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Toward Development of the Tornado Impact-Community Vulnerability Index

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Abstract

Given the recognition that not only physical processes, but also social, political, and economic aspects of hazards determine vulnerability to and impact of an event, a classification system that addresses those factors is needed. Current classifications for natural disasters, such as the Fujita Scale for tornadoes and the Saffir-Simpson hurricane scale, focus on the physical properties of the event, not the impact on a community. Pre-event vulnerability to a natural hazard is determined by factors such as age, race, income, gender, infrastructure, density of the built environment and health of the industrial base. The behavior of residents in the community, construction quality of shelters, and warning system effectiveness also affect vulnerability. If vulnerability is influenced by such factors, post-event impact should be, at least in part, as well. The goal of this research was to develop the Tornado Impact-Community Vulnerability Index (TICV) that utilizes variables such as the number of persons killed, economic impacts, and social vulnerability to describe to the level of impact a tornado event has on community. As tornadoes that strike unpopulated areas are often difficult to classify, even in the traditional sense, the TICV will take into consideration only events that strike communities defined as "places" according to the U.S. Census Bureau. By assigning a rating to the impact, this index will allow the severity of the storm to be understood in terms of its effect on a specific community and hence its impact, rather than in terms of its physical strength.

Keywords: Tornadoes; Tornado impact; Disaster recovery; Community vulnerability; Impact index

Introduction

Hazard researchers have long been interested in examining the physical characteristics of extreme natural events such as tornadoes and hurricanes. Such knowledge is essential to a complete understanding of these events, particularly their ability to cause damage and destruction; also, it is necessary to the creation and promotion of sound disaster management practices [1,2]. Physical characteristics or parameters of extreme natural events include duration, seasonality, frequency, rate of onset, diurnal factors, and magnitude [3]. The final physical property in this list is probably the most important. In general, the greater the magnitude of the event, the greater is its potential to cause fatalities, injuries, and damage to property.

Every natural disaster has a measure of magnitude. For example, from 1971 through 2007, tornado magnitude was measured on the Fujita (F) Scale. This scale was introduced by Fujita [4] and ranged from F-0 through F-5. On 1 February 2007, the Enhanced Fujita (EF) Scale EF Scale replaced the F-Scale [5]. Although the EF Scale has the same basic design as the original F-Scale, it was revised to better reflect examinations of tornado damage surveys, specifically to align wind speed more closely with associated storm damage [6]. The EF Scale, as with the F-Scale, focuses exclusively on the physical properties of tornadoes, not their impact on a community.

Those studying disasters have increasingly realized that the losses stemming from a disaster do not result exclusively from the physical aspects of the phenomenon; they can also be exacerbated or alleviated to some degree by the dynamics of the society that was struck [1,7-10]. Researchers now believe that disasters are socially constructed events, and as such the impact of a disaster is seen as the product of its physical characteristics, and the social, economic, demographic and political make-up of the affected community. Hazard researchers frame this dynamic in the concept of social vulnerability, defined by Finch [11] as "a measure of both the sensitivity of a population to natural hazards and its ability to respond to and recover from the impacts of hazards."

The principal goal of this paper is to fill the above research gap by developing the Tornado Impact-Community Vulnerability (TICV) index that utilizes data such as the number of persons killed, the monetary damage incurred, and selected social profiles of the affected community to describe to what level a tornado event has impacted a community. This index is based on all tornado events that occurred in the coterminous United States from 2000 through 2009 and struck communities with defined political boundaries, or "places" according to the U.S. Census Bureau. More specifically, this paper presents a method for calculating the TICV and applies the results across the U.S. with emphasis for descriptive purposes on four selected communities. It further seeks to examine how the TICV can serve to effectively stand as an indicator of the level of impact for each selected community, and how each of these communities view the event as unique to their set of circumstances.

By assigning a rating to the impact, the TICV will allow the severity of the storm to be understood in terms of its effect on a specific community, rather than an absolute rating that provides only a broad, general indication of its physical strength, and hence its impact. This index will be useful to emergency managers and others involved in disaster recovery efforts who need to understand the severity with which a tornado event has impacted a community.

The remainder of this paper first presents a review of the pertinent literature concerning hazards and the application of vulnerability studies and indices related to that concept. Next the methods by which the TICV was developed are described, including its sub-components of the damage and vulnerability scores, and the methods used to aggregate those scores into the TICV and subsequent TICV Categories, or TCs. Finally, those measures are evaluated through a description of four recent tornado events and the impact on each community they struck. Summary and conclusion are presented in the last section.

Hazard Vulnerability and Indices

In developing an index that suggests the extent to which a community has been impacted by a disaster, it is necessary to understand why an individual, household, or community may suffer more or less than another as a result of a natural disaster of the same magnitude. Hazard researchers explain the level to which these entities may be affected by extreme events in terms of vulnerability. An examination of the literature concerning hazard vulnerability reveals a wide range of definitions, but a common theme emerges from these definitions: vulnerability is the degree to which a person, group of people, or community is at risk for harm from an extreme event [2,12,13].

Vulnerability refers to the social, economic, physical, psychological, and other characteristics of individuals, households, groups, or communities in terms of their capacity to anticipate, cope with, resist, and recover from the impact of a disaster [7]. Vulnerability is not simply a product of the intensity or magnitude of a disaster; rather, it evolves over a long period of time and involves a combination of physical as well as socio-economic, demographic, and other factors, including attributes of the built environment. It needs to be understood in the context of social, economic, and political systems that operate on different scales [7]. According to Bolin [14], vulnerability concerns complex social, economic, and political circumstances in which people's lives are embedded, and these factors structure the choices and opinions they have in coping with environmental hazards.

In developing vulnerability indices on different scales, hazard researchers have used a large number of variables. Because many of these variables are strongly correlated, most of these researchers have developed a composite measure of hazard vulnerability [6]. They have examined a variety of hazard and disaster contexts identifying various dimensions of vulnerability, along with conceptual frameworks, or models. An examination of available vulnerability indices and models will help in developing the TICV.

In their Pressure and Release (PAR) model, Wisner [7] posited that a disaster occurs because people are vulnerable – that, for physical, economic or social reasons, they are exposed and will suffer damaging losses if a hazard strikes. This vulnerability is the result of a set of unsafe conditions (e.g., being unable to afford safe housing, having to engage in dangerous livelihoods, living in a location with high incidence of hazard events), which are then nested in explanatory fashion within dynamic pressures (e.g., lack of education, training, and appropriate skills), and those, in turn, within what are termed root causes (e.g., limited access to power and resources).

