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THE POLITICAL ECOLOGY OF DISASTER: AN ANALYSIS OF FACTORS INFLUENCING U.S. TORNADO FATALITIES AND INJURIES, 1998-2000

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This study examines the causes of tornado fatalities and injuries in the United States between the years 1998-2000. A political model of human ecology (POET) was used to explore how the environment, technology, and social inequality influence rates of fatalities and injuries in two models. Data were drawn from four sources: John Hart's Severe Plot v2.0, National Weather Service (NWS) Warning Verification data, Storm Prediction Center (SPC) watch data, and tract-level Census data. Negative binomial regression was used to analyze the causes of tornado fatalities and injuries. Independent variables (following POET) are classified in the following manner: population, organization, environment, and technology. Tornado area represents environment; tornado watches and warnings, as well as mobile homes, correspond to technology; rural population, population density, and household size operationalize population; and racial minorities and deprivation represent social organization. Findings suggest a strong relationship between the size of a tornado path and both fatalities and injuries, whereas other measures related to technology, population, and organization produce significant yet mixed results. Census tracts with larger populations of rural residents was, of the non-environmental factors, the most conclusive regarding its effects across the two models. The outcomes of analysis, while not entirely supportive of the model presented in this paper, suggest to some degree that demographic and social factors play a role in vulnerability to tornadoes.

Human societies adapt to environmental hazards through a process of cooperation, learning, and development. Technological innovation, a major force adaptation, allegedly reduces the environmental threats communities face and thus plays a central role in protecting human populations from natural and technological disasters. Yet, in spite of advancements in radar technology and warning systems, tornadoes continue to cause fatalities and injuries in the United States. It is therefore necessary to move beyond technology in our investigations of disaster vulnerability by developing a more demographically- and sociologically-focused analysis of tornado fatalities and injuries.

Dynes (1994) and Aguirre (2000), among others, reject the notion that bureaucratic control and technology are central to effective emergency response. Other studies on society and disaster, such as those by by Quarantelli (1998), conceive of "disaster" in terms of how a society is organized rather than the scope, intensity, or duration of a hazard. Taken together, these two criticisms suggest that we must move beyond research that investigates disasters exclusively in the context of technology and the natural environment. Disaster vulnerability, it has been elsewhere argued (Mileti 2003; Tierney, Lindell, and Perry 2001; Aguirre 2000; Doswell III 1999; Drabek 1986; Fritz 1961), is a characteristic of human populations and is shaped by the diverse cognitive, social, and demographic qualities of the people who compose them.

The following research intends to identify important causes of tornado fatalities and injuries within two models built of independent demographic, social organizational, technological, and environmental factors. Analysis is grounded in the human ecological tradition developed by Hawley (1950) and Duncan and Schnore (1959), yet expanded to incorporate social inequality and power differentials (Oliver-Smith 1998). Social inequality, power differentials, and the distributions of populations in space and time have been shown to place some social groups at greater risk to disasters (Peacock, Morrow, and Gladwin 2000; Albala-Bertrand 1993; Burton, Kates, and White 1978).

Three questions specifically follow from this approach. First, which environmental, technological, population, and social organizational variables are associated with fatalities and injuries? Second, which of these factors are the strongest predictors of tornado fatalities and injuries? Finally, what do these outcomes mean from the perspective of political ecology?

THE HUMAN ECOLOGICAL COMPLEX

Human ecological perspectives model not only the environmental causes (e.g., strong winds, collapsing structures) of tornado fatalities and injuries, but also the influences of technology, social organization, and population characteristics. One of its advantages is that it allows researchers to more comprehensively develop an understanding of catastrophic events by simultaneously directing attention towards social and environmental factors.

According to Hawley (1950: 68), human communities are "complex cooperative arrangements" the goal of which is the survival of members. Within a stable ecosystem, the environment does not prevent people from meeting basic physical, psychological, and social needs. When environmental changes and, especially, environmental extremes, are common, needs presumably become difficult or impossible to meet. A process of organization, or "the relating of individuals to one another in such a way as to increase the efficiency of their actions" (178), begins as a means by which communities attempt to eliminate or moderate the negative impacts of the environment on the needs of members. In contrast, therefore, to earlier concerns with population distributions (Park 1936), Hawley highlights the central role of social relationships in human ecosystems. Competition, he continues in a notably Durkheimian ([1893]1984) vein, among people with similar needs organizes the community into a web of functional relationships. These functional relationships stabilize the ecosystem by fulfilling the unmet needs of members. Developing further Hawley's argument, Duncan (1950) suggests human ecosystems are constituted by four dynamic components: population, organization, environment, and technology (what is commonly summarized by the acronym *POET*). Duncan (1950) and Duncan and Schnore (1959) later proposed the "human ecological complex" in order to arrange and classify propositions about the relationship between human populations and their environments, making POET able to adjust to many different research questions (Faupel 1981). Thus, Duncan (1950: 685) tells us that "demographic variables [deduced from the population component of POET] come into the scope of ecological research 1) as 'independent variables,' or limiting conditions of ecological organization; 2) as 'dependent variables,' concomitants, or consequences of variation in ecological organization; and 3) as 'indicators' of one or another aspect of ecological organization."

FROM HUMAN ECOLOGY TO POLITICAL ECOLOGY

The human ecological complex is a useful tool, but its components remain difficult to operationalize (Faupel 1981) and politically neutral, so that often researchers ignore inequality and take for granted the cooperative and functional attributes of human relationships within an ecosystem. Although sociological studies indicate that the presence of cooperation during disasters is normal (Fischer III 1998), long-standing and deeply-embedded inequalities within the class, prestige, and power structures of society may be expected to place certain groups at greater risk. The environmental justice literature, for example, demonstrates how social inequality influences exposure to hazardous landfills (Pellow 2002) and polluted industrial zones (Pulido 2000). Does the same, however, hold for natural disasters?

Indeed, the risk of being killed or injured by severe weather may vary by social group. Educational, socio-economic, racial, and ethnic statuses (Gladwin and Peacock 2000; Balluz et al. 2000; The H. John Heinz Center 2000; Blaikie et al. 1997) influence evacuation behavior, warning response behavior, and vulnerability to a range of severe weather events. Perry, Lindell, and Greene (1982) observed differences in perceived risk and warning comprehension between ethnic and racial populations. Other research confirms the role of race, ethnicity, and gender influences in risk perception and the process of risk communication (Lindell and Perry 2004; Satterfield, Mertz, and Slovic 2004; Flynn, Slovic, and Mertz 1994; Turner and Kiecolt 1984; Perry and Mushkatel 1986). In his analysis of response to the September 20, 2002, Indianapolis tornado, Mitchem (2003) reports that African-Americans experienced difficulty grasping the significance of tornado watches and warnings. Moreover, special needs populations, such as the deaf, are at greater risk (Wood and Weisman 2003).

In some cases, culture engenders differences in the needs experienced by populations. Aguirre (1988), for instance, demonstrates that tornado warnings ultimately failed during the outbreak in Saragosa, Texas, on May 22, 1987, because government and the media unsuccessfully addressed the cultural and linguistic differences of the region's Mexican-American population. Finally, trailer parks, which account for a disproportionate number of tornado fatalities and injuries in comparison to other locations (Storm Prediction Center 2004a), are typically occupied by lower class families.

