organized into four larger themes: Socioeconomic Status (SS), Household Characteristics (HC), Racial & Ethnic Minority Status (REMS), and Housing Type & Transportation (HTT). SS encompasses factors including poverty, unemployment, and education in order to represent populations whose economic status may hinder their resilience to disasters. REMS intends to account for both economic and language barriers. Similarly, HC comprises variables including age and disability status to represent populations who may require additional assistance when reacting to disasters. Finally, HTT accounts for homes that may be more susceptible to damage, while also accounting for transportation access, accounting for those who may not be able to leave during a disaster due to a lack of transportation.

To quantify SVI indices, this study utilized the 90th percentile flags provided in the census tract level 2022 SVI ESRI Geodatabase. If an SVI variable's value in a census tract was greater than 90% of all values, that variable was flagged. This method gave overall SVI a possible range of 0–16, with 0 representing the lowest vulnerability and 16 representing the highest. For each of SS, HC, REMS, and HTT, the ranges of possible values were 0–5, 0–5, 0–1, and 0–5 respectively.

3.2 *Tornado/ Tornado Warning Data*

Tornado data was gathered from the Official Verification Stats on Demand Interface from the Severe Weather Verification section of verification.nws.noaa.gov, which contains verified tornado data from October 2007 to the present. The tornado dataset contains: start time, end time, WFO, start location, end location, number of one-minute segments, number of warned segments, official lead time, initial lead time, and percent of events warned. Data files from the Stats on Demand Interface were separated by Enhanced Fujita (EF) rating, so the files were merged after an additional column containing event EF rating was created in each file. When inputting EF data into the files, EFU was classified with EF0. Tornado warning data was collected from the same website, and contained: issuance time, expiration time, WFO, the number of warned counties, event tracking number, warning area, and any verifying events. Both the tornado and tornado warning datasets were filtered to only contain events beginning between 1 January 2015 and 31 December 2024 in order to focus the analysis on recent history.

3.3 *CWA Scaling (Tornado Data)*

Tornadoes and tornado warnings were scaled to the CWA level based on four non-meteorological factors: false alarm rate (FAR), probability of detection (POD), mean lead time (LT), and significant tornado occurrence (STO). To calculate FAR, a flag was first created in the tornado warnings datafile, where 1 indicated an unverified warning, and 0 indicated a verified warning. Then, a summary statistic was calculated to find the sum of all warnings and the sum of all flags within each CWA. Finally, FAR was calculated as: $FAR = \frac{sum\ of\ unverified\ warnings}{sum\ of\ all\ warnings}$. POD was calculated as: $POD = \frac{sum\ of\ all\ warned\ tornadoes}{sum\ of\ all\ tornadoes}$, and its calculation also utilized flags. For POD flagging, 1 indicated a tornado that was warned prior to touching down, and 0 indicated a tornado that was unwarned. LT was calculated with a summary statistic for the mean initial lead time value within each CWA, excluding events with 0 minutes of initial lead time. Finally, STO was calculated by using a summary statistic to find the sum of EF2+ tornadoes in each CWA.

3.4 *CWA Scaling (SVI Data)*

To maintain consistency, SVI data was scaled to the CWA level. The SVI data was obtained as a shapefile containing every US census tract. Then, the SVI shapefile was intersected with a shapefile containing every CWA east of the 105th parallel in GIS software. From the intersection, each tract was associated with its respective CWA, and all tracts outside of the study area were excluded. After the intersection was completed, a weight field was created, and calculated as $weight = \frac{tract\ area}{CWA\ area}$ for every census tract. Then, a weighted field for total SVI and each of the four main SVI variable themes was created, and was calculated for each variable by multiplying the tract weight by the respective variable's number of flags. Finally, a summary statistic was calculated as the sum of each weighted value within a CWA.