According to the PAR model, vulnerability is associated with a lack of power and, accordingly, groups marginalized through poverty, illiteracy, race, ethnicity, or immigration and minority status. Vulnerability perspectives further claim that members of vulnerable or disadvantaged groups suffer more from disasters because public sources unintentionally and/or systematically discriminate against them in the provision of disaster assistance [15-17].

Boruff [18] developed the Social Vulnerability Index (SoVI) for environmental hazards for U.S. counties. Using 42 variables reduced from an original set of 250 by testing for multicollinearity, principal component analysis (PCA) was applied to discover what variables described the most variance within the dataset. The PCA produced 11 factors that explained 76.4% of the variance across all U.S. counties. The results showed that personal wealth (per capita income being the dominant variable) was the highest rated factor, explaining 12.4% of the variance in the dataset, followed by age at 11.9%, and density of built environment (number of commercial establishments per square mile) at 11.2%.

In order to produce the SoVI, the authors then placed the factor scores for each county into an additive model that resulted in a composite index score of vulnerability for each county in the U.S. and then displayed the results as a measure of standard deviation. Lower z-scores equate to lower levels of vulnerability and higher z-scores equate to higher levels of vulnerability. The results showed that counties with high density of the built environment, high degrees of racial and ethnic inequality, and socially dependent populations all contributed to high levels of vulnerability in a given county. Conversely, counties on the low end of the SoVI all exhibited large Caucasian populations, as well as wealthy and highly educated persons in suburban (less densely populated) areas. The work of Boruff [18] illustrates a collection of a wide range of variables narrowed down through intense statistical calculation, with the final result, the SoVI, producing a single number that described the potential for counties in the U.S. to be harmed by environmental disasters.

Earlier, Mitchell [17] examined the vulnerability of Georgetown County, South Carolina, in terms of exposure to harm from technological and natural disasters. They used the term "place vulnerability" and claimed that the interaction between biophysical and social vulnerability creates the place vulnerability, which then connects back to risk and mitigation, in that depending on the level of vulnerability, risk is either increased or decreased, and mitigation practices can be adjusted to lessen vulnerability. Their place vulnerability was based on eight social and 16 environmental factors (the frequency of 16 different environmental hazards); [1] this implies that both place and profile of a community must be considered when determining vulnerability. Both of the above indices were developed for multiple hazards and did not employ a weighting scheme in their calculation.

Another application of vulnerability indices deals with coastal vulnerability, usually focused on the impact of hurricanes or storm surge associated with them. Dixon [19] examined Texas Gulf Coast communities' vulnerability to hurricanes. Using Saffir-Simpson intensity categories for historical hurricanes as well as population and property value data for each county, the authors developed an additive model resulting in five categories of risk scores and five exposure scores. Their Hurricane Vulnerability Index (HVI) was then derived by adding the two scores. This method illustrates an attempt to combine not only data on events that have already occurred, but to couple those data with the potential for harm to a county given the population and assumed worth of the property in that community, creating an index value that, while time-dependent, serves to assign a measure of potential loss in the event of a future hurricane.

Research Methods

Data sources and data extraction

Tornado-specific data included the location and length of tornado tracks, their intersection with a community, physical area of the affected community, the number of fatalities, and the monetary damage inflicted. These data indicate the physical impact of the event and were collected from the Storm Prediction Center (SPC). Injuries were not included since there is a vast range of the effects of events on injuries [20]. The Abbreviated Injury Scale (AIS) and Organ Injury Scale (OIS) both rate injuries on a scale from one (minor) to six (unsurvivable) 2008; AAST [21]. Minor injuries such as broken fingers are recorded in the SPC data just the same as major injuries such as head trauma that may ultimately be fatal. The SPC tornado record provides no description or coding that indicates the severity of an injury. Thus, the impact of an injury cannot be reasonably described based on the methods presented here, as doing so would have introduced a component of great uncertainty as to its overall contribution to the index and category scheme.

Data from the 2000 U.S. census, including social, economic, housing, and demographic characteristics, were collected from the United States Census Bureau for all U.S. communities that experienced at least one tornado during 2000–2009 study period. Data were also collected from a variety of other sources, including the National Climatic Data Center (NCDC) [22], the National Atlas, Internet-based news articles focusing on specific tornado events or outbreaks, and personal communication (via email or phone) with county-level emergency management personnel.

In order to assemble an initial base map, shapefile data containing U.S. states, 3,116 counties, and 25,148 communities was obtained from the National Atlas, henceforward referred to as the states, county (or counties), and community (or communities) shapefiles, respectively [2]. Those data were imported into a geographic information system (GIS) and projected using Albers conic equal-area, North American Datum 1983. An equal-area projection was chosen to facilitate the spatial analysis of the vulnerability scores via the Moran's I test as described further below. Equal area projections are best-suited for those types of spatial analysis, as they best preserve the area, and therefore, the distance between areas, which is essential to the Moran's I statistic.

Within a GIS, data from the states and community shapefiles were reduced to only those attributes within the coterminous United States. Point data containing the beginning and ending latitude and longitude of all tornado events (herein named points) as well as line data for 26,431 U.S. tornado tracks (herein named tracks) from 1950–2009 were obtained through the SPC's GIS data portal (SPC 2010) (Figure 1). The points and tracks shapefiles were imported into a GIS and all tornadoes that occurred before 2000 were removed; the result of 12,657 tornado events was added to the GIS document as a new shapefile (again, named tracks), replacing the previous file of the same name.

As noted, this study considered only those tornadoes that passed through a community with U.S. Census-defined political boundaries that appear in the community shapefile described above. To reduce the initial tracks subset of 12,657 tornado events from 2000–2009 down to those events striking communities, only lines from the tracks shapefile that intersected the community shape file were considered. Removal of non-intersecting tracks resulted in 1,885 community-intersecting tracks that were added to the GIS document (Figure 2).

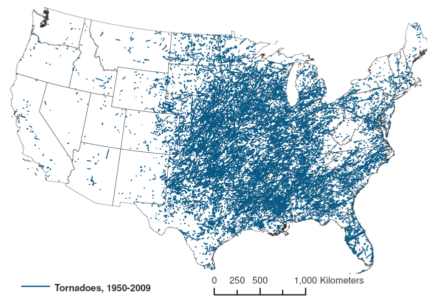

Figure 1: Tornado Tracks, 1950–2009.