In summary, it is suggested that there exists a variety of psychological and social barriers to appropriate response, raising significant questions about vulnerability to disasters. Social groups whose members are likely to *respond incorrectly* (due to intellectual, psychological, or social barriers) to tornados may be expected to face *greater risks of physical harm* during tornados. This assumption, however, has never been confirmed, and therefore may be false, even though the argument is indeed valid. It remains an empirical question whether these psychological and social disadvantages, which allegedly manifest in incorrect response, are a sign of vulnerability in the form of the greater likelihood of being killed or injured by a tornado. So, for instance, as previously discussed, African-Americans are less likely to understand warning messages (Mitchem 2003) and people of lower education are less likely to seek shelter (Balluz 2000). Thus, one can justifiably hypothesize that African-Americans and people of lower education are more likely to be physically harmed by a tornado. Of course, *vulnerability to tornadoes* is merely part of a broader category of vulnerability of which disadvantage is a determining factor—whether it be tornadoes, famine, or disease, for instance, the poor seem more susceptible. Variables operationalizing the organizational components of POET in particular thus are presumed to represent *vulnerable* groups, which are those observed to respond incorrectly to hazard. The extent to which a group is vulnerable can be measured to the degree that it is observed to be more likely than other groups to be harmed by a tornado.

This paper aims to understand the causes of tornado fatalities and injuries through the use of a human ecological perspective that models the effects of power and inequality on society's relationship to the natural environment, as well as to its own technological achievements. Regions having larger poor, racial, and ethnic minority populations are anticipated to experience larger numbers of tornado fatalities and injuries. Until now, however, these social factors have not been considered in the analysis of tornado deaths and injuries. Rather, according to claims made by the National Weather Service (NWS) and Storm Prediction Center (SPC), tornado watches and warnings reduce the number of deaths and injuries associated with a tornado. Tornadoes with larger impact areas, moreover, cause larger numbers of fatalities and injuries. In this test, however, a combination of factors—socio-political, technological, and environmental—are hypothesized to influence observed counts of tornado fatalities and injuries and thus to define vulnerable populations.

The literature, therefore, suggest a need to reevaluate a human ecology in which notions of vulnerability are absent. POET provides useful concepts and powerful tools through which an understanding of human ecosystems can be achieved. The aforementioned literature appears to suggest, however, that POET must move beyond the notion of functional relationships and cooperation towards a more conflict- and competition-oriented approach. Human populations are not homogenous; they consist of different groups with different interests and abilities to protect themselves from severe weather. Human ecology, as with animal ecology, assumes that adaptation to environmental changes in time benefits all segments of the community. The literature appears to indicate that it may not, for competition, in a politicized human ecology, does not play out among equals, but is one-sided, favoring the survival of some groups over others. It is precisely these competitively disadvantaged groups that should experience the highest number of deaths and injuries. As Oliver-Smith (1998: 189) states, "A political ecology perspective on disasters focuses on the dynamic relationships between a human population, its socially generated and politically enforced productive and allocatable patterns, and its physical environment, all in the formation of patterns of vulnerability and response to disaster."

METHODS

Data Collection

Application of the POET model to address these questions required the use of various datasets from a number of different institutions. John Hart's *Severe Plot v2.0* (n.d.) provided information on severe weather events, including data on tornado death, injury, and Fujita ratings from 1950-2000. The 2000 U.S. Census offered demographic information at the census tract level. National Weather Service (NWS) Warning Verification data included tornado touchdown times, times at which warnings were issued, and the geographic areas in which warnings were issued. Lastly, Storm Prediction Center (SPC) watch data presented information on activation times and geographic coordinates of watch parallelograms.

Dataset construction began by selecting meaningful time period in which to analyze tornado fatalities and injuries. The years 1998-2000 were chosen to control for the effects of advancements in forecasting skill (Bieringer and Ray 1996). Severe weather reports began to steadily improve prior 1998 following the introduction of Doppler (WSR-88D), which increased the accuracy of severe weather detection and prediction relative to earlier time periods. This technological innovation made it necessary to restrict the time period in which the test is done.

Data were then combined through the use of Geographic Information Systems (GIS). *ArcGIS* was used to plot the points at which tornadoes began and ended according to longitudinal and latitudinal coordinates drawn from *Severe Plot*, and the coordinates were then geocoded upon a shapefile containing census-tract boundaries and census-tract demographic information. The geographic position of each beginning and ending tornado coordinate allowed for the extraction of matching demographic information from the census tracts in which those coordinates fell. In cases where beginning and ending coordinates fell in two different tracts (the result of longer tornado paths), the values generated by these two points were added and divided by the appropriate population universe (e.g., population size, total number of households, etc.) to produce an average value for the demographic variables of interest. We realize the limitations of such a method, but currently available information does not include the complete path of a tornado at the census tract level.

There were approximately 3,810 tornado events between January 1, 1998, – December 31, 2000, available for analysis. Of those 3,810 cases, data loss can be attributed to two sources. First, cases whose beginning and ending points were over water or in Canada could not be used because census tract information could not be obtained. In total, there were 65 cases in which a tornado did not begin over land and end over land in the United States. There were 19 tornados that either began over land in the United States and ended over water or a Canadian province (n=7) *or* began over water or Canadian province and ended over land in the United States (n=12). These cases were analyzed. A total of 46, therefore, were rejected because the tornado tract did not pass over land in the United States.

The second major source of data loss was due to incongruity between the SeverePlot (SPC) dataset and the warning dataset (NWS), resulting in the elimination of 171 cases. I cannot offer a strong explanation for the incongruity, other than hypothesizing that the organizations (SPC and NWS) may have a different method for classifying tornados. These cases were dropped from the data set, leaving 3,639 cases total after this and 3,593 (from 3,574 in the initial analysis) after subtracting tornados that occurred over water and/or Canada. Three cases held missing values for key census variables and were omitted, leaving 3,590 cases in the final analysis.

The final step was to merge data describing tornado watches and warnings to the combined tornado-characteristic and demographic dataset. Tornado watches are issued by the SPC and ideally precede warnings. They are usually preceded by a Convective Outlook, which is a general survey of potential severe and non-severe weather. As the areas in which severe weather is likely to occur become more clearly defined, Mesoscale Discussions (MDs) are issued. Watches are issued by the SPC "if development of severe thunderstorms is imminent, or likely to occur in the next several hours" (Storm Prediction Center 2004b) after the forecasters compose and issue MDs. Watches remain in effect for several hours after issuance and their shapes are typically parallelograms. Tornado warnings, in contrast, are issued when tornadoes are imminent and their existence is detected by local NWS offices and verified by storm spotters. Increasing levels of sophistication in radar technology has consequently produced a more effective warning system, if we define "effectiveness" by accurate tornado prediction and extended lead times.