3.5 *Analysis Method*

Analysis was conducted primarily by qualitative map analysis. The eight meteorological and non-meteorological parameters being explored were mapped at the CWA level with GIS software. Monochromatic colormaps were used for each parameter, with lighter colors indicating lower vulnerability and darker colors indicating higher vulnerability. Each map's color scheme consisted of five bins whose ranges were determined by natural breaks classification. In addition to looking at the individual distributions of each parameter, the overall vulnerability distribution was visualized as the sum of parameters for which a CWA was in the highest quartile of vulnerability, with CWAs receiving a flag for each parameter they were in the highest quartile of vulnerability for. To test for a numerical relationship between vulnerability and tornado deaths, linear correlation coefficients (CCs) between each parameter and the death rate of killer tornadoes (tornadoes that caused at least death) were calculated as $CC = \sqrt{R^\wedge 2}$, where R^2 is the coefficient of determination calculated in the GIS software.

4. RESULTS

This study was exploratory in nature and had no primary hypothesis. Analysis was driven by two broad research questions:

1. How are social vulnerability indices related to tornado deaths in the Appalachian region?
2. How does tornado vulnerability in Appalachia compare to tornado vulnerability outside of the region?

Results first focus on a qualitative map analysis of the four non-meteorological vulnerability

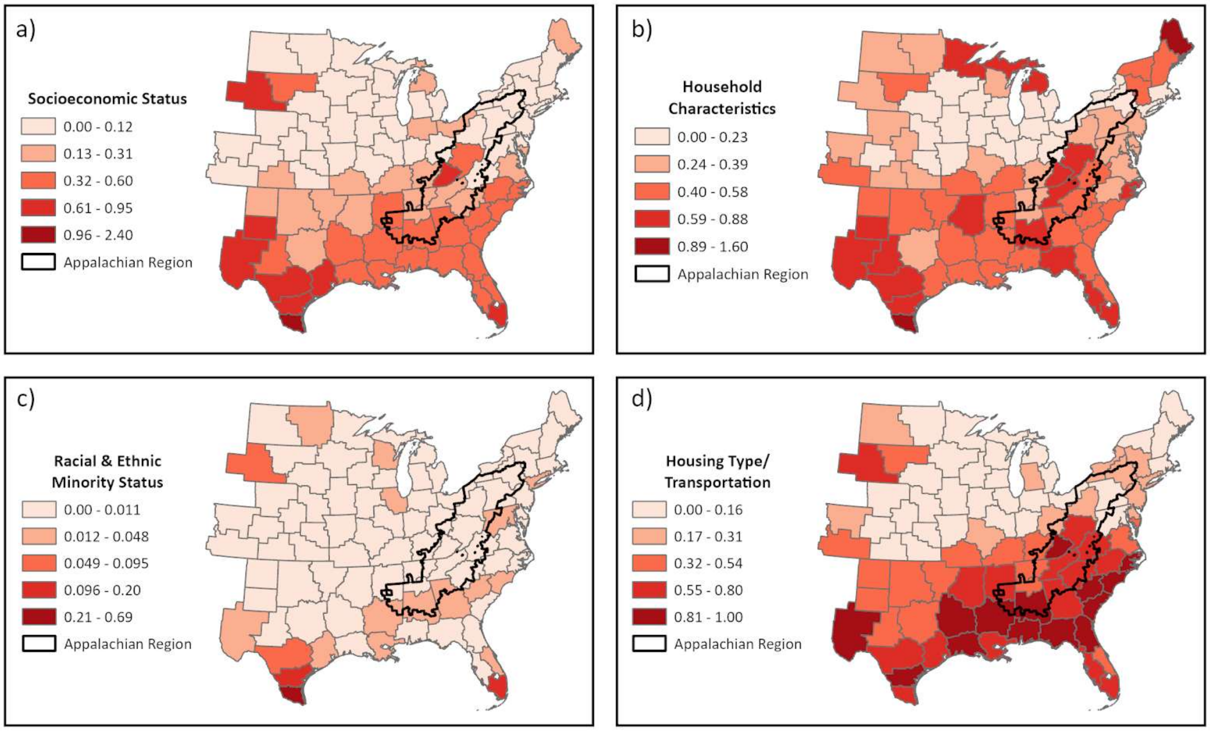

Figure 1 Map of a) Socioeconomic Status, b) Household Characteristics, c) Racial & Ethnic Minority Status, and d) Housing Type/ Transportation vulnerability at the CWA scale.

