Population Influences on Tornado Reports in the United States

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ABSTRACT

The number of tornadoes reported in the United States is believed to be less than the actual incidence of tornadoes, especially prior to the 1990s, because tornadoes may be undetectable by human witnesses in sparsely populated areas and areas in which obstructions limit the line of sight. A hierarchical Bayesian model is used to simultaneously correct for population-based sampling bias and estimate tornado density using historical tornado report data. The expected result is that F2–F5 compared with F0–F1 tornado reports would vary less with population density. The results agree with this hypothesis for the following population centers: Atlanta, Georgia; Champaign, Illinois; and Des Moines, Iowa. However, the results indicated just the opposite in Oklahoma. It is hypothesized that the result is explained by the misclassification of tornadoes that were worthy of F2–F5 rating but were classified as F0–F1 tornadoes, thereby artificially decreasing the number of F2–F5 and increasing the number of F0–F1 reports in rural Oklahoma.

1. Introduction

Tornado report data form messy datasets. Direct measurement of tornado wind velocity is infrequent, because most tornadoes are short lived and have a horizontal dimension smaller than the minimum resolvable length of operational measurement systems. Human eyes and human interpretation of landscapes misaligned by windy storms are the basis of our best tornado detection system. Despite well-intentioned efforts, many nonmeteorological influences have corrupted the data. Among these are inconsistent reporting standards, unreported tornadoes, and reports of fictitious tornadoes (Forbes and Wakimoto 1983; Doswell and Burgess 1988). The number of tornadoes that occur in the United States is, therefore, an unknowable quantity, and estimates of tornado frequency are challenged by this circumstance in which human errors rather than meteorological factors are a primary cause of the spatial and temporal variabilities of tornado report frequency (Schaefer and Galway 1982; Grazulis and Abbey 1983; Brooks et al. 2003). Our interest is in quantifying such factors with the ultimate goal of isolating, to the extent possible given imperfect datasets, the human and meteorological influences.

An often-used, reasonable methodology for estimating tornado frequency is as follows: 1) select a region where the tornado climatology is expected to be nearly uniform, 2) estimate tornado frequency in a region where it is unlikely to be inaccurate, and 3) use statistical models to adjust the tornado frequency elsewhere by using explanatory variables that quantify obstructions to the line of sight (Twisdale 1982; Tescon et al. 1983; King 1997; Nixon et al. 2001; Ray et al. 2003). The statistical model, therefore, accounts for systematic miscounts as well as irregular errors arising from, for example, nonstandardized procedures for estimating tornado wind speed. Such models are valid to the extent that the tornado climatology is homogenous, the

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TABLE 1. Population centers and surrounding counties for which tornado reports were pooled. The first county listed contains the population center.

City and state	Surrounding counties
Atlanta, GA	Fulton, Cherokee, Forsyth, Gwinnett, Dekalb, Clayton, Fayette, Coweta, Carroll, Douglas, Cobb, Pickens, Dawson, Hall, Jackson, Barrow, Walton, Rockdale, Henry, Spalding, Pike, Meriwether, Troup, Heard, Cleburne, Cherokee, Haralson, Paulding, Bartow, Gordon
Champaign, IL	Champaign, Ford, Vermilion, Douglas, Piatt, McLean, Iroquois, Benton, Warren, Vermillion, Edgar, Coles, Moultrie, Macon, De Witt, Logan, Tazewell, Woodford, Livingston
Des Moines, IA	Polk, Story, Marion, Warren, Madison, Dallas, Boone, Hamilton, Hardin, Marshall, Tama, Pottawattamie, Mahaska, Monroe, Lucas, Clarke, Union, Adair, Guthrie, Greene, Webster
Oklahoma City, OK	Oklahoma, Canadian, Kingfisher, Logan, Lincoln, Pottawatomie, Cleveland, Caddo, Blaine, Major, Garfield, Noble, Payne, Creek, Okfuskee, Seminole, Pontotoc, McClain, Grady
Omaha, NE	Douglas, Pottawattamie, Harrison, Shelby, Cass, Montgomery, Mills, Sarpy, Saunders, Dodge, Washington, Monona, Crawford, Carroll, Audubon, Adair, Adams, Taylor, Page, Fremont, Cass, Lancaster, Seward, Butler, Colfax, Cuming, Burt
Tulsa, OK	Tulsa, Creek, Osage, Washington, Rogers, Wagoner, Okmulgee, Lincoln, Pawnee, Chautauqua, Montgomery, Osage, Nowata, Craig, Mayes, Cherokee, Muskogee, Mclntosh, Hughes, Seminole

explanatory variables are appropriate, and the mathematical relationship between tornado reports and explanatory variables is apparent.