Lead time is defined as the difference between the time at which a tornado warning is issued and the time at which a tornado touches down. Warnings were merged to the dataset by matching the times at which *Severe Plo*t data indicated tornado touchdown and the times at which the NWS warning dataset indicated tornado touchdown. This provided the linking variable through which the datasets were combined: each tornado that occurred with a warning is associated with a lead time variable measured in minutes and varies according to the time at which the warning was issued and the time at which the tornado occurred in the community in which the warning was issued. A *lead time variable* was created by subtracting these two values. There was no lead time for some tornadoes because they occurred without a warning or the warning produced no lead time.

The raw watch data was less tractable. The format of SPC watch data required the creation of a computer algorithm that mathematically and geometrically established the incidence of effective watches through a series of logical commands. The original dataset did not contain information about specific tornadoes. The raw data only presents information on the longitudes and latitudes of the four points around which the watch parallelogram was based, the time at which the parallelogram was in effect and the time it ended, and the general area in which it occurred. Tornado watches had to be manually merged to the information from Severe Plot based on geographic coordinates and time.

Tornado watches were operationalized through the use of a program that allowed for the "observation" of tornadoes in relation to polygonal watch areas specified by four longitudinal and latitudinal coordinates. To determine if a tornado track fell within a watch area, computer algorithms were created to verify that 1) the linear path specified by a tornado's beginning and ending points fell within the polygonal watch coordinates 2) that were active between the time the tornado touched down and by the time it dissipated.

If the tornado, according to the algorithms, passed through the watch polygon within the times at which those coordinates were active, the tornado received a "1," indicating it that it occurred within a watch. It received a "0" if it 1) did not fall within the coordinates while the coordinates were active, 2) moved through the area before the watch was in effect or 3) moved through the polygon after the watch was cancelled. Thus, the dummy variable "watch" indicates whether each tornado in the dataset occurred within a watch ("1") or outside a watch ("0"). The tornado did not have to pass through the full watch area in order to be assigned a "1."

DEPENDENT VARIABLE

Two models for two dependent variables of interest are included. The two dependent variables are the number of fatalities and the number of injuries per tornado event. The variables are observed to follow a count distribution the consequences of which are discussed below.

INDEPENDENT VARIABLES

Population

Population factors include census tract indicators of population density, rural population, household size. The population component is intended to represent the distribution and density of populations across the continental United States. *Population density* is simply a tract's total population divided by its area in square miles. *Rural population* is specified as the percentage of persons living in rural areas and *household size* is specified as the average number of people living within a household per census tract. Rural population, in particular, was used because there is considerable debate in the literature over whether rural regions are more vulnerable. Although speculations have been offered regarding urban populations and disasters (see Mitchell 1999), an empirical test of whether people in rural regions are more likely to be harmed by a tornado remains to be seen. Moreover, no clear consensus exists regarding the role of household size in vulnerability, although there is some evidence that group size (particularly when a group has meaningful bonds) influences evacuation time.

One might hypothesize that tracts with larger average household sizes will be more likely to experience higher rates of deaths and injuries. There is, however, mixed evidence regarding this proposition. In their study of victims of the 1993 World Trade Center bombing, Aguirre, Wenger, and Vigo (1998) observe a direct relationship between group size and evacuation time. Of course, it is not advisable to evacuate during tornadoes and doing so may place one at greater risk; nevertheless, an argument can be made that large families take longer in organizing themselves for other forms of protective action appropriate for tornadoes, such as seeking basement refuge or moving to a public shelter. These activities may not be considered evacuation in the sense that they can be accomplished more quickly, but it should be remembered that tornadoes can strike within minutes—even seconds—of warning broadcasts. On the other hand, larger households and families may be more likely to respond to warnings, as documented evidence suggests that people with children are more likely to respond to warnings (Edwards 1993; Carter, Kendall, and Clark 1983).

Organization

Organization measures the presence of disadvantaged groups whose characteristics are hypothesized to make them more vulnerable to disasters. In the politicized POET model, organization is intended to measure social stratification, rather than organized response to disaster. "Organization" reflects, as a variable, the relative presence of disadvantaged groups within a census tract. Thus, this emphasis on inequality and vulnerability breaks from human ecology's more common focus on cooperation among organized groups. Four variables originally specified organization in the politicized POET model—percent households below poverty level, percent African-American population, percent disabled, and percent of population with less than a 12th grade education. They may be expected to share a direct relationship with tornado deaths and injuries, thus revealing the presence of vulnerability at lower levels of the social hierarchy.

While it would be ideal to run these measures independently, multicollinearity between the variables unfortunately prevents doing so.[1] Factor loadings indicate that percent household poverty, percent disabled, and percent below 12th-grade education load on a common factor and should be indexed in order to avoid methodological problems due to inefficient estimates. These variables are added, creating an index that henceforth will be referred to as "deprivation," which ranges from 0-300. Tracts with higher ratings on this index house populations with fewer resources and, hence, greater

[1] Contact the author for a copy of the factor analysis.

levels of vulnerability to tornadoes. Thus, the two variables representing organization are *percent African-Americans* and a *deprivation index*.

Environment

Area, rather than the Fujita[2] scale, was chosen to represent the environment. Fujita ratings of tornadoes appear to be biased estimates of a tornado's real magnitude (Phan and Simiu 1997). These concerns are shared with other meteorologists (Doswell III and Burgess 1988). Other scholars have found additional problems with the scale, charging that it lacks consistency, an awareness of variations in construction quality, and, in absence of damage indicators, does not produce accurate results (McDonald 2002). It is no longer used operationally, notes the SPC (n.d.), cautioning users of the data: "Without a thorough engineering analysis of tornado damage in any event, the actual wind speeds needed to cause that damage are unknown."

Another problem regards explaining deaths and injuries using an independent variable that is directly a measure of damage, which, in all likelihood, is already a strong correlate of deaths and injuries (most tornado deaths and injuries are a result of being in collapsing structures or being hit by debris). A direct relationship observed between Fujita scale and, for instance, injuries may be due to the fact that the Fujita scale is already measuring something that shares a strong relationship to injuries; an association not due to causation, but simply to measurement. Considerable difficulties would be involved in determining what portion of the change in the dependent variable was due to windspeed and what portion of the relationship was due simply to the manner in which the independent variable was measured as damage.

[2] The Fujita scale is a measure of wind velocity and ranges from weak (F1) to extremely violent (F5).

Technology

The technological component of the POET model is represented by the variables tornado watch and lead time, two key products prepared for and distributed by the SPC and NWS. It is also represented by the variable "mobile homes." Mobile homes rarely offer basements in which residents can find shelter during severe weather and tend to be structurally incapable of resisting the effects of strong tornadic winds. These technological differences in infrastructure between census tracts may be expected to place populations at greater risk.

ANALYTIC APPROACH

As noted above, the two dependent variables are the counts of tornado deaths and injuries per tornado. Ordinary Least Squares (OLS) regression is the standard approach for modeling statistical relationships in which the dependent variable is continuous and normally distributed. Given that tornado fatalities and injuries are, however, known to be exceptionally rare and irregular in occurrence, their distributions were expected to be non-normal, following what is commonly known as a Poisson distribution. Poisson distributions describe how many times an event has occurred within a period of time—time being represented, in this case, by the duration of a tornado; the event, by the occurrence of a fatality or injury. Each tornado represents a finite number of trials within which each person has a small chance of being killed or injured. Counts naturally consist of positive integers and likely contain large frequencies of "zeros." Indeed, according to Figures I and II, this suspicion is confirmed: a small number of tornadoes were responsible for many of the deaths and injuries that occurred between 1998-2000.