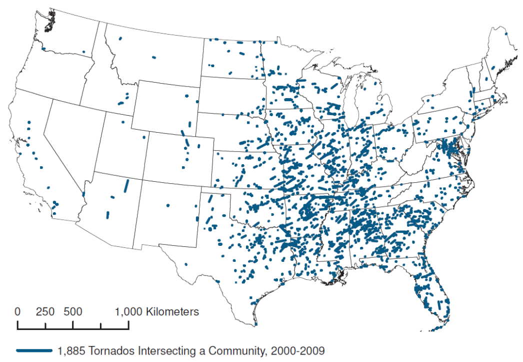

Figure 2: 1,885 Tornadoes that Intersected a Community, 2000–2009.

The use of the methods described above presented a limitation involving the accuracy of the SPC points and tracks shapefile and their intersection with the community shapefile, and a problem with tracks that passed through more than one community. Those two problems are referred to here as the accuracy of track estimation and the track-intersect problems, respectively. In order to properly prepare the data set for constructing the TICV, those issue were corrected [3]. After carefully editing and consulting with relevant emergency managers, all tornado tracks in the dataset were associated with exactly one community.

These procedures resulted in a final dataset of 981 usable events that intersected a community, hereafter referred to as USTOR2000 (Figure 3). This means many tornado tracks were elimiated from inclusion in USTOR2000 because those tracks did not pass through a community. In another words, tornadoes that remained in unpopulated or sparsely populated areas, or those not politically defined as "placed" by the U.S. Census Bureau were not considered in this study. Of the 12,657 events from 2000–2009, 981 were retained, for an overall retention percentage in the U.S. of 7.75.

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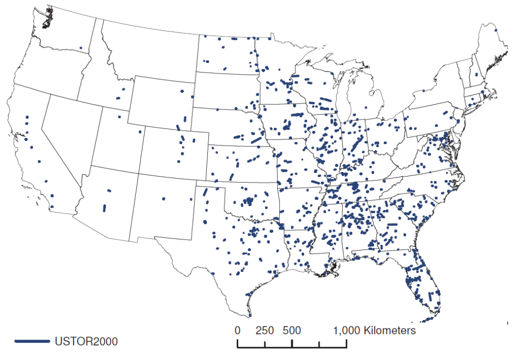

Figure 3: 981 Tornadoes in USTOR2000.

Some states exhibited high retention values while others showed very low values. Colorado experienced 405 tornadoes during the study period, of which seven were retained, for a retention percentage of 1.73 – the lowest of non-zero values. Conversely, Maryland exhibited a retention percentage of 18.82 – the highest of non-zero values. The seemingly low retentionpercentages in some states can be attributed to the relative dispersion of both large and small population centers existing in those areas. In contrast, high retention percentages were found in states with more densely populated areas, and thusly containing more census-defined communities [23]. Tornadoes that tounched down in seven states (Delaware, Montana, Nevada, Oregon, Vermont, Rhode Island, and West Virgina) during the study period did not directly affect any communities; as a result, those states showed a retention rate of zero and were excluded from consideration, resulting in a total of 41 states within the study area (Figure 4).

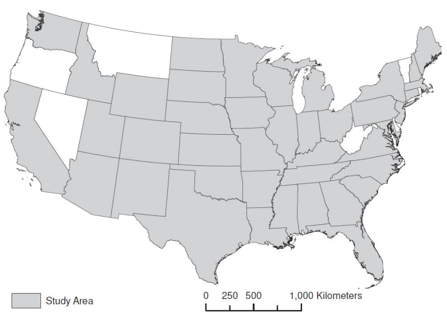

Figure 4: Study area.

Census data were collected using the 2000 U.S. Census Download Center (Census 2010). Summary files one and three were accessed via the Census Download Center, and 17 complete summary file tables were downloaded. Using the program Statistical Package for the Social Sciences (SPSS), 375 variables from those tables were placed in a correlation matrix, to identify variables that were highly correlated and further identify a subset of variables to be used in constructing the community vulnerability score. A total of 19 variables were chosen to represent community vulnerability via correlation coefficients and the vulnerability literature as cited above, most notably, Cutter. The variables were entered into a Microsoft Excel spreadsheet and either used as raw values or normalized per capita by population of the community, as percentages of the community population, or as density functions by the size of the community in square kilometers. Variables were then assigned descriptive names and imported into an SPSS table.

Included variables are: total housing units; percent African-American; percent Hispanic; percent female; percent under age 5; percent over age 65; median age; average number of people per household; percent female householders, no husband present, with own children; percent renter-occupied houses; percent housing units that are mobile homes; median dollar value of owner-occupied houses; percent population over age 25 with no high school diploma; percent population unemployed, age 16 and older; percent population employed in the service industry; percent households earning $75,000 per year or more; median household income; per capita income; and percent individuals below the poverty level.

TICV calculation methods

Upon completion of the data extraction and cleaning procedures, the data were in the proper format to calculate the TICV. This was accomplished by: (1) calculating the damage component, consisting of the number of fatalities and the monetary damage recorded for a community normalized by population; (2) using principal components analysis to calculate a community vulnerability score for each community in the dataset; (3) combining the previous two measures to calculate the TICV; and (4) using Jenks natural breaks to construct the TICV Categories (TCs) based on the array of TICV values.

The number of fatalities and the monetary damage resulting from a tornado event make up the damage component (D) of the TICV. At least one fatality occurred in 61 (6.2%) of the 981 events in the dataset. To convert the fatality figure for an event (if one existed) to a monetary value, the number of fatalities resulting from a particular event was multiplied by the mean Value per Statistical Life (VSL) of seven million 2008 USD [24,25].