influences explored (SS, HC, REMS, HTT) and a qualitative map analysis of the four meteorological vulnerability influences explored (POD, FAR, LT, STO). These analyses are followed by an analysis of the highest vulnerability quartiles that CWAs fall within. Finally, there is a quantitative analysis of the linear correlation coefficients between each influence explored and tornado death rates.

4.1 *Non- Meteorological Influences*

When normalized to the CWA level, SS ranged from 0.00 to 2.40 out of a possible 5, with values near 0.00 indicating the lowest SS vulnerability, and values near 2.40 indicating the highest vulnerability from SS. As seen in figure 1a, CWAs in southern and western Texas generally had the highest SS, with relatively high SS' extending across the southeastern US. Both inside and outside of Appalachia, there was an overall south to north decrease in SS. However, Jackson, KY (JKL) and Charleston, WV (RLX) were notable exceptions to this pattern within Appalachia. Outside of Appalachia, Rapid City, SD (UNR) and Aberdeen SD (ABR) posed as similar exceptions.

CWA scaled HC values ranged from 0.00 to 1.60 out of a possible 5, with lower values indicating lower vulnerability and higher values indicating higher vulnerability. In general, CWAs at equal or lower latitude than Norman, OK (OUN) had relatively high HC, whereas CWAs north of OUN had relatively low HC, as seen in figure 1b. This pattern was less applicable in Appalachia, where HC remained high as far north as RLX. Many of the CWAs along the US/Canada border also had relatively high HC.

REMS ranged from 0.00 to 0.69 out of a possible 1 at the CWA level. As seen in figure 1c, REMS was less than 0.048 across most of the study area, indicating that most CWAs have low REMS vulnerability. With CWAs REMS ranging from 0.049 to 0.69, south Texas was the broadest region of higher vulnerability from REMS. UNR and Miami, FL (MIA) also stand out as CWAs with locally high REMS.

Scaled HTT values ranged from 0.00 to 1.00 out of a possible 5, with higher HTT indicating higher vulnerability. As seen in figure 1d, HTT was high across the entire southern portion of the study area, and the southeastern US stood out as a broad area with the highest HTT. With the exceptions of

UNR and ABR, HTT does have a general northward decrease, but the decrease begins further north in Appalachia than outside of the region.

4.2 *Meteorological Influences*

During the 2015–2024 study period, CWAs in the study area had STOs ranging from 0 to 105. As seen in figure 2, the line of CWAs extending from OUN to Birmingham, AL (BMX) had the highest STOs in the study area, with CWAs consistently having STOs greater than 19. North of that line, STOs were generally lower, especially in the northernmost CWAs. Additionally, the northeastern US was a region where CWAs consistently had STOs less than 7, and that region extended into Appalachia to JKL.

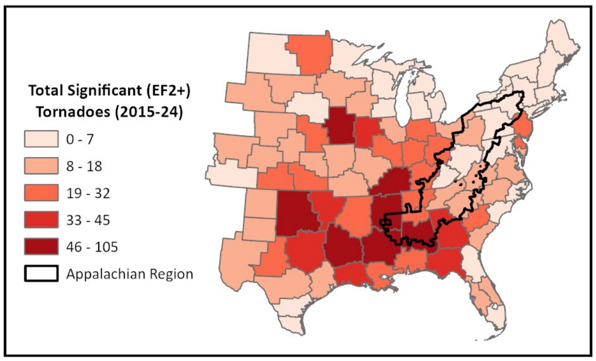

Figure 2 Map of the total number of significant tornadoes that occurred in each CWA between 2015 and 2024.

