Population Influences on Tornado Reports in the United States

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28 April 2005

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. We use a hierarchical Bayesian model 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 to F0-F1 tornado reports would vary less with population density. The results agree with this hypothesis for the following population centers: Atlanta, GA; Champaign, IL; Des Moines, IA. However, the results indicated just the opposite in Oklahoma. We speculate the result is explained by misclassification of tornadoes that were worthy of F2-F5 Fujita scale 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. Despite well intentioned efforts, many non-meteorological influences have corrupted the data. Among these are inconsistent reporting standards, unreported tornadoes, and reports of fictitious tornadoes (Doswell and Burgess 1988, Forbes and Wakimoto, 1983). A difficult analytical circumstance has evolved in which human errors are a primary cause of spatial and temporal variability of tornado report frequency (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, human and meteorological influences.

Direct measurement of tornadoes is unusual, since most tornadoes are short-lived and have horizontal dimension smaller than the minimum resolvable length of operational measurement systems. Human eyes and human interpretation of landscape misaligned by windy storms are the basis of our best tornado detection system. Since exact measurements of tornadoes are not made, adjustments rather than exact corrections of tornado counts are applied to account for effects of nonstandard observing practices and irregular errors. However, results depend on choices of adjustment model and explanatory variables. Many explanatory variables have been proposed (the most extensive list is given in Tescon et al. 1983). Variable selection is governed by the common theme that each variable quantifies some sort of hindrance to human detection of tornadoes – lakes, trees, hills, absence of roads, and so on. Population density measures are the most popular explanatory variables. Because these data are readily available from census bureaus and relate directly to landscape measures, adjustment models based upon population density measures are relatively simple and interpretable models that require minimal data collection effort.

Model design is inspired by characteristics of the data set. Thus, a variety of models have been proposed (Tescon et al. 1983, King 1997, Nixon et al. 2000, Ray et al. 2003). It is less important to adopt a single modeling approach than it is to determine whether conclusions and quantitative results are in agreement when different modeling approaches are used. Results from Schaefer and Galway (1982), Nixon et al. (2000), and Ray et al. (2003), which all use very different methodologies, suggest a conservative estimate of the fraction of reported to actual tornadoes is about 0.6. Evidence is presented in King (1997) and Nixon et al. (2000) that this fraction has geographic variation.

This note describes a novel approach for estimating population influences on tornado report frequency that 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 may be incorporated into statistical inference, while mathematically rigorous estimation procedures are retained. The methodology outlined in subsequent sections permits separate, yet probabilistically linked, models for the probability of detection and climatological frequency of tornadoes. A fundamental assumption of our model in this application is that the region under analysis is small enough to presume homogeneous climatological tornado frequency. Variability of aggregated tornado counts over relatively small spatial regions is modeled from two primary sources. First, the variability associated with probability of detection is modeled via a nonlinear dependence on population density. Second, the natural spatial variability of true tornado intensity around its climatological mean is modeled via a homogeneous Poisson process. The results shed new insight into how these different sources of variability contribute to tornado report differences over relatively small spatial domains.

2 Data

We obtained tornado reports for the period 1953-2001 from the Storm Prediction Center (SPC) archive of storm reports (http://www.spc.noaa.gov) and the Grazulis significant tornado volumes (Grazulis 1993). We summed the reports by county and various subperiods of the 1953-2001 period. We computed tornado report counts for large population centers and the surrounding two tiers of counties (Table 1). Population centers in our analysis are Atlanta, GA; Champaign, IL; Des Moines, IA; Oklahoma City, OK; Omaha, NE; and Tulsa, OK. These population centers are located along the C-shaped axis of relatively high tornado probability reported by Brooks et al. (2003).

Previous studies have measured county 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 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 obtained population density data from the 1990 United States census (http://www.census.gov).

3 Methodology

Generally, we have counts of tornado reports n_{ikt} for the i-th Fujita scale (F-scale) rating, $i = 0, \ldots, 5$, aggregated over the k-th county, $k = 1, \ldots, K$ and t-th 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 or F2-F5) and years (e.g., 1953-2001). However, we know that we have not observed the actual number of tornadoes that have occurred in a particular county over the time period of interest. We make the assumption that we have an “undercount”. 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. Furthermore, it is likely that this probability of detection varies geographically according to population density (Nixon et al. 2000). To motivate the nature of this relationship, we note that the present problem bares a striking similarity to the problem of estimating animal density in ecological applications, using “distance sampling” methods (Buckland et al. 2001; Williams et al. 2002).

3.1 “Distance” Sampling Approach

In classical distance sampling methods, animals are counted by an observer from a stationary point or transect, and the distance from the point of observation to the animals is measured. In some applications where it is difficult to obtain precise distance measurements, animals are counted relative to K discrete distance