The monetary damage figure per event was available both in the tabular and GIS data taken from the SPC, although the figures reported in the SP C GIS shape file attribute table were reported as categorical values (1 = 1,000,000 through 1,999,999 million dollars, 2 = 2,000,000 through 2,999,999 dollars, and so on). Because of this difference, the tabular SPC data, which reported a more accurately estimated damage figure, was spatially joined to the tracks GIS data to populate the damage column with that more accurate damage data. In the case of long-track events that struck more than one community and that were segmented into discrete tracks associated with exactly one community, the data were taken from the NCDC record and/or narrative, news reports, FEMA reports, county emergency managers, or a combination of those sources. The damage figures were then adjusted for inflation to 2008 dollars in order to maintain temporal consistency with the VSL. The inflation-adjusted fatality figure was then added to the inflation-adjusted damage figure and the sum normalized by the population of community c to arrive at Dc:

$$D_c = [F_c(VSL) + E_c] / Pop_c$$

where Dc = TICV damage component for community c, Fc = fatalities in community c, VSL = 2008 Value of Statistical Life constant of seven million USD, Ec = monetary damage done to community c, and Popc = 2000 U.S. Census population of community c.

The census data collected for each of the 25,148 communities in the U.S. was imported into SPSS. All U.S. communities were used to produce category breaks for vulnerability into which the communities in USTOR2000 would fall. This allowed for the vulnerability of the communities in USTOR2000 to be represented by their vulnerability score (as explained below) as compared to all U.S. communities, rather than only the 981 within the TICV dataset. Proper data formats for each of the 19 variables (Table 1) were assigned, and a principal components analysis (PCA) was performed using varimax rotation to produce a factor solution including only eigenvalues greater than one. The rotated solution produced six factors that explained 71.05% of the total variance.

Summary File - Table	Table description	Variable(s) used
SF1-H2	Urban and rural housing units	Total housing units
SF1-P3	Race	Percent African-American
SF1-P11	Hispanic or Latino, total population	Percent Hispanic
SF1-P12	Sex by age, total population	Percent female Percent under age 5 Percent over age 65
SF1-P13	Median age by sex, total population	Median age
SF1-P17	Average household size	Average number of people per household
SF1-P18	Household size, household type, and presence of own children under 16 years of age	Percent female householders, no husband present, with own children
SF1-H4	Tenure (household)	Renter-occupied houses
SF3-H30	Units in structure (housing types)	Percent housing units that are mobile homes
SF3-H76	Median value (USD), specified owner occupied housing units	Median value, owner occupied houses
SF3-P37	Sex by educational attainment, population age 25 years and older	Percent population over 25 years of age with no high school diploma
SF3-P43	Sex by employment status, population age 16 years and older	Percent population unemployed, age 16 and older
SF3-P50	Sex by occupation, employed civilian population age 16 years and older	Percent population employed in the service industry
SF3-P52	Household income	Percent households earning >$75,000/yr.
SF3-P53	Median household income	Median household income
SF3-P82	Per capita income	Per capita income
SF3-P87	Poverty status by age	Percent individuals below the poverty level

Table 1: Census data used in vulnerability calculations.

To calculate the vulnerability component for each community in USTOR2000, census data was extracted and placed into a new spreadsheet. The data were then arranged according to factor group from highest to lowest eigenvalue. Using the 25,148 communities as the rank array, which is the column of data by which an individual value is compared in order to determine its percentile position within that column, the percentile rank of each census datum for each community in the community dataset was calculated.

Four of the 19 variables needed further adjustment before proceeding with the TICV calculation: median dollar value of owner-occupied houses, % households earning $75,000 per year or more, median household income, and per capita income. In calculating the percentile rank for those variables, a higher rank (closer to 1) indicates higher vulnerability. However, an increase in percentile rank should indicate a decrease in vulnerability, not an increase. For example, higher median household income equates to lower vulnerability, an inverse relationship, whereas 15 variables exhibit a direct relationship between their rank value and an increase in vulnerability. For those four components where an increased percentile rank score decreased the overall vulnerability score rather than increased it, the calculated percentile rank value was subtracted from 1.00 in order to invert the component [26].

Each percentile rank value was then weighted with the eigenvalue for the factor in which that component belonged, and this served as the weighting value. For each of the six factor groups, the sum of the weighted percentile ranks for each component within that factor group was found. Finally, for each community in the community dataset, the sum of each of the six factor group's weighted percentile rank sums was found, resulting in the vulnerability component for community c. This procedure is given by:

$$V_c = \sum_{k=1}^{6} \sum_{n=1}^{19} [\beta rank(n_c)]\lambda_k$$

where Vc = TICV vulnerability score component for community c, βrank (nc) = percentile rank score of vulnerability component n in

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community c (percentile rank array = 25,148 U.S. communities, U.S. Census, 2000), and λk = principal components analysis eigenvalue for factor k.

Using Dc and Vc calculated as described above, the TICV is given by:

$$TICV_c = \sqrt{D_c(V_c)}$$

where TICVc = the Tornado Impact-Community Vulnerability Index value for community c. The array of TICV values was then imported into the tracks shapefile attribute table in order to calculate the category break values, on [0, 5], where zero indicates the least impact and five indicates the most severe. Finally, Jenks [27] natural breaks were applied to the TICV column, defining the six TCs. The calculation process is summarized in Figure 5.

Damage component for community *c* =	[Damage $ / (Fatalities x VSL)]/Population
Vulnerability component for community *c* =	Σ [Percentile rank for each census value (19) • Weight (eigenvalue) for that census value]
TICV for community *c* =	√[Damage component • Vulnerability component]
TC (TICV category score) for community *c* =	Jenks natural breaks (six classes, [0,5]) applied to the TICV

Figure 5: Calculation summary.

Results

Damage component score

At least one fatality occurred in 62 (6.3%) of the 981 events considered in this study, with a mean occurrence of 0.23, and a maximum of 20 (Evansville, IN, 6 November 2005). The damage component ranged from zero to $648 million (Arlington, TX, 28 March 2000), with an approximate mean of $7 million, a median of $75,000, a standard deviation of $32.4 million, and a variance of over 10. The damage score ranged from zero to 434,783 (Hallam, NE, 22 May 2004), with a mean of 2,292, a median of 7.98, a standard deviation of 18,015, and a variance of 324,883,758. Nearly one-third of the events in USTOR2000 (308 of 981) returned a damage score of zero, resulting in a power law distribution for both the raw damage component and the damage score.

A careful examination of the raw damage score (i.e., not yet normalized by population) reveals that the number of fatalities in the affected communities influences the score more than its other component, namely monetary damage. This is an important finding since property damages resulting from a tornado are harder to reduce than fatalities once a warning has been issued; people can move out of the way, structures cannot [28]. However, the monetary damage component has influenced the raw damage score for the overwhelming majority of the impacted communities because only 6.3% of them experienced one or more tornado fatalities. This finding is consistent with the relationship between tornado intensity and damage in the United States, with stronger events generally producing greater damage [28] and more frequently resulting in death [29,30] but occurring less frequently [31,32]. The above finding suggests providing timely tornado warnings and encouraging people to comply with such warnings can reduce the damage score by reducing the number of fatalities occurring from a given event.