CWA PODs ranged from 0.00 to 0.74, with 0.00 indicating that 0% of tornadoes had advanced warning, and 0.74 indicating that 74% of tornadoes had advanced warning. As seen in figure 3a, CWAs in the southern portion of the study area generally had the highest PODs, and there was an overall northward decrease. A few of the CWAs along the Gulf Coast, most notably Brownsville, TX (BRO), did not follow this pattern, as they had lower PODs than other CWAs at their latitude. Many of the CWAs in Appalachia had relatively low PODs, but most of those CWAs had comparable PODs to other CWAs at their latitude. JKL stands out as an exception to this pattern, standing out as having a noticeably low POD.

FARs in the study area ranged from 0.45 to 1.00, with 0.45 indicating that 45% of tornado warnings did not verify, and 1.00 indicating that 100% of tornado warnings did not verify. As seen in figure 3b, FARs west of Appalachia tended to vary, but were below 0.67 in the majority of CWAs. In and east of Appalachia, most CWAs had FARs greater than 0.67

Within the study area, LTs ranged from 2.5 min to 20.83 min. As seen in figure 3c, LTs were consistently high across the line from western TX to AL, with BRO and Corpus Christi, TX (CRP) standing out as CWAs with local minimum LTs. Throughout the rest of the study area, there was a slight northward decrease in LTs, especially in and northeast of Appalachia. Despite the general northward decrease, the only two CWAs that had LTs below 3.5 min were BRO and JKL. It is also important to note that Marquette, MI (MQT), Burlington, VT (BTV), and Caribou, ME (CAR) did not experience a tornado during the study period and thus did not have LTs.

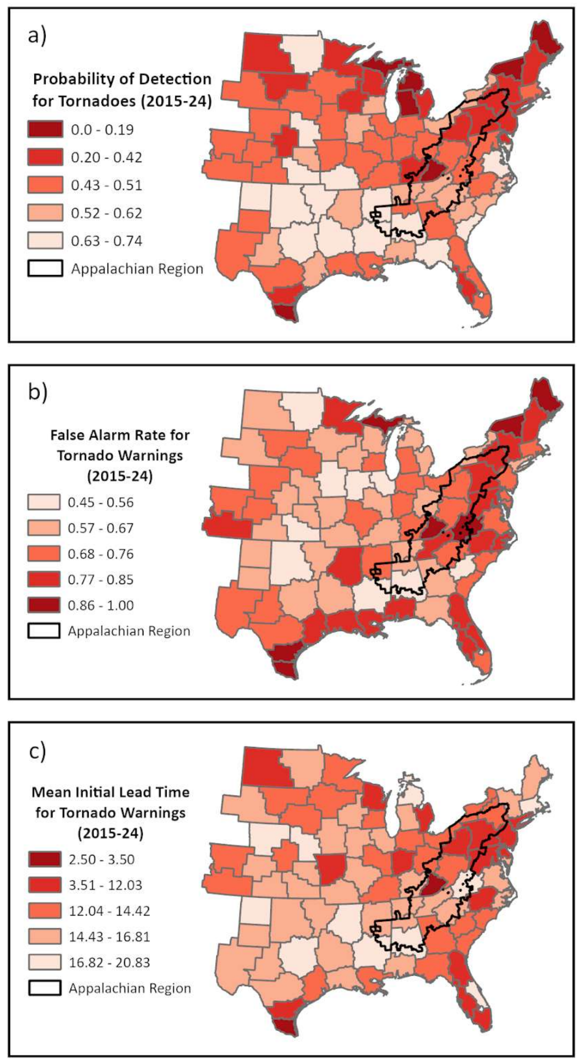

Figure 3 Maps of 2015–2024 a) probability of tornado detection, b) tornado warning false alarm rates, and c) mean initial lead time for verified tornado warnings.