[FIGURES 1 AND 2 ABOUT HERE]

Thus, OLS regression, which assumes that regression errors are normally distributed (analysis violates the assumption of homoskedasticity), would be inappropriate for these data (Osgood 2000; Gardner, Mulvey, and Shaw 1995). Another problem arises because count data are, by nature, discreet. Accordingly, OLS is inappropriate in the context of this study because the mathematics through which its operates assumes the dependent variable is continuous. If these assumptions are violated, analysis is likely to produce "inefficient, inconstant, and biased estimates" (Long 1997: 217).

Fortunately, Poisson regression has been developed to account for non-normal errors and discreet values of count data during analysis. The Poisson distribution is defined by a single parameter: $\mu = t\lambda$, where t is the rate of time per interval, λ is the expected rate of occurrence per unit of time, and μ is the expected occurrence over time t (Rosner 1995). The "occurrence," in this case, is a tornado fatality or injury.

A characteristic of the Poisson distribution is that the conditional mean is equal to the variance: $\mathrm{Var}(y)=E(y)= \mu$, an assumption termed *equidispersion*. As is commonly the case in count distributions, however, the observed variance is greater than the conditional mean, which results in *overdispersion* (Long and Freese 2003).

Long (1997) describes the Poisson model, its assumptions, and potential weaknesses. Equidispersion, he argues, reflects the omission of the error term in Poisson model, which is represented by the structural equation: $\mu_i = E(y_i \mid x_i) = \exp(x_i\beta)$, where the conditional mean of y given x is $u = \exp(x_i\beta)$. The exponentiation of $x_i\beta$ transforms the expected count μ into positive integers, as Poisson distributions cannot contain negative values. The error term, as noted, is omitted under the assumption that the independent variables explain *all* the variance in the dependent variable. As this is unrealistic, this study uses negative binomial regression, a generalization of Poisson, which can be expressed as $\tilde{u}_i = E(y_i \mid x_i) = \exp(x_i\beta + \varepsilon_i)$. The term $\tilde{u}$, in contrast to μ, represents variation in x_i as well as variation in the residual term ε_i, thus accounting for both observed *and* unobserved heterogeneity, as Long describes.

The full models for this study are:

$$\widetilde{FATALITY}_i = \alpha + \exp(\text{TORNADO MI}^2{}_i(\beta) + \text{LEADTIME}_i(\beta) + \text{WATCH}_i(\beta) + \text{DEPRIVATION}_i(\beta) + \text{\%RURAL POPULATION}_i(\beta) + \text{\%AFRICAN-AMERICAN}_i(\beta) + \text{AVERAGE HOUSEHOLD SIZE}_i(\beta) + \text{\%MOBILE HOME}_i(\beta) + \text{POPULATION DENSITY}_i(\beta) + \varepsilon_i) \quad (1)$$

$$\widetilde{INJURY}_i = \alpha + \exp(\text{TORNADO MI}^2{}_i(\beta) + \text{LEADTIME}_i(\beta) + \text{WATCH}_i(\beta) + \text{DEPRIVATION}_i(\beta) + \text{\%RURAL POPULATION}_i(\beta) + \text{\%AFRICAN-AMERICAN}_i(\beta) + \text{AVERAGE HOUSEHOLD SIZE}_i(\beta) + \text{\%MOBILE HOME}_i(\beta) + \text{POPULATION DENSITY}_i(\beta) + \varepsilon_i) \quad (2)$$

DESCRIPTIVE RESULTS

[TABLE 1 ABOUT HERE]

Fatalities and Injuries

The mean for fatalities was 0.07 and the standard deviation was 1.03. The mean for injuries was 1.23 and the standard deviation was 13.48.

Tornado Area (mi^2)

The average area covered by a tornado event in the years 1998-2000 is 0.23 mi^2. The smallest of these tornadoes is approximately 0 mi^2 and the largest is approximately 40 mi^2. The standard deviation of tornado area is 1.44 mi^2.

[FIGURE 3 HERE]

Lead time

According to the data, the average lead time in minutes for all tornadoes in the dataset is 11.08, with a standard deviation of 13.71. These values reflect national averages: the National Atmospheric and Oceanic Administration (NOAA) (2002) estimates that the average lead time in the years 1994-2001 is 12 minutes.

[FIGURE 4 ABOUT HERE]

Watches

According to the watch algorithm created for this study, approximately one-third of tornadoes (approximately 36%) fell within at least one watch area at some point during their paths.

Percent People Living in Rural Areas

For tornado-impacted tracts, the mean percentage of people living in rural areas is 77.86 and the standard deviation is 34.13.[3]

Population Density

The mean population density for census tracts in this study is 306.36 and the standard deviation is 1306.5.

Average Household Size

The mean of the average household size for tracts impacted by a tornado is 2.58 with a standard deviation of 0.27.

Percent African-Americans

The mean population percentage of African-Americans residing in a U.S. Census tract experiencing tornadoes in the years 1998-2000 is 6.35 and the standard deviation is 13.10.

Percent Mobile Homes

The average percentage of mobile homes within a census tract impacted by a tornado event is 17.07 (as a percentage of all households), with a standard deviation of 12.3. The national mean is 7.6% (Bennefield and Bonnette 2003).

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[3] Nationally, only 22% of the total census-tract population lives in rural areas (U.S. Bureau of the Census 2000). The data indicate that tornadoes are more likely to occur in rural tracts. Tornadoes are not geographically-random events; their frequency and duration is determined by characteristics of the man-made environment. Likelihood of tornado formation and velocity is, for instance, reduced due to the heat differentials and surface roughage created by cities (Elsom and Meaden 1982, Snider 1977).

Social Deprivation Index

The social deprivation index—composed of the variables percent of households below the poverty level, percent disabled, and percent of population below 12th grade education—has an average value of 70.89 and a standard deviation of 24.37. Although the theoretical maximum value for this scale is 300 (the sum of three percentage-based variables), the highest value in the data is 197.42 and the lowest is 15.89.

ANALYTIC FINDINGS

Tornado area and *percent rural population* revealed consistent results, but the remaining variables—namely, *lead time, watch, percent African-Americans, deprivation, percent mobile homes, average household size, and population density*—introduce unexpected findings in the two models. For example, larger households appear to be at significantly greater risk of injury, but not fatality, according to the standardized coefficients (see Tables 3 and 4). In order to draw meaningful conclusions about this and similar outcomes, it is necessary to explore issues of statistical reliability as they relate to the process of collecting tornado injury data.

Preliminaries

The findings of this study are limited to generalizations made at the census tract level of analysis. This paper is not concerned with either individual phenomena or the specific causal pathways taken by the independent variables. Its intentions are broader and more general: an attempt to demonstrate the validity of political ecology to a wider audience and, moreover, make obvious the limitations of theoretical models available nowadays that explain tornado fatalities and injuries solely in terms of environmental or technological concepts.