Vulnerability score

The vulnerability scores displayed a normal distribution with a minimum score of 11.33 (Hebron, TX), a maximum of 38.99 (Cotton Plant, AR), a mean of 24.77, a median of 24.99, a standard deviation of 5.53, and a variance of 30.65. Table 2 presents vulnerability scores and corresponding descriptors. Based on vulnerability scores, a Moran's I test was performed to spatially display any pattern among the communities included in USTOR2000 (Figure 6). Results show high levels of vulnerability (Z-score standard deviation >2.58) from east Texas (Dallas-Fort Worth metro area) through deep southern states, including Arkansas, Louisiana, South Carolina, Mississippi, Alabama and Georgia. The latter three also show mostly low to moderate resiliency, the inverse of vulnerability to natural hazards as described by Cutter. As indicators of social vulnerability typically include race, poverty, education, and social class, it follows that areas with higher concentrations of African-Americans, Hispanics, the less-affluent, and the less-educated exhibit increased levels of vulnerability. Other areas with high Z-score values, indicating high vulnerability, include the Minneapolis-St. Paul, MN, metro area and surrounding suburbs, the Milwaukee WI-Chicago, IL, corridor extending to Madison, WI, and the Baltimore, MD, metro area (Figure 6).

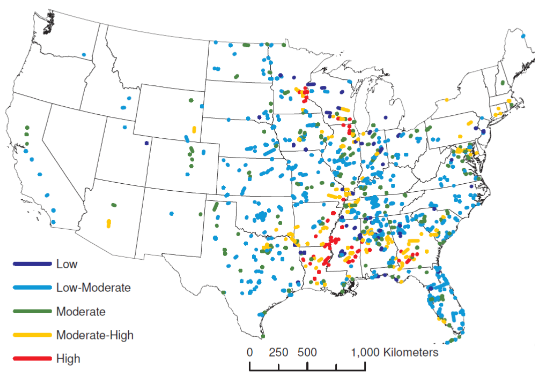

Figure 6: Moran's I applied to vulnerability scores.

Vulnerability Score Range	Frequency	Vulnerability Level
11–18	139	Low
19–22	230	Low-Moderate
23–26	250	Moderate
27–30	211	Moderate-High
≥ 30	151	High

Table 2: Vulnerability scores and descriptors.

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TICV score

The TICV scores ranged from zero to 2,743 (Hallam, NE, 22 May 2004), with a mean of 84.48, a median of 13.96, a standard deviation of 222.87, and a variance of 49,669. Figure 7 displays the frequency distribution of TICV scores, with those scores grouped heavily towards the low end, and comparatively few exceeding a score of 250. A log-log plot of TICV scores and frequency (Figure 8) shows a pattern similar to the damage score, again resulting in a power law distribution. This suggests that the TICV score is heavily influenced by the damage score, with the vulnerability score exerting a lesser influence. The standard beta coefficients resulting from a multiple regression analysis, with TICV score as the dependent variable and the damage and vulnerability scores as the independents, support this suggestion. The damage score showed a β of 0.81 while the vulnerability scored showed a β of 0.09.

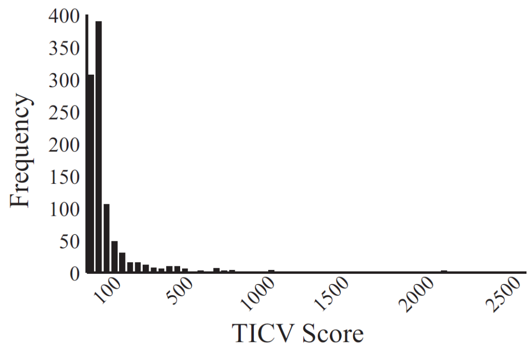

Figure 7: TICV score frequency.

A Spearman's test for linear correlation confirms this suggested influence, with r = 0.999 (p = 0.000) and r = 0.179 (p = 0.000) for TICV scores correlated to damage and vulnerability scores, respectively. It could be argued that the vulnerability score is not a necessary component of the TICV. However, the concept of vulnerability as calculated by indicators such as those used here relate to the overall impact on the community post-event, and does influence the TICV score; although its influence may be less than that exerted by the damage score, vulnerability nonetheless relates to the concept of community impact. Vulnerability analysis results such as these can be seen not as a measure of the direct physical impact, but rather the overall social profile of the community; they also suggest that the physical impact is heightened by higher vulnerability.

TICV categories

The creation of category schemes is well established and frequently employed, as seen in some of today's most recognizable scales (e.g., the EF Scale for tornadoes, the Saffir-Simpson scale for hurricanes, and the Modified Mercalli scale for earthquakes). The purpose of an index value is to provide a meaningful measure that can be easily interpreted [33,34]. Grouping the TICV scores into discrete categories allows those measures to be better understood, since the initial scores were not ordinal or ranked, but interval and not distributed normally (Figure 9), thus displaying a grouping that presents itself as averse to quick interpretation.

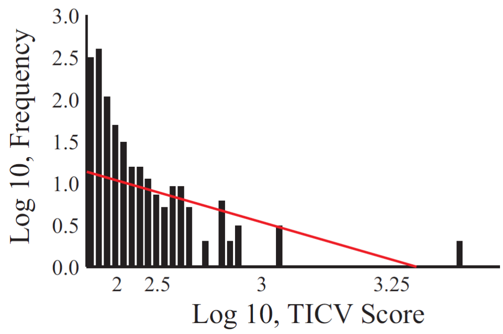

Figure 8: Log-Log, TICV score frequency.

The TICV scores were classified into six categories using Jenks natural breaks, which seek to minimize variance within a class and maximize variance between classes, to produce the TC (Table 3). The categories were fit onto [0, 5] (TC0, TC1,…,TC5). The frequency of the categories show a similar distribution to the TICV scores, as should be expected, since the category breaks were based on those scores; the distribution also conforms to a power law distribution (Figure 9).