4.3 *Vulnerability Quartiles*

The majority of CWAs in the central region of the study area were not in the highest vulnerability quartile, or had no quartile flags, for any of the vulnerability parameters explored. As seen in figure 4, northern CWAs both inside and outside of Appalachia had a tendency to have 3–4 quartile flags, with a few having 1–2 flags, and two having 5–6 flags. In the southern portion of the study area, including southern Appalachia, most CWAs had 3–4 quartile flags, with two non-Appalachian CWAs having 5–6 flags, and two non-Appalachian CWAs having 7–8 flags. JKL had 7 quartile flags, and was the only Appalachian CWA to have more than 4 flags. There was at least one CWA that had no flags in each Appalachian subregion.

For all CWAs with flags in southern and central Appalachia, non-meteorological flags were prominent, with 6/7 being flagged for at least one non-meteorological influence. In northern Appalachia, meteorological flags were more prevalent, with 6/7 CWAs being flagged for at least two meteorological influences, and the last CWA (Buffalo, NY) having one meteorological influence flag. Outside of Appalachia, 5/7 southern states that contained at least one CWA with at least one flag had at least one flag for each non-meteorological influence. Of the non-southern states containing at least one CWA with at least one flag, most states had at least one flag in each meteorological influence.

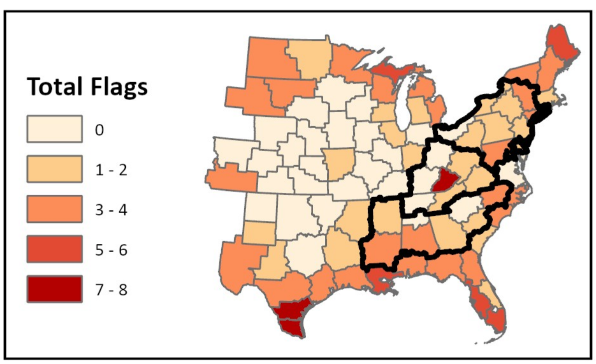

Figure 4 Map of the total number of flags each CWA received for being in a parameter's highest vulnerability quartile.

4.4 *Quantitative Results*

The correlation coefficients between non meteorological tornado vulnerability influences and killer tornado death rates ranged from 0.025 (HC) to 0.120 (HTT). Correlation coefficients between meteorological tornado vulnerability influences and killer tornado death rates were slightly higher, ranging from 0.180 (POD) to 0.401 (LT). None of the correlations found were great enough to prove statistically significant linear relationships between tornado deaths and any of the variables explored.

Table 1 Linear correlation coefficient between each vulnerability parameter and killer tornado death rates.

Parameter	CC
Socioeconomic Status	0.045
Household Characteristics	0.025
Racial & Ethnic Minority Status	0.097
Housing Type/ Transportation	0.120
Initial Lead Time (min)	0.401
Probability of Detection	0.180
False Alarm Rate	0.211
Sigtor Frequency	0.224

5. DISCUSSION

This study was exploratory in nature and had no primary hypothesis. From the qualitative map analyses, it was found that there was a general south-north decrease in vulnerability from the non-meteorological influences explored, and a south-north increase in vulnerability from the meteorological influences explored. There was also no statistically significant linear relationship between any influence explored and tornado deaths. The upcoming discussion will focus first on the results' implications about sampling methodology, followed by a section about implications for disaster planning, and ideas for future research inspired by project limitations.

5.1 *Appalachian SVI vs Tornado Deaths*

The first question that this study focused on was: how are social vulnerability indices related to tornado deaths in the Appalachian region? Tornado vulnerability in this study was defined as a measure of how likely a community is to be impacted by a tornado, and how much potential it has to recover, inspired by definitions of vulnerability by Kasi and Saha (2023) and Deziel et al. (2023). No statistically significant linear relationships between any of the vulnerability indices explored and