[TABLES 2, 3, AND 4 ABOUT HERE]

The two dependent variables in the study vary in their expected validity. Reliable statistics on tornado deaths are generally easy to obtain: all—or, at least, a majority—of the deceased make it to the morgue. Total injuries, however, are less discernable because not all victims may reveal their injuries to authorities for a variety of reasons: some do not seek medical treatment for minor wounds, such as cuts and bruises; others cannot afford it; and there are still others who actively avoid places at which authorities are present or where they are thought to be present. It is reasonable to assume that the same holds for hospitals, public shelters, or other place at which one's illegal status faces the threat of exposure. The result is that some groups may not be fully represented in the total number of injuries tallied for each event. This should be kept in mind when interpreting the following statistics.

The injury model, though based on the best data currently available, should be approached with some caution regarding its reliability. Greater confidence can be placed in the model of fatalities for two reasons. First, a greater degree of variation in fatalities was explained in (Fatality Model: R^2=0.112; Injury Model: 0.065). Second, there is a strong possibility that the count of fatalities *vis-à-vis* injuries holds greater external validity. Variations in statistical significance of the predictions of the two models may be due to a) substantive differences between fatalities and injuries in their relationships to the independent variables or, more likely, b) errors in collecting statistics on tornado injuries. Substantive effects are difficult to interpret without further information, and, at this point, are best left to future empirical research rather than conjecture. To emphasize the variables in which similarities and differences are present, the effects of fatalities and injuries are discussed for each variable.

Tornado area

A one standard deviation ($s=1.44$ mi^2) increase in the area a tornado covered increases the expected count of tornado deaths by 8.44. When compared to other variables in the fatality model, tornado area has the strongest effect on the dependent variable. Similarly, a one standard deviation increase in the area covered by a tornado predicts a significant increase in the expected count of tornado injuries by 10.48. As with the fatality model, tornado area reveals itself as the best predictor of a census tract's count of injuries.

Leadtime

It was anticipated that as lead time increased, the expected count of fatalities would decrease. This, however, was not the case: according to the data, there is no relationship between lead time and fatalities ($p=.885$). This may be due to an alleged curvilinear relationship between lead time and vulnerability, which is later discussed. Lead time, on the other hand, as predicted, is associated with a significant reduction in the estimated count of injuries; 0.75 for each additional 13.71 minutes of warning preceding the onset of a tornado.

Watch

The result for watches indicates, contrary to prediction, that the presence of a tornado watch had little effect on the probability that a census tract would experience fatalities and injuries.

Percent People Living in Rural Areas

Census tracts whose populations are more likely to be rural are less vulnerable to tornados. A one standard deviation (s=34.13%) increase in percent rural population significantly decreases the expected count of fatalities by 0.66. Similarly, a one standard deviation increase in percent rural population significantly decreases the expected count of injuries by 0.62.

Percent African-American

African-Americans were hypothesized to be more vulnerable to tornados than other groups because they experience greater levels of poverty and have historically experienced widespread institutional discrimination. However, this expectation was not supported by the findings in this study; census tracts with larger African-American populations did not have statistically greater number of tornado fatalities. The percentage of African-Americans within a given tract had no effect on a tract's count of injuries.

Deprivation index

Also contrary to predictions, levels of socioeconomic deprivation were unrelated to the expected count of fatalities. This was not the case in the injury model, in which a one standard deviation (s=24.37-point) increase on the *deprivation index* significantly increased the expected count of injuries by 1.40.

Percent Mobile Homes

As predicted, a one standard deviation increase (s=12.30%) in *percent of mobile homes* significantly increases the expected count of fatalities by 1.55. However, this was not the case for tornado injuries.

Average Household Size

Contrary to prediction, the average size of a household has no effect on the likelihood of fatalities. *Average household size*, however, is a significant predictor of injury, of which a one standard deviation increase (s=0.27) in average household size predicts a 1.33 increase in the count of injuries.

Population Density

Contrary to prediction, population density has no effect on fatalities. It had a weak, yet significant, effect on injuries: a one standard deviation increase (s=1306.5) in population density of a census tract significantly increases the predicted count of tornado injuries by 1.38.

DISCUSSION

Population, organization, environment, and technology were theorized to influence the survival of human ecosystems and, therefore, to shed some light on the causes of tornado vulnerability. The results are somewhat at variance with this assertion. Mixed support notwithstanding, a variety of important and unexpected outcomes reveals demographic and organizational factors do play a role in shaping the vulnerability of social groups.

Area covered by a tornado, as well as the percentage of total populations living in rural communities, yielded significant outcomes in both models. Again, environmental characteristics seem to outweigh the impacts of other factors. Larger tornadoes come into contact with larger numbers of people, increasing the probability of fatalities and injuries. *Controlling for population density*, census tracts with large proportions of rural residents were less vulnerable to tornadoes. One conclusion that can be drawn from this outcome is that tornado fatalities and injuries would increase if census tracts become more urbanized. Moreover, since population density was controlled for, the reason rural reasons are less vulnerable may be due to the distinct nature of their social relationships or culture. The types of social relationships rural communities engender, as well as the awareness people in such regions hold of their habitats, can be inferred to foster resilience in such regions. Perhaps there is greater social capital in these areas, so that strong social bonds expand the scope and availability of potential sources of weather information, shelter access, and other resources that help facilitate protective action. Yet another reason might be that the rare occurrence of tornadoes in urban communities leads to lack of preparedness among residents, along with the proliferation of skepticism about tornado risks.

How does the model fare from the standpoint of technology? As anticipated, tracts with larger percentages of mobile homes were more likely to experience fatalities. Mobile homes are structurally vulnerable to intense winds and are, therefore, less capable of resisting tornados. Injuries, however, were observed to neither increase nor decrease as the percentage of mobile homes within census tracts varied. Despite claims to the contrary by the NWS, watches did not decrease fatalities or injuries. The public, it has been shown (Greene, Perry, and Lindell 1981; Mileti and Beck 1975; Fritz 1957), is less mindful of risk communicated ambiguously or indecisively. Watches, containing information of an uncertain nature defines tornado risks (both temporally and spatially) too broadly to function as an effective public safety tool, without a clear sense of threat or appropriate course of action. Lead time was also expected to be a strong and consistent predictor in both models, for a central goal among public officials involves issuing tornado warnings early enough to generate as much lead time as possible. Evidence for this expectation is primarily derived from the anecdotes and narratives of forecasters, meteorologists, and survivors. As anticipated, an increase in lead time reduced the expected count of injuries in the first model. However, lead time had no effect on the predicted outcome of tornado fatalities. These findings raise a variety of complex questions beyond the explanatory scope of this research. Our knowledge of the warning process is limited, so that a sound theoretical explanation cannot be developed at this time. More specific research is needed in order to replicate and augment the validity of these findings, which place doubt on a major emphasis of NWS.