We have applied to this problem a statistical modeling framework that is an alternative to the more traditional framework in which time series of tornado reports are viewed as independent, identically distributed (iid) samples from a theoretical population given by a probability distribution. Our approach uses the framework of Bayesian hierarchical models (BHMs; e.g., Berliner et al. 1999; Wikle 2003; Gelman et al. 2004). The advantage of BHMs is that complex process models that explain fluctuations of tornado reports, which are considered data inhomogeneities to be avoided from the iid perspective, may be incorporated formally into statistical inference, while mathematically rigorous estimation procedures for model parameters are retained. The potential utility of BHMs to the problem of estimating tornado frequency is that the variability of tornado reports due to societal and meteorological factors may be modeled simultaneously by separate models, so long as appropriate data are identified. In this initial implementation, we present results from the model applied under the assumption of a homogenous tornado climatology to examine its validity by comparison to results from other models developed under that assumption.

2. Data

We obtained tornado reports for the period 1953–2001 from the Storm Prediction Center (SPC) archive of storm reports (available online at http://www.spc.noaa.gov) and the Grazulis significant tornado volumes (Grazulis 1993). We counted tornado reports for counties in which large population centers reside and in surrounding less populated counties. We selected population centers located along the C-shaped axis of relatively high tornado probability reported by Brooks et al. (2003): Atlanta, Georgia; Champaign, Illinois; Des Moines, Iowa; Oklahoma City, Oklahoma; Omaha, Nebraska; and Tulsa, Oklahoma (Table 1).

The tornado report data supplied to the model are organized as follows. Generally, we have counts of tornado reports n_{ikt} for the ith Fujita scale (F scale) rating, $i = 0, \ldots, 5$, aggregated over the kth county, $k = 1, \ldots, K$, and tth year, $t = 1, \ldots, T$. However, because the number of annual counts for F4 and F5 tornadoes can be small, we aggregate additionally over the F-scale rating and time. Thus, we have spatially varying counts n_k summed over ranges of F-scale ratings (F0–F1 and F2–F5) and years (1953–2001).

A wide variety of data have been used to account for factors that make tornadoes difficult to observe, such as the density of trees and hills, the absence of roads and buildings, and population density (Twisdale 1982; Tescon et al. 1983). Because the public has not always actively reported tornado sightings or chased after thunderstorms in hopes of seeing a tornado, we use a measure of population as a covariate, presuming that for some level of population a tornado is extremely hard to ignore, even with an unmotivated observing system. Furthermore, the population data facilitates comparisons with previous work. Previous studies have measured population with either county population density or rural population density. County population density can be skewed by the presence of a few cities and large towns and may not be representative of the density of humans and human-built structures in rural areas. Changnon (1982) argues, therefore, that rural population density rather than county population density is a more faithful measure of capability for tornado detection. The central counties in our analysis contain large metropolitan areas that cover a large fraction of the county area. Because the population density is large over much of the county rather than concentrated in isolated towns, rural population density is not a reasonable explanation of why tornado frequency is expected to be observed well in the central counties. Therefore, we use population density as an explanatory variable. We compute county population density as the average of population density reported in the 1960–2000 U.S. decennial censuses (information online at http://www.census.gov).

3. Methodology

a. "Distance" sampling approach

We know that the reported number of tornadoes in a particular county over the time period of interest is unlikely to be the true number. We make the assumption that the reported tornadoes are an "undercount" of the actual incidence of tornadoes. That is, the true number of tornadoes over the same level of aggregation (N_k, an unobservable quantity) is greater than or equal to that reported ($N_k \geq n_k$). In other words, we must account for the fact that the probability of detecting a tornado is most likely not one. However, as will be seen in the model description, the a priori condition of the model is no population effect, and relationships between population density and tornado counts emerge in the *posterior* distributions formed by updating with the tornado count data alone.