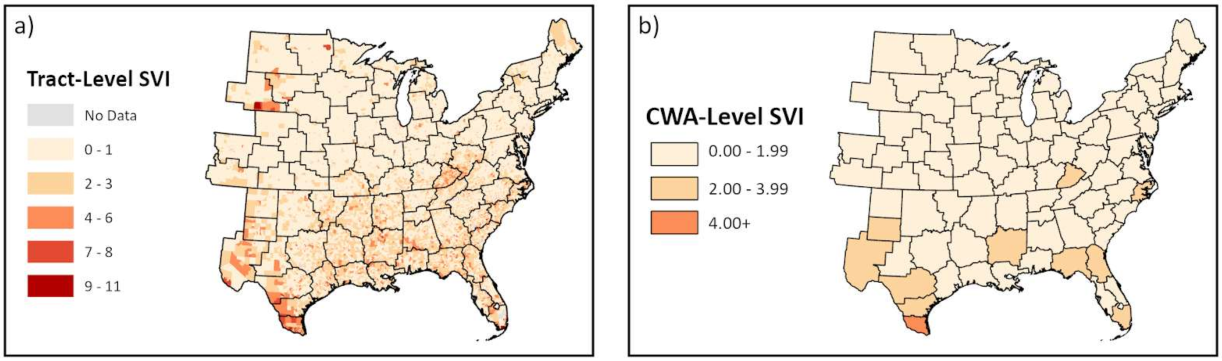

Figure 5 Map of overall SVI scaled to a) census tracts and b) CWAs.

tornado deaths could be proven, as all of the linear correlation coefficients calculated were insignificant. While this does not prove relationships, it also does not disprove them. Non-linear relationships, which would not be observed from this analysis method, could exist between some or all vulnerability indices and tornado death rates. Relationships could also exist on a smaller scale than the one observed. The SVI can be scaled as finely as the census tract level, and at the census tract level, local vulnerabilities are highlighted that do not get resolved at the CWA level. For example, figure 5a depicts multiple tracts in southern UNR with SVIs ranging from 4 to 11, whereas figure 5b depicts UNR as having an SVI of less than 2 due to the many census tracts with low SVIs in the CWAs northern region. Similar issues can also be seen in BRO, CRP, and JKL. These localities hold implications for Impact-Based Decision Support Services (IDSS), as they depict regions where a more generalized IDSS plan may be inadequate. IDSS requires a fine enough understanding of local vulnerabilities to tailor disaster response to communities, meaning a CWA level understanding may fail to succeed in some areas.

The limitations of the large sample area raise a different concern about small sample sizes. Even at the CWA scale, some sample size issues arise. Some of the CWAs sampled had as few as 4 tornadoes, 0 killer tornadoes, or 8 tornado warnings throughout the entire study period. Reduction of the sampling area further reduces sample sizes, making the already present concerns even more prevalent. This conundrum raises important methodological considerations about gathering a large enough sample size at a small enough scale. One option would be extending the study period, but doing so could make results less relevant to modern vulnerability. Extending the sample period does not necessarily add enough data either, as tornadoes' rare and local nature means that many areas with high social vulnerability have not directly experienced any tornadoes in recorded history. Another option to mitigate the sample size issue would be to group similar areas together, but the ideal grouping method is unclear. Grouping could be done by geographic location, topography, vulnerability, community type, or some other factor that has yet to be determined. Studies like this one aim to understand vulnerability in a way that mitigates devastation from significant events like London, KY, but the sampling issues encountered in this study imply that a different conceptualization of vulnerability may be required to gain such an understanding.

5.2 *Appalachian vs Non-Appalachian Vulnerability*

The second research question explored in this study was: how does tornado vulnerability in Appalachia compare to tornado vulnerability outside of the region? As mentioned in section 4c, the spatial distributions of vulnerability type are similar inside and outside of Appalachia, with southern CWAs having greater non-meteorological vulnerability, and northern CWAs having greater meteorological vulnerability. It is relatively unsurprising that northern CWAs have high meteorological vulnerability per the parameters explored, as the low regional tornado frequency means statistics are based off of very few events, and can very easily be skewed. Additionally, tornado forecasting may not be the expertise of forecasters in areas that are not tornado-prone, which may impact tornado warning performance. Within the southern CWAs, it makes sense that regions with high vulnerability for at least one non-meteorological parameter are also highly vulnerable for at least one more, as the non-meteorological parameters explored in this study tend to influence one another. An example of these influences is illustrated in Holmes et al. (2021), which describes the interconnectedness of SS, REMS, and HTT within the context of the 3 March 2019 EF-4 tornado in Beauregard, AL. The similarities between Appalachian and non-Appalachian vulnerability could either be indication that Appalachian vulnerability is no different from non-Appalachian vulnerability, or it could hold the implication that vulnerability differences could be seen better either through different parameters or at a finer scale.