Future research may reveal that the risk of being killed or injured during a tornado, contrary to expectations, increases as lead times become longer. This appears counterintuitive, but it is reasonable to speculate that while shorter lead times give people too little time to engage in the *right* kinds of protective behavior, prolonged periods of forewarning, in contrast, present individuals with more opportunities to behave in a manner that places them at considerable risk. There may be a "U-Shaped" relationship between lead time and the likelihood of a tornado casualty occurring. In cases where lead times are very long, say, 40 minutes, those aware of the warning may engage in a variety of unsafe behaviors, most notably that of attempting to evacuate, which is not advised for tornadoes. Moreover, after waiting in a basement or public shelter for some time, victims may begin to grow incredulous, emerging from their place of refuge only to be injured or killed by a tornado. The irony of such circumstances is that the tornado was warned *too effectively*. What is critical is that these findings call into question the taken-for-granted assumption that a linear increase in lead time will lead to greater public safety.

Population variables yielded important, yet equivocal, outcomes. As the average size of a household increases within census tracts, so does the census tracts' counts of injuries. There is a need to examine whether group size influences how people sharing significant relationships go about organizing themselves for protective action during the often brief period prior to the onset of a tornado; larger households may take longer to organize members for protective action. The amount of time it takes to organize these individuals for protective action cuts into the amount of time the group has to protect itself. This finding suggests a need to explore the impact of group size on a variety of disaster-related activities, including warning response, risk communication, and evacuation behavior. Finally, contrary to predictions, population density performed poorly as a predictor of fatalities, and was a weak predictor of injury.

The organizational component—again, in the context of a *politicized* POET model, a measure of socio-structural inequality—consists of variables also exhibiting a variety of complicated outcomes. The only statistically-significant variable in the model within the organization component was deprivation, and its significance only extended to injuries, so that the census tracts experiencing high levels of deprivation had greater chances of a tornado causing injuries. A variety of explanations may be offered for this observation. Populations living within census tracts prone to high rates of deprivation may be more disabled and lack the income to afford shelters and sustainable housing. These findings would appear to indicate that social inequality plays a role in creating vulnerability within populations. Finally, and the finding contrary to expectations, was that populations living within census tracts occupied by larger percentages of African-Americans are neither more nor less likely to be killed or injured by a tornado. Past research indicates that minority groups experience difficulties understanding and interpreting warnings, and thus assumed that tracts with larger proportions of African-Americans would have more people killed or injured in a tornado event. Yet, the findings indicate this is not the case. A possible way to interpret this finding may be that, as some scholars have noted (Wilson 1980), the significance of race is declining in U.S. society, and poverty has come to overtake race as the dominant factor determining survival and well-being.

The differences thus observed between fatalities and injuries present challenges to interpretation. As there is no precedent in the literature regarding substantive differences between fatalities and injuries, it is difficult to form reasonable conjectures about these differences. It is strongly suggested that future research be conducted to determine whether there is indeed something substantive in the differences between fatalities and injuries *vis-à-vis* similar variables, or whether different data collection strategies produced these results.

CONCLUSION

Are tornado deaths random events or can they be predicted, within a reasonable degree, by a model? The findings in this paper reveal that tornado deaths are not completely random, and that there are a host of environmental, organizational, demographic, and technological factors that appear to influence the chances of fatalities and injuries. This paper suggests a need for future research investigating the role of demographic and structural features of society in producing populations vulnerable to tornado events. Moreover, there is a need for further demographic analysis to determine why rural regions appear less vulnerable to tornados. Finally, another important area of future research is the role of warnings in public safety. For instance, it is strongly recommended that future studies should evaluate the shape of the relationship between lead time and the likelihood of tornado casualties. Findings may support challenging the established approach to protecting populations from tornadoes in the United States.

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Table 1. Descriptive Statistics (N=3590)

	Mean	Std. Dev.	Min	Max
Fatalities	0.07	1.03	0	36
Injuries	1.23	13.48	0	583
Tornado Area (mi^2)	0.23	1.44	0	39.74
Lead time	11.08	13.71	0	75
Percent Population in Rural Areas	77.86	34.13	0	100
Percent Mobile Homes	17.07	12.3	0	82.07
Average Household Size	2.58	0.27	1.03	4.62
Population Density (per mi^2)	306.36	1306.5	0.1	48539.5
Deprivation	70.89	24.37	15.89	197.42
Percent African-American	6.35	13.1	0	98.02

Table 2. Correlation Matrix (N=3590)

	X1**	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
X1	--										
X2	0.878*	--									
X3	0.331*	0.407*	--								
X4	0.040*	0.030	0.050*	--							
X5	0.020	0.017	0.030	-0.009	--						
X6	0.027	0.037*	0.008	-0.012	0.003	--					
X7	0.018	0.019	-0.001	0.069*	0.011	0.471*	--				
X8	-0.028	-0.052*	0.020	0.088*	0.013	-0.196*	-0.007	--			
X9	0.034*	0.008	0.003	0.063*	-0.011	0.248*	0.462*	0.257*	--		
X10	0.004	0.029	-0.015	-0.077*	-0.006	0.129*	0.045*	-0.455*	-0.209*	--	
X11	0.014	0.014	-0.008	-0.009	-0.016	0.022	-0.010	0.052*	0.149*	-0.034*	--

* $p<.05$

** X1 = Fatalities

X2 = Injuries

X3 = Tornado Area

X4 = Lead Time

X5 = Watch

X6 = Percent African-Americans

X7= Deprivation

X8= Percent Rural Population

X9 = Percent Mobil Home

X10 = Population Density

X11 = Average Household Size

Table 3. Model 1: Negative Binomial Regression, Fatalities (N=3590)

	b	z	P>z	e^b	e^bStdX	SDofX
Tornado Area (mi²)	1.49*	5.22	<.001	4.42	8.44	1.44
Lead Time	<0.01	0.14	0.885	1.00	1.03	13.71
Watch (1=Within, 0=Outside)	-0.05	-0.14	0.886	0.95	0.98	0.48
Percent African-American	<0.01	0.21	0.835	1.00	1.03	13.1
Deprivation Index	<0.01	1.06	0.291	1.01	1.24	24.37
Percent People Living in Rural Areas	-0.01*	-1.96	0.05	0.99	0.66	34.13
Percent Mobile Homes	0.04*	2.33	0.02	1.04	1.55	12.3
Population Density (per mi²)	<0.01	0.57	0.572	1.00	1.15	1306.5
Average Household Size	1.08	1.62	0.104	2.94	1.33	0.27
Constant	-7.32	1.98	-3.70	--	--	--

* *$p<.05$*

** Deviance: 863.078[4]

Chi-Square (H_0: All β_k=0): 109.32 ($p<.001$)[5]

McFadden's R^2: 0.112[6]

[4] Compares estimated model to a model with one parameter per observation so that the model reproduces perfectly the data.

[5] Tests the hypothesis that all regression weights are equal to zero.

[6] Compares model with just intercept to another with all parameters.