The nature of the relationship between population density and tornado underreporting in our stochastic model is motivated by noting its striking similarity to the problem of estimating animal density in ecological applications, using "distance sampling" methods (Buckland et al. 2001; Williams et al. 2002). Like the tornado undercount problem, animal density estimates presume an undercount because hindrences to line-of-sight observations. In that context, the probability of detecting an animal decreases as a function of distance from the observer. In the case of tornado observations, we reduce the probability of detection as the population density becomes smaller.

Royle et al. (2004) developed a hierarchical formulation of the classical distance-sampling model that is amenable to modeling spatial variations in animal abundance. We adopt that basic formulation here, in which we first specify a binomial model for the reported number of tornadoes in a given county conditional on the local abundance N_k, which corresponds to the true number of tornadoes in the kth county. The binomial distribution is a discrete distribution (Bain and Engelhardt 1992) widely used in situations in which one thinks of n_k as the number of "successes" (in our case, reported tornadoes) in N_k independent Bernoulli trials (in our case, actual tornadoes), where the probability of success for each trial (in our case, the probability of detecting a tornado when it occurs) is given by $p_k(\theta)$, which, as shown below, is an increasing function of population density at the kth spatial location. The formal relationship between the reported number of tornadoes n_k and the actual number of tornadoes N_k is given by the following conditional binomial data model:

$$n_k | N_k, p_k(\theta) \sim \text{Binomial}[N_k, p_k(\theta)]. \quad (1)$$

We have selected small geographical regions, so that it is reasonable to expect that the climatological frequency of tornadoes is similar across the region. We would not expect this number to be identical at all locations, since, by chance, irregular spatial variations may occur. Thus, we model the true climatological tornado count in the kth county, N_k, as a homogenous Poisson process (Bain and Engelhardt 1992) conditioned on a climatological frequency λ:

$$N_k | \lambda \sim \text{Poisson}(\lambda a_k), \quad (2)$$

where a_k is the area of county k. The Poisson parameter λ, referred to as the Poisson intensity, may be interpreted as a measure of the climatological tornado frequency per unit area.

We note that the probability of detection in (1) is a function of a parameter, θ, that is related to the population density. We assume that the probability of detection will be higher when the population density is greater. Thus, a plausible model is the exponential model:

$$p_k(\theta) = g(x_k; \theta) = \exp(-\theta / x_k), \quad (3)$$

where x_k is the population density of the kth county. In this model, when the ratio of θ to the population density is large, the probability of detection is near zero, and when the ratio is small, the probability of detection is near one.

We have tested alternative formulations of $g(x_k; \theta)$, including a step function, and we have reached the same general conclusions concerning population density and the probability of detection. We suspect the reason for this relative insensitivity to model specification is the flexibility of the exponential function. The parameter θ determines the magnitude of change of the probability of detection when the population density is changed. For very small values of θ, the graph of $g(x_k; \theta)$ when plotted as a function of x_k is similar to a step function; whereas, the graph when θ is large approaches that of a linear function. More complicated functions of many parameters could, in principle, be considered. However, note that with the relatively small amount of data available here, there may not be sufficient information to adequately estimate those parameters.

b. Estimation

We use a Bayesian approach for parameter estimation. Unlike the simple algorithms used in maximum likelihood and least squares estimation procedures, Bayesian estimation contains many design considerations. For a general overview of Bayesian modeling and inference see, for example, Congdon (2001) and Gelman et al. (2004). For recent examples in the atmospheric science literature see Berliner et al. (1999), Elsner and Jagger (2004), Elsner et al. (2004), and Wikle and Anderson (2003). Although one can use likelihood approaches to estimate λ and θ (Royle et al. 2004), the corresponding estimates of N_k in those cases do not account for the uncertainty associated with the parameter estimates of λ and θ. The Bayesian approach allows one to account for this uncertainty. In this context, we must specify prior distributions for θ and λ. We assign prior distributions that are flat—containing no peaks—because we have no information guiding our choice of the most likely values. Prior distributions of this type are called noninformative, because the data will determine whether the posterior distributions contain peaks.

For the population effect parameter, θ, we specify the following prior distribution:

$$\exp(\theta) \sim N(\mu_\theta, \sigma_\theta^2), \tag{4}$$

where this simply states that $\exp(\theta)$ follows a normal distribution with mean μ_θ and variance σ_θ^2 [or, equivalently, that θ follows a lognormal distribution with the same mean and variance; Bain and Engelhardt (1992)]. The prior mean and variance are 0.5 and 10 000, respectively. Note that the large variance implies that this prior distribution is noninformative.