Low event frequencies such as those in the northern CWAs raise questions about how to prepare for the generational significant event. Aspects of disaster preparation have associated costs, and while the value of those costs may be evident in tornado-prone CWAs such as OUN or BMX, their value may be more unclear in CWAs like MQT and CAR, which have not experienced a significant tornado in decades. The importance of still finding regionally- relevant disaster plans, however, can be seen from the 16 May 2025 tornado in London, KY, which supports that devastating tornadoes do occur in regions that are not tornado-prone. CRP and BRO are the two CWAs that, similarly to JKL, stand out as having high social vulnerability and low tornado frequency. Neither CWA has recently experienced a significant tornado, however, in April 2007, an EF-3 tornado destroyed portions of Eagle Pass, TX, which is located in what is now the San Antonio, TX CWA (National Weather Service Austin/San Antonio 2007). Such an event occurring so close to CRP and BRO supports that one of those CWAs could also be directly impacted by another, and them having similar vulnerability to JKL supports that devastation from such an event could be as catastrophic as that in London, KY.

5.3 *Limitations & Ideas for Future Work*

Applications of findings from this project are limited by the sampling area, the parameters looked at, and the analysis method used. Validity of results at finer or coarser scales than the CWA level may be reduced due to vulnerability's regional dependence. Future research could explore scales beyond the CWA level, looking especially at census tracts, counties, or states depending on intended use.

This study is also limited by the primary analysis method used. The exploratory nature of this study allowed a qualitative GIS analysis to be adequate, but the resulting limited statistical analysis was not robust enough to objectively prove or disprove any relationships. A more thorough statistical analysis could be completed to look for any non-linear relationships, and additional vulnerability parameters could be added to broaden the scope of the study.

Section 5.1 mentions grouping of regions when working with smaller scales, however, utilization of that method could be limited by the grouping method selected. A precursor to a study involving data grouping could utilize tools such as machine learning to determine which method of grouping would be the most robust and/ or relevant.

6. CONCLUSION

The Appalachian region is outside of the zone traditionally known as the tornado alley. As seen by the devastating EF-4 tornado in London, KY on 16 May 2025, however, the region is not immune to significant tornadoes. Appalachia also bears an adverse socioeconomic status, indicating potentially high tornado vulnerability from non-meteorological influences. Using the CDC's SVI and an official NWS tornado database, this study used a GIS analysis to assess the relationships between social vulnerability and tornado deaths at the CWA scale.

Amongst the parameters explored, non-meteorological influences (socioeconomic status, household characteristics, racial & ethnic minority status, and housing type/ transportation) had a south-north decrease in vulnerability, and meteorological influences (probability of detection, false alarm rate, mean initial lead time, and significant tornado occurrence) had a south-north increase. No statistically significant linear relationship was found between any parameter explored and tornado death rates, however, the lack of relation may be attributable to a too-large sampling area or too-small sample sizes.

The concept of what this study aims to solve can sensibly be represented by London, KY, a recent example of what can happen when a significant tornado impacts a highly vulnerable community. At a large scale, it is easier to say that an event will occur within a jurisdiction, but planning and response occurs at a local level, where confidence of event occurrence in the near future is lower. IDSS is centered around local planning and response, but its effective implementation requires understanding local vulnerabilities. Reducing vulnerability goes beyond tornadoes, but first, vulnerability must be understood such that a justifiable preparation method for a generational disaster can be found.

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