Table 4. Model 2: Negative Binomial Regression, Injuries (N=3590)

	b	z	P>z	e^b	e^bStdX	SDofX
Tornado Area (mi²)	1.64	7.76	<.001	5.14	10.48	1.44
Lead Time	-0.02*	-3.11	<.001	0.98	0.75	13.71
Watch (1=Within, 0=Outside)	-0.11	-0.56	0.57	0.9	0.95	0.48
Percent African-American	0.01	1.42	0.16	1.01	1.15	13.1
Deprivation Index	0.01*	3.04	<.001	1.01	1.4	24.37
Percent People Living in Rural Areas	-0.01*	-3.98	<.001	0.99	0.62	34.13
Percent Mobile Homes	0.02	1.84	0.07	1.02	1.24	12.3
Population Density (per mi²)	<0.01*	2.18	0.03	1.00	1.38	1306.5
Average Household Size	1.06*	3.29	0	2.89	1.33	0.27
Constant	-4.16	0.99	-4.19	--	--	--

* *p<.05*

** Deviance: 3971.264

Chi-Square (H_0: All β_k=0): 274.10 (p<.001)

McFadden's R^2: 0.065

Figure 1. Count Distribution of Fatalities

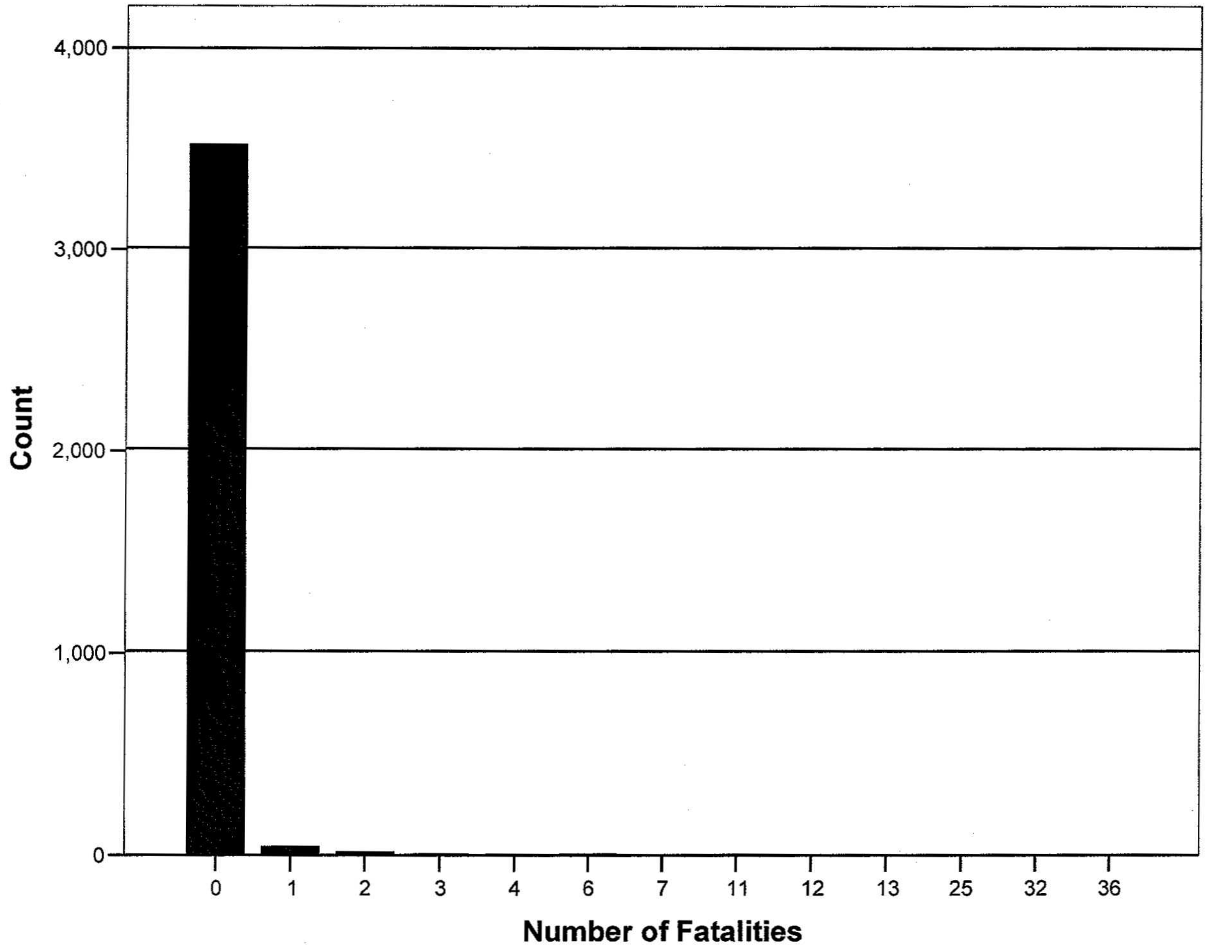


Figure 2. Count Distribution of Injuries

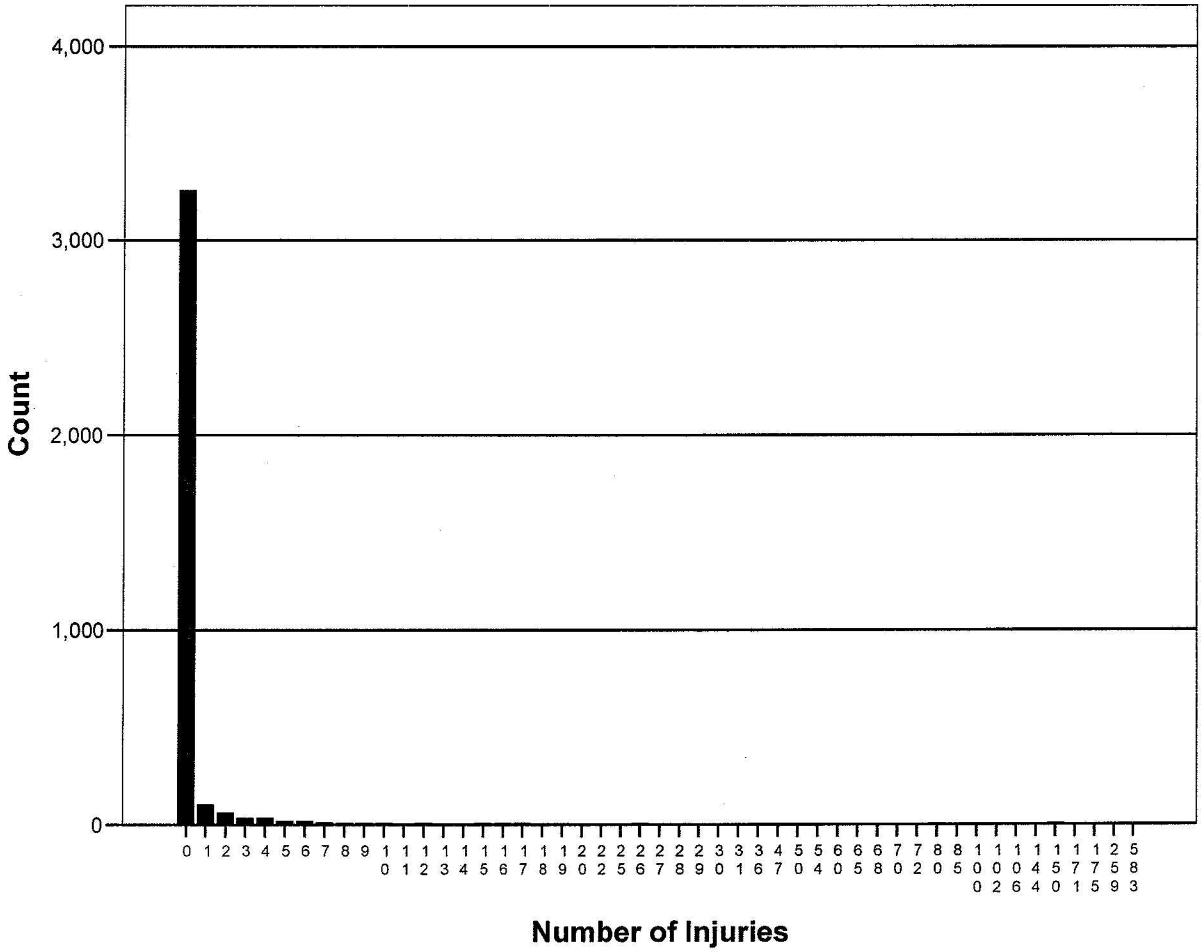


Figure 3. **Area Affected by Tornado**

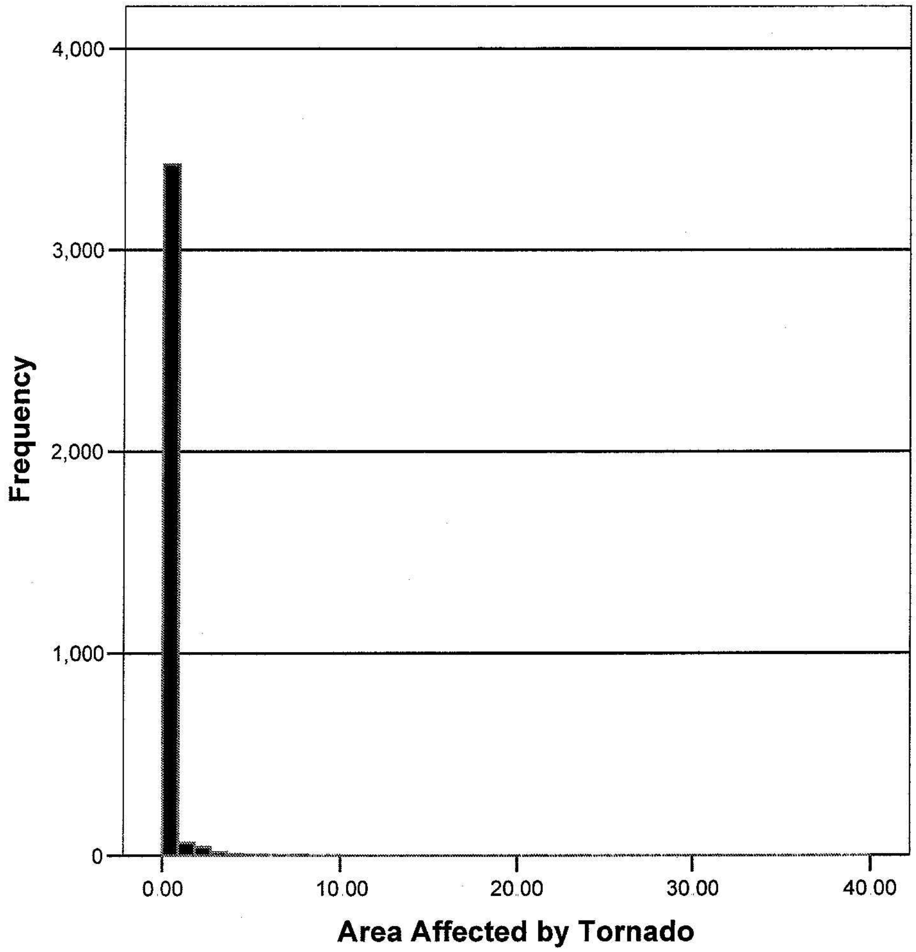
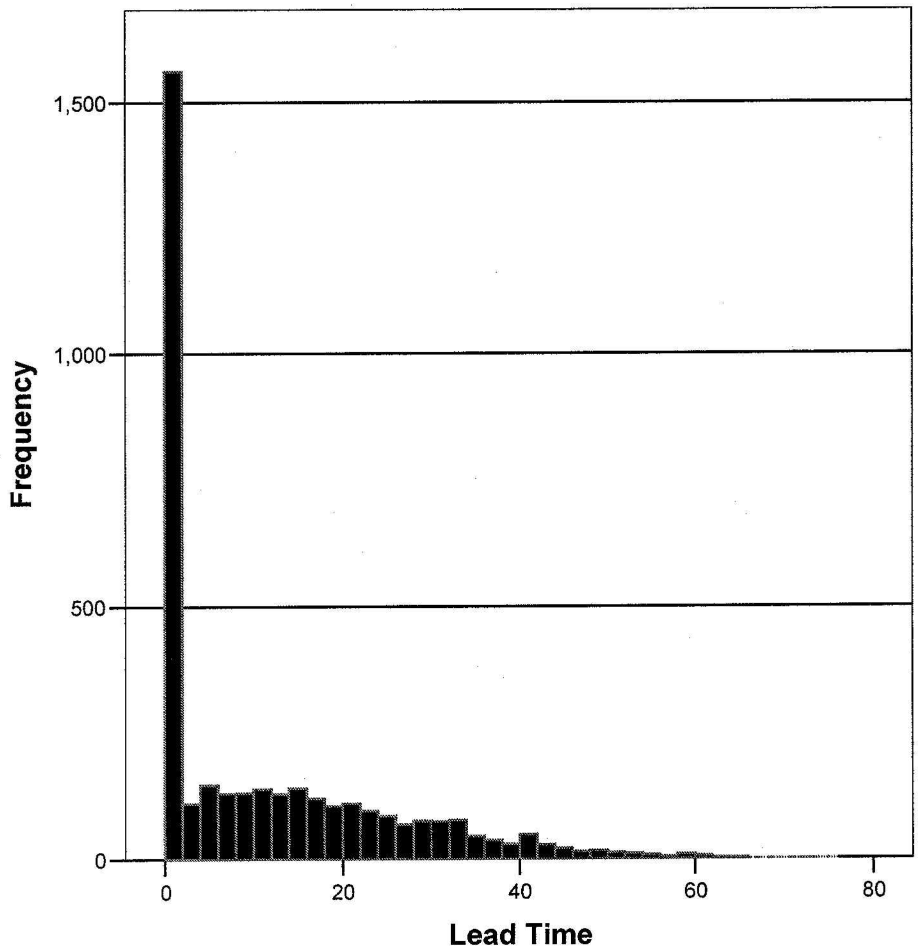


Figure 4. **Lead Time**[7]



[7] It should be noted that "0" represents cases in which no warning was issued, a warning was issued simultaneously with the onset of a tornado, or a warning was issued after the tornado went through a community. NWS data does not list lead time in seconds, thus inflating the number of "0s."