For the climatological frequency parameter λ, we specify the following prior distribution:

$$\lambda \sim \text{gamma}(q, r), \tag{5}$$

where gamma(q, r) refers to a gamma distribution (Bain and Engelhardt 1992) with a shape parameter q and a scale parameter r such that the mean is given by q/r and the variance by q/r^2. The values are $q = 0.001$ and $r = 0.001$ (corresponding to a prior mean of 1 and a prior variance of 1000). Again, the large variance implies that the prior is noninformative.

In this Bayesian paradigm, rather than considering the point estimates of the true tornado counts and parameters of interest, we obtain an updated (i.e., posterior) distribution of all parameters given the tornado reports: $p(\theta, \lambda, N_1, \ldots, N_k | n_1, \ldots, n_K)$. By Bayes's rule, this posterior distribution is proportional to the binomial data model [(1)] times the homogenous Poisson process model [(2)] times the prior distributions [(4) and (5)]:

$$p(\theta, \lambda, N_1, \ldots, N_k | n_1, \ldots, n_K) \propto \prod_{k=1}^{K} p(n_k | N_k, \theta) p(N_k | \lambda) p(\theta) p(\lambda), \tag{6}$$

where the proportionality constant is given by the integral of the right-hand side of the equation with respect to $N_1, \ldots, N_k$, θ, and λ [i.e., the marginal distribution of the data, $p(n_1, \ldots, n_K)$]. For all but some very simple cases, one cannot find this proportionality constant analytically. However, one can use numerical procedures such as a Markov chain Monte Carlo (MCMC) scheme to obtain Monte Carlo samples from this posterior distribution [see Congdon (2001), Gelman et al. (2004), and Robert and Casella (2004) for discussions of Bayesian estimation and numerical approaches].

We use the freely available WinBUGS software (online at http://www.mrc-bsu.cam.ac.uk/bugs/welcome.shtml) to perform the MCMC analysis of the Bayesian model with these data. An example of the WinBUGS code for this analysis is given in the appendix.

4. Results

In the following discussion of the results, we refer to λ as the climatological tornado density, although strictly this is a parameter of a Poisson distribution. We refer to θ as the population effect. When θ is large, the ratio of θ to x_k is large for counties with small population density, and (2) dictates a small probability of detection for those counties. If θ is small, the ratio is small for all counties, so that the probability of detection is near one for all counties. We report the maximum ($p_{\max}$) and minimum ($p_{\min}$) probabilities of detection as alternative measures of the population density effects that may be roughly thought of as the maximum and minimum fractions of the climatological tornado counts that are reported and classified correctly.

TABLE 2. Population effect parameter (θ), tornado density parameter (λ), and maximum and minimum probabilities of detection (p_{max}, p_{min}) for all tornado reports and F2–F5 reports (in parentheses), where N/A means not available. All results are valid for the SPC severe storm archive, except those labeled "Oklahoma City, Grazulis" for which data were obtained from the Grazulis volumes.

City	θ	λ	p_{max}	p_{min}
Oklahoma City, Grazulis	N/A (11.960)	N/A (0.0176)	N/A (0.9849)	N/A (0.2558)
Oklahoma City	7.343 (13.020)	0.0723 (0.0314)	0.9907 (0.9836)	0.6022 (0.2177)
Oklahoma City, 1953–73	10.540 (14.690)	0.0385 (0.0201)	0.9847 (0.9787)	0.4463 (0.1740)
Oklahoma City, 1974–2001	3.541 (10.740)	0.0343 (0.0124)	0.9959 (0.9876)	0.6931 (0.3192)
Tulsa	9.920 (14.060)	0.0406 (0.0260)	0.9880 (0.9830)	0.2800 (0.1700)
Atlanta	22.010 (0.0800)	0.0189 (0.0080)	0.9880 (1.0000)	0.4000 (0.9970)
Champaign	24.150 (0.0010)	0.0644 (0.0099)	0.8910 (1.0000)	0.3400 (0.9950)
Des Moines	17.410 (0.0007)	0.0410 (0.0115)	0.9687 (1.0000)	0.3600 (0.9960)
Omaha	0.003 (0.0030)	0.0253 (0.0193)	1.0000 (1.0000)	0.9998 (0.9980)

a. Sensitivity to the dataset

We examined the model sensitivity to reporting procedures by comparing results obtained from two different datasets: the SPC severe weather log and the Grazulis volumes. The Grazulis dataset is unique in that a single person classified all tornado reports, and, therefore, it is less susceptible to variability caused by inconsistent reporting standards. The Grazulis significant tornado reports are comparable to F2–F5 tornado reports in the SPC log. We summed tornado reports for the entire period of record, 1953–2001, for the Oklahoma City, Oklahoma, region.