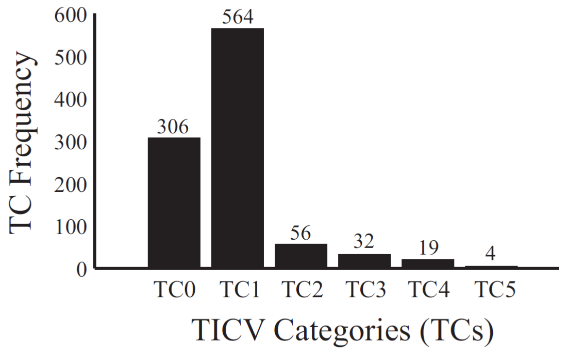

Figure 9: TICV category (TC) frequency.

TICV Score Range	TICV Category	Impact Descriptor
0	0	Low
1–181	1	Low-Moderate
182–390	2	Moderate
391–720	3	Moderate-High
721–1,300	4	High
≥ 1,301	5	Extreme

Table 3: TICV categories (TCs).

TICV score and category relationship to fujita scale

Since the EF Scale is the standard scale by which tornado strength is rated in the U.S. [5,35], it seemed necessary to examine the

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relationship between the EF Scale and the TICV results presented here [9]. Spearman's rho was used to correlate EF Scale values to vulnerability, damage, and TICV scores, and to correlate the TC to the EF Scale in USTOR2000. The correlation between EF Scale and vulnerability scores was low, with r = 0.137 (p = 0.000), similar to the relationship between the vulnerability and TICV scores as shown above. Correlating the damage scores to EF Scale values produced a result of r = 0.535 (p = 0.000). A relatively high correlation should be expected, since the damage score consists of actual physical damage estimates, and wind speed estimates (EF Scale) heavily influences those data [36]. The correlation of the TICV to the EF Scale produced an interesting result, with r = 0.535 (p = 0.000); the same value exactly (to three decimal places) as the correlation between the damage scores and EF Scale values. These results suggest the damage score is the primary driver of the TICV.

The TC was compared to EF Scale values for each event in USTOR2000 to further examine the relationship between the two measures. Overall, the TC scores follow the traditional magnitude versus frequency pattern (Magnitude α 1/Frequency, which can be re-stated here as Impact α 1/Frequency), with many events causing little or no damage (none to light impact) and few events causing extensive damage (heavy to devastating impact). TC0 contains 306 of the 981 events (31.2%), and TC1 contains 564 of the 981 events (57.5%). These two categories together accounted for 88.7% of all tornado events considered in this study. Table 4 displays the TICV category values compared to the number of EF Scale events that occurred in that category, as well as the percentage of the total (n = 981). TC0 consists of events resulting from EF-0 through EF-3 events, with no EF-4 or EF-5 resulting in a TC0 event. TC1 events resulted from EF-0 through EF-4s, with the plurality (and near-majority) resulting from EF-1 events (256 out of 564 or 45.39%). TC2 events also resulted from EF-0 through EF-4 events, with the plurality resulting from EF-2s. TC3 events resulted from EF-1 through EF-4s, with exactly half occurring as a result of an EF-3. TC4 events resulted from EF-2 through EF-5 events, with the majority resulting from EF-3 tornadoes (10 of 19 or 52.63%). Finally, TC5 events resulted from EF-3 through EF-5s, with two of the four resulting from an EF-4 event.

TICV-EFS	EF-0	EF-1	EF-2	EF-3	EF-4	EF-5	Totals
TC0	179 (18.25%)	88 (9.00%)	29 (2.96%)	10 (1.01%)	0	0	306 (31.20%)
TC1	188 (19.16%)	256 (26.10%)	85 (8.66%)	29 (2.96%)	6 (0.61%)	0	564 (88.70%)
TC2	1 (0.10%)	10 (1.01%)	22 (2.24%)	19 (1.94%)	4 (0.41%)	0	56 (5.71%)
TC3	0	3 (0.31%)	9 (0.92%)	16 (1.63%)	4 (0.41%)	0	32 (3.26%)
TC4	0	0	4 (0.41%)	10 (1.01%)	3 (0.31%)	2 (0.20%)	19 (1.94%)
TC5	0	0	0	1 (0.10%)	2 (0.20%)	1 (0.10%)	4 (0.41%)
Totals	368 (37.51%)	357 (36.39%)	149 (15.19%)	85 (8.66%)	19 (1.94%)	3 (0.31%)	981

Table 4: TC and EFS comparison.

Simmons et al. [25] stated that tornadoes, while generally not large enough to affect entire regions, can still devastate small communities. As defined by Fujita [4] and Grazulis [37], weak tornadoes (EF-0 and EF-1) generally produced events of lesser impact; yet, in three cases, a weak EF-1 tornado produced heavy TC3 impact (Redings Mill, MO, 15 April 2001; Poynor, TX, 29 December 2006; McIntosh, AL, 10 January 2009). EF-2 and EF-3 tornadoes were powerful enough to have caused 15 of the 25 events (60%) rated at TC4 or TC5, the two highest categories resulting from these methods. No violent tornado (EF-4 or EF-5) resulted in a TC0 event. But the EF-4 column shows that violent tornadoes of that magnitude caused a wide range of impacts, ranging from light (TC1) to devastating (TC5). While the inverse relationship between magnitude and frequency can be seen in these results, 4 also displays exceptions. From this it can be concluded that a tornado does not have to be a violent EF-4 or EF-5 to have a severe or devastating impact on a community; weaker tornadoes can inflict greater impact than their seemingly low EF Scale values (EF-1 and/or EF-2) may indicate.

The correlation between the TC and the EF Scale was found to be r = 0.533 (p = 0.000), indicating a similar relationship to the EF Scale as the TICV scores before category breaks were applied. Given the methods presented here, and that the TC was based on the TICV scores, this similarity in rho values was expected. In relation to the EF Scale, the correlation between that scale and the TICV scores and the TC indicated that while both scales provide an indicator of impact, the TICV and TC provide a perspective of the event that the EF Scale, by design, does not. Large tornadoes are generally linked to more damage and deaths [28], so it follows that there should be a relationship between the two values.

However, the purpose of this research was to construct an indicator that describes the impact of a tornado event from a perspective unique to the event and the community affected. While a correlation was found, it is not strong enough to support a claim that the EF Scale and the TICV are providing near-identical measures of the same event. This supports the presupposition that the TICV and TC, as an indicator specific to the social profile of, and tornado damage done to, an individual community is unique. Furthermore, these indicators can stand as separate from the EF Scale, as evidenced by weak tornadoes producing heavy impact and violent tornadoes producing light impact; the TICV and TC offer distinctive insight into the impact of a tornado event.