Comparison of λ (Table 2) indicates that a higher climatological tornado density is derived from the SPC reports of F2–F5 tornadoes compared with significant tornado reports in the Grazulis volumes. This is consistent with the results reported in Brooks (2000) that show a higher incidence of national F2–F5 reports in the SPC log compared with Grazulis's number of significant tornadoes. Despite the disparity in climatological frequency, the differences between p_{max} and p_{min} are similar in the two datasets, indicating a similar population effect. These results suggest that the inconsistency of reporting standards may have substantially influenced the overall frequency but had less impact on the spatial variability of the reports.

b. Regional dependence of population effects

We present results of population effects derived from the SPC dataset only, and, unless otherwise stated, the results are valid for the entire period of record, 1953–2001. When a tornado occurs, there are four possible report outcomes: correct classification, underestimated F-scale rating, overestimated F-scale rating, or unreported. The SPC log may also include reports of phenomena mistakenly thought to be tornadoes, which are unaccounted for in our statistical model.

It has been argued that because F2–F5 tornadoes are generally larger and longer lived than F0–F1 tornadoes and are, therefore, harder to either be ignored or go unseen, the reported incidence of F2–F5 compared with F0–F1 tornadoes is less affected by unreported tornadoes (Concannon et al. 2000; Brooks 2004). Thus, the disparity of tornado reports between high and low population density counties might be expected to be smaller for F2–F5 compared with F0–F1 tornado reports. In the context of our model, such a relationship would be manifested as higher p_{min} for F2–F5 compared with F0–F1 tornado reports. This expected relationship is evident in Champaign, Illinois; Atlanta, Georgia; and Des Moines, Iowa. Results for Omaha, Nebraska, show an almost perfect probability of detection in all counties for both F2–F5 and F0–F1 tornadoes. However, in the Oklahoma City and Tulsa regions, the results show the opposite, where p_{min} is larger for F0–F1 compared with F2–F5 tornadoes.

A number of factors may explain the unexpectedly large disparity of F2–F5 tornado reports between population centers and rural areas in Oklahoma. First, it is possible the tornado climatology is inhomogeneous. Three of the four lowest values of population density, and, therefore, probability of detection, occur in counties along the northwestern periphery of the Oklahoma City region (Major, Blaine, Kingfisher; Table 3). Nixon et al. (2001) identified regions in which temporal variations of monthly tornado counts were similar, using principle component analysis. A dividing line between two regions was found in central Oklahoma. Thus, it is possible that two factors are at play in these three counties: a lower incidence of actual tornadoes, and a population effect. Our model accounts only for the population effect. We have tested the sensitivity of our results to the data from these three counties by removing them from the dataset and updating the a priori distributions. Results differ only in that the minimum probability of detection is larger than when including the three northwestern-periphery counties. The unexpected popula-

TABLE 3. County population density (x_k, persons per square mile), county area (a_k, mi^2), reported number of tornadoes (n_k), and mean, standard deviation, and 2.5 and 97.5 percentiles from the posterior distribution of the adjusted number of tornadoes (N_k) and the probability of detection (p_k).

County	Population density	County area	No. of reported tornadoes	Posterior			Posterior		
				Mean	Std dev	2.5 and 97.5 percentiles	Mean	Std dev	2.5 and 97.5 percentiles
K	x_k	a_k	n_k	N_k	N_k	N_k	p_k	p_k	p_k
Oklahoma	788.298	709	74	74	0.698	74, 76	0.9907	0.00168	0.9874, 0.9940
Cleveland	240.537	536	45	46	1.118	45, 49	0.9699	0.00541	0.9592, 0.9805
Payne	83.630	686	38	42	2.259	39, 47	0.9161	0.01470	0.8870, 0.9450
Pottawatomie	67.049	788	47	52	2.759	48, 59	0.8964	0.01794	0.8611, 0.9319
Canadian	61.236	900	61	68	3.152	63, 75	0.8872	0.01944	0.8490, 0.9256
Creek	57.205	956	46	54	3.420	49, 62	0.8798	0.02064	0.8393, 0.9206
Garfield	53.984	1058	56	65	3.771	59, 74	0.8731	0.02171	0.8305, 0.9160
Pontotoc	43.856	720	41	49	3.330	43, 56	0.8462	0.02590	0.7957, 0.8977
Seminole	41.419	632	40	47	3.170	42, 54	0.8380	0.04943	0.7850, 0.8920
Logan	34.414	745	37	47	3.902	41, 56	0.8085	0.03153	0.7473, 0.8715
McClain	34.307	570	35	42	3.291	37, 50	0.8079	0.03161	0.7466, 0.8712
Grady	33.732	1101	52	67	5.135	59, 79	0.8050	0.03203	0.7429, 0.8691
Lincoln	26.322	959	57	73	5.376	64, 85	0.7575	0.03864	0.6833, 0.8354
Caddo	23.179	1278	88	113	7.123	100, 128	0.7297	0.04227	0.6489, 0.8153
Okfuskee	18.207	625	29	44	4.864	35, 54	0.6699	0.049430	0.5766, 0.7711
Noble	14.877	732	28	48	5.980	38, 61	0.6129	0.001219	0.5098, 0.7275
Kingfisher	14.354	903	45	71	7.070	58, 86	0.6022	0.056400	0.4974, 0.7191
Blaine	13.086	929	33	61	7.527	48, 78	0.5735	0.058950	0.4648, 0.5706
Major	8.300	957	30	70	9.164	53, 89	0.4183	0.068040	0.2989, 0.5655

tion effect was unaffected. Furthermore, the Tulsa region is contained within a homogenous region in the analysis by Nixon et al. (2001), and, yet, the unexpected relationship is evident in that region. Such vagaries in our analysis and others may be removed if meteorological data independent of tornado reports are used within the statistical model that accounts for population effects, which is possible with the BHM approach.

Second, it is possible that changes in reporting standards over the period may be a factor. Brooks and Craven (2002) present evidence that suggests the national database of F2–F5 reports contains overrated tornadoes prior to 1973. Prior to 1974, tornado ratings were assigned by reviewing newspaper articles. After that time, National Weather Service (NWS) employees performed on-site damage analysis when determining F-scale ratings. If the results for Oklahoma City were consistent with the national database, $p_{\min}$ during 1953–73 would be larger for F2–F5 compared with F0–F1 tornadoes, because F2–F5 reports that were overrated would be increased at the expense of F0–F1 reports. We examined this possibility by accumulating tornado reports and averaging census data for the subperiods 1953–73 and 1974–2001. The effects of the change in reporting standards are obvious in the values for λ. The value of λ for F2–F5 tornado reports during 1953–73 is nearly twice that in 1974–2001, despite a shorter period of record; whereas a comparatively small change is evident in λ for F0–F1 tornado reports. However, the results show that the unexpected large disparity of F2–F5 tornado reports occurred in both periods, although the population effect is, as expected, much smaller in the 1974–2001 period (θ is smaller in that period). Caution is warranted when interpreting these results as the small sample size for the subperiods creates significant overlap of the posterior distributions for the two periods, meaning the differences in parameter estimates may not be statistically significant. Nevertheless, the results do not support the notion that the unexpectedly large disparity of F2–F5 tornado reports was related to the change in the reporting methodology in 1974.

Third, it is possible that tornado statistics in Oklahoma might differ from elsewhere in part because of the activities of the National Severe Storm Project (NSSP), which sent scientific teams in search of tornadic storms beginning in the late 1950s (NSSP 1963). It is not clear how these efforts might affect the tornado climatology, because the NSSP database was not consulted by the persons responsible for assigning F-scale ratings prior to the change in the reporting methodology in 1974.

Fourth, it is possible that some tornadoes in Oklahoma were underrated because of sparse buildings or poor construction, so that the number of F0–F1 tornadoes reported was inflated by reports of tornadoes that would have produced F2–F5 damage. Excluding Major and Blaine Counties (it is possible the tornado climatology is different there, as discussed above), the fraction of F0–F1 tornadoes that would need to be reclassified as F2–F5 tornadoes in order for their results to be similar to those found for Champaign, Atlanta, and Des Moines is 10%–30% in 12 counties, 50% in 3 counties, and 0% in 1 county.