Comparing and contrasting the TICV across four tornado events

Three tornado events were chosen for further examination due to the authors' familiarity with those events (Greensburg, KS; Ladysmith, WI; and Manhattan, KS), and a fourth was added to include an event

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that occurred in a region that displayed higher vulnerability scores than the regions housing the previous three. Further, all four events rate either as strong (EF2-3) or violent (EF4-5) on the EF Scale, providing a backdrop to compare the difference between applying an EF Scale rating to describe community impact as opposed to the TICV.

The Greensburg, KS, event: On 4 May 4 2007 a devastating tornado struck Greensburg, Kansas, at approximately 9:45 CST. According to the NCDC, the width of the funnel was 2.74 kilometers (1.7 miles) wide. A distance measurement in a GIS revealed that Greensburg is approximately 2.1 kilometers (1.3 miles) across at its widest point and 1.1 kilometers (0.7 miles) across at its narrowest. Total damage resulting from the event stands at $250 million with 11 fatalities for a damage component of $327 million. Greensburg placed in the moderate-high category for vulnerability, and received the second highest TICV score in the dataset (behind only Hallam, NE) at 2,440, landing the event in the TC5 category.

The Enterprise, AL, event: At approximately 1:05 CST on 1 March 2007, a tornado entered Enterprise, Alabama, from the southwest, and moved directly through the community. The hardest hit area of the town was the high school, which suffered major damage to the stadium, a partial collapse of the school's walls, and eight students who sought shelter inside were killed. One additional death brought the toll to nine. Overall, 239 homes were destroyed and over 900 homes suffered major or minor damage (NCDC 2010). The damage figure reported by the NCDC is $250 million for a damage component of $323 million and a damage score of 15,252. Enterprise's community vulnerability score came in at 23 (moderate), and the TICV score at 596, ranking this event a TC3.

The Ladysmith, WI, event: Founded along the Flambeau River in the Wisconsin Northwoods as a railroad community in 1885, Ladysmith has since grown to a population of 3,932 as of the 2000 census. Up until 2002, a tornado had never passed through the town. But at 4:20 CST on 2 September 2002, a supercell produced a funnel that made contact with the ground just a few kilometers west of the entrance to the city. Initially rated as F0, the tornado picked up strength as it moved east. It followed a path directly down Lake Street/ Highway 8 (the main road through town), growing from F1 up to F3 strength in the center of town, but began to weaken to F2 strength as it moved across the river, eventually exiting Ladysmith on the east end.

The twister continued for another 15 kilometers (nine miles) before dissipating at F0 strength a few kilometers south of the town of Ingram; no other communities were struck by this event. The tornado completely destroyed 40 buildings with another 159 damaged within the community (NCDC 2010). Luckily, no one was killed, and the total damage is recorded as $25 million for a damage component of $29.75 million, and a TICV score of 471, TC3. Ladysmith scored 29 (moderate-high) on the community vulnerability scale.

The Manhattan, KS, event: Beginning approximately 21 kilometers (13 miles) southwest of the Manhattan city limits, a tornado moved into the community of Manhattan, KS, at approximately 10:56 CST on 11 June 2008. A residential area suffered major damage as the tornado passed at EF-4 strength. Along its continued path, several businesses were severely damaged, with EF-3-level damage inflicted on the Kansas State University campus. The tornado continued through campus flipping vehicles, blowing out windows, and damaging trees. The funnel dissipated within the city limits at approximately 11:03 CST. No deaths resulted from the event, but damage was in the amount of $66 million, resulting in a damage score of 1,472. Manhattan scored low-moderate vulnerability at 22. The TICV score stands at 181, for a rating of TC1.

Comparing the Four events: With a low-moderate vulnerability score, and a damage swath that was small in comparison to the community size as a whole, there remained many persons able to assist those who were located in the path of the tornado. The lower vulnerability indicates a community that can absorb the loss quickly, and begin rebuilding almost immediately. Just a year after the event, a large majority of the homes and businesses damaged had been repaired, and the university campus showed very few remaining signs of the storm. When viewed alongside the Enterprise, AL, event (rated at TC3), a tornado rated on the EF Scale as an EF-4 (the same as Manhattan), it can clearly be seen that those two events, although similar in physical magnitude, cannot be seen as similar in impact. Enterprise suffered the loss of nine residents, eight of whom were children, and much more physical damage, all with less than half of the population (when compared to Manhattan) to absorb the loss.

Ladysmith, smaller in size than both Manhattan and Enterprise, saw 40 buildings destroyed and another 159 damaged. No deaths occurred as a result of the 2002 tornado, but it did tally $25 million in damage. Upon a visit to the community in January 2012, it was noted that several lots still remain empty and unimproved, but the vast majority of the visible impact from the event is gone. "The TC3 rating applied to this event, in comparison to the previous two, indicates a community that was initially hit hard by the storm, and recovery took some time, not unlike in Enterprise, but in terms of size and resources available, more than in Manhattan" [23].

Since the May 2007 tornado, Greensburg, KS, has been facing difficulty in rebuilding as a "green" community [6]. As of 2013, about half of the homes damaged remain unrepaired, and residents continue to struggle to put the town back together. However, many new and modern buildings are apparent in the town, such as the hospital, the Silo Eco-home, the "Business Incubator," and the new high school. Approximately one-third of the residents have since moved away, presumably permanently, which has furthered weakened the recovery effort [38].

The Greensburg tornado score the second highest TICV score within all of USTOR2000, and easily placed in the TC5 category, with an impact descriptor of "devastating." A comparison of the Manhattan, Enterprise, and Ladysmith tornadoes to the Greensburg event demonstrates the difference in the levels of description tied to the TICV categories. The community of Manhattan was certainly affected by the 2008 tornado, but not to the level as either Enterprise or Ladysmith, as the scores of TC1 (Manhattan) and TC3 (Enterprise and Ladysmith) show. Impact was distributed over a larger and less vulnerable community in Manhattan, and thus, the overall impact was lower. Greensburg, with a TC5 rating, illustrates a community that was impacted greatly, with recovery still ongoing to this day.

Limitations, Potential Practical Applications, and Future Research

Small-scale variability may present a barrier to implementation in larger metropolitan areas (e.g., Dallas, Texas; Minneapolis, MN; St. Louis, MO), as the vulnerability calculation is based on population at the level of the city. The main issue that may be difficult to overcome is the availability of these data on smaller scales, which might provide more focused insight into impact in smaller geographic units [39]. Future work will include the examination of methods to scale the

TICV down to finer scales without losing the overall spirit of this attempt to quantify impact.

In the context of this research, the TICV may prove a useful tool for community leaders and/or emergency responders in the immediate aftermath of a tornado, so long as a government office, such as the city assessor, has access to an estimated damage figure. If fatalities are known to have occurred, they too could be used to calculate the TICV as described in this research, or eliminated if only the spatial extent of damage is desired. Even if the initial TICV and TC scores are revised at a later date, the immediate preliminary estimate may provide officials with a sense of the extent of the impact across the community. The TICV could, however, be modified to use estimated population via Landscan data to identify sub-sections of impacted communities.

The TICV scores and category scheme created here could be used to provide a baseline from which officials could then create hypothetical scenarios in which differing levels of impact occur within their communities to examine the range of TICV scores possible. By examining potential impact scores for communities with similar social profiles and population sizes, officials may be better able to anticipate the immediate need for assistance, and better determine, by researching the recovery process of those communities, what may be in store for them in the event of a tornado. Future research may include relating TICV scores to recovery times, which would aid in any process of comparing events across similar communities. An application using one component of the TICV, the vulnerability score, may be able to inform officials of the potential for impact as well, as the vulnerability score provides an indication of the degree to which the population is at risk from any wide-spread traumatic event, not only tornadoes. Finally, as calculated using PCA, the vulnerability scores may be compared across time (i.e., the 2000 compared to the 2010 census) to examine increases or decreases in patterns of community vulnerability.

Future research in this area may include "re-tuning" the index to function at finer scales, as mentioned above. In order to accomplish this, the general framework of the index could be reused, but the demographic data would need to be collected for areas other than "community" in name and size (e.g., "places", census tracts, or census blocks). Inclusion of a "time-of-day" variable was considered in this research, and may be re-visited, as night tornadoes are known to increase the risk of death and injury [25,29], and vulnerability concerning tornadoes (exposure to risk if injury and death) are increased for nocturnal events [30]. Extension of this concept to tornado events in countries outside of the United States is another potential area that is being explored.

Summary and Conclusion

Scales indicating the level of physical strength of natural disasters are commonly used to relay information such as estimated wind speeds, atmospheric pressure, energy released, and overall size. What is less commonly reported is the impact a particular event carries with it and delivers to the communities struck, except for the usual news reports that describe the destruction. As our understanding of the human factor as a key component of disaster impact has matured, the development of scales that attempt to quantify this impact has lagged behind, and therefore an attempt has been made to quantify tornado impact by constructing the Tornado Impact-Community Vulnerability Index (TICV) and TICV Category values (TC).

Through the construction of the TICV and TC, several major findings emerged. A tornado does not have to be physically strong or violent to impart major impacts on a community. While wind speed is undoubtedly an important factor in the amount of destruction that can occur, if a tornado strikes a populated section of town, killing several, or otherwise does a great deal of monetary damage, then the wind speed rating becomes less of a concern than does the overall impact. The damage component is the key driver of the TICV and TC. While higher instances of damage are, again, inextricably linked to more powerful events, overall impact is a major concern not only for those affected by the event, but also for those directing recovery; weak tornadoes can have a strong overall impact. The degree to which a community will be affected by a tornado is also determined, in part, by social vulnerability. While damage is the key driver, social vulnerability affects the ability of individuals and households to recover in the wake of a disaster.

States with a high occurrence of tornado events annually may not necessarily record a high number of events that directly impact a community. This was found to be a function of the density with which communities populate the state taken together with the frequency of tornado events. Small communities are more likely to suffer a greater degree of impact than are larger communities, even if the events striking both communities are of similar physical strength. Small communities, especially those in rural areas, are often more vulnerable to hazards and possess fewer resources from which to draw upon in order to initiate and sustain recovery.

This research has shown that different communities can be impacted at different levels in the wake of a tornado. Although the inverse relationship between impact and frequency holds true here, it is concluded that EF Scale classifications do not always relay the level of impact realistically; the EF Scale is often times misinterpreted as an indicator of severity. Weak tornadoes can impart heavy impact on a community, and violent tornadoes can produce light impact. The index presented here is intended to allow the level of impact from a tornado event to be described. While an index value cannot be seen as the final answer to the question of impact, it can be used to help put the event into context. Additionally, measures such as the TICV could potentially serve in a practical capacity, in that they could provide information that may be of use to emergency planners and other community officials should a disaster occur.

While some potential does exist to modify these methods, in its present form, the TICV can be seen as an indicator of severity, and as a measure of sensitivity as well. While many of the scores grouped in the lowest two categories (TC0 and TC1), the category values TC2 through TC5 show sufficient levels of increasing impact to allow them to be categorized in a more qualitative manner, as is shown by the category impact descriptors of moderate, heavy, severe, and devastating respectively. While these descriptors are qualitative measures, they serve to illustrate the use of an index of this nature: to make a difficult situation easier to understand through the application of research into the dynamics that make up such events.

The vulnerability scores presented here give insight into the level of risk these communities possess pre-event, and those, in concert with the physical impact of a tornado, provide a baseline measurement against which future events may be mitigated. Additionally, the vulnerability score based on the 2000 census may provide a baseline against the 2010 census by which changes in the level of vulnerability for these communities (or for all U.S. communities) could be estimated. Measures such as these can also provide a window into the advancement of issues of social justice, as social vulnerability can be used as an indicator of access to resources.

Research on both the physical and social aspects of the impact of extreme weather events must continue. It is apparent that people and their communities are an integral part of the natural world, and we must continue to strive to understand the complex human-environment relationship.

Should a tornado run through an abandoned town, one to which no one has property of value, or to which no connections to that place exist, then the impact on that "community" will be zero. However, with population increasing every day, and more and more people moving into non-rural communities, we are furthering the potential for tornadoes to move through built areas where property does matter and, people are at risk for harm [23].

The physical onset of extreme weather events cannot be avoided, nor can the assignment of an index score mitigate against impact and tangible loss. But it is hoped that this research can aid in bringing an increased understanding and improved perspective on the level of impact resulting from tornado events, regardless of their physical magnitude.

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