The primary purpose of the statistical adjustment of tornado counts has been to improve estimates of tornado risk in hazard models (Tescon et al. 1983; Schaefer et al. 1986; Nixon et al. 2001; Meyer et al. 2002; Ray et al. 2003). Though the intended use of our model differs, it also may be used to estimate the number of unreported tornadoes. We report for the Oklahoma City region a range of the ratio of reported to adjusted tornado counts, using the adjusted counts at the 2.5 and 97.5 percentiles in the posterior distribution of N (Table 3). In Oklahoma County (highest population density), the range is 0.97 to 1.00; whereas, in Major County (lowest population density), the range is 0.33 to 0.54. The ranges are consistent with results from previous studies, though the range for Major County is near the lower end of the reported values. Thus, different statistical approaches have resulted in different ranges that overlap the results of our model, lending confidence that our modeling approach provides a reasonable estimate of the actual range.

5. Conclusions

We have evaluated the relationship between the probability of detection of tornadoes and the population density for regions around several large cities in the central and eastern United States. The results indicate that population density effects have regional variability. This may reflect one or many demographic factors including, but not limited to, quality of construction, rural construction density, or regionally varying reporting standards. The following are our main conclusions.

- In Oklahoma, the probability of detection of F0–F1 tornadoes in rural areas exceeds that of F2–F5 tornadoes. We hypothesize that in rural areas F2–F5 tornadoes have been underestimated on the Fujita scale, inflating the incidence of F0–F1 tornadoes in these areas. The estimated ratio of the reported to the actual number of tornadoes varies between 0.97 and 1.00 in Oklahoma County and 0.33 and 0.54 in Major County, within the range reported elsewhere.
- Near Atlanta, Georgia; Des Moines, Iowa; and Champaign, Illinois; the probability of detection of F2–F5 tornadoes in rural areas is greater than that for F0–F1 tornadoes, which is consistent with the hypothesis that F2–F5 tornadoes are more faithfully detected because of their comparatively large size and long duration.
- Population effects in the Omaha, Nebraska, area were not evident.

The results indicate that some of the spatial variability found in tornado reports may be modeled by a measure of human population density. In this pilot study, we limited the domain of analysis to the vicinity of population centers, where we presumed a uniform climatological frequency of tornadoes over the analysis region. We used population density to adjust tornado counts for population effects. The ability of the model to uncover different but sensible relationships between the probability of detection and the population density lays the groundwork for more ambitious studies of population and meteorological effects in all regions. An extension of this work might be to use climatological information such as meteorological indices relevant to tornado frequency (Brooks and Craven 2002) or radar velocity data. Furthermore, alternative measures of human activity should be examined, such as maps derived from nighttime lights. It is a challenge to estimate the statistical model parameters given the spatial and temporal variabilities of the climatological data. However, Bayesian hierarchical models provide a rigorous estimation procedure and have been used effectively in similar climatological studies (Wikle and Anderson 2003; Elsner and Jagger 2004; Elsner et al. 2004).

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APPENDIX

WinBUGS Code for Oklahoma City Region

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model
{
   alpha~dnorm(0.5, 0.0001)
   beta < -exp(alpha)
   lambda~dgamma(0.001, 0.001)
   for (i in 1:19) {
     p[i] < -exp(-beta/x[i])
```

```
     lambdal[i] < -lambda*area[i ]
     bign[i]~dpois(lambdal[i])
     sn[i]~dbin(p[i], bign[i])
  }
}
Data
list(
sn = c(33, 18, 12, 13, 23, 21, 18, 31,
       6, 9, 16, 6, 14, 18, 9, 23, 19,
       10, 22),
area = c(709.2, 899.9, 903.1, 744.6,
         958.6, 787.9, 536.2, 1278.4,
         928.6, 956.8, 1058.5, 732.0,
         686.4, 955.6, 624.8, 632.5,
         719.7, 569.7, 1101.0),
x = c(788.297518, 61.235693, 14.354335,
      34.413914, 26.322136, 67.049118,
      240.537486, 23.178504, 13.086367,
      8.300376, 53.983562, 14.876503,
      83.629662, 57.204897, 18.207106,
      41.419447, 43.856051, 34.306828,
      33.732425)
)
Inits
list(alpha = 0.5,
     lambda = 1,
     bign = c(100, 100, 100, 100, 100,
              100, 100, 100, 100, 100,
              100, 100, 100, 100, 100,
              100, 100, 100)
)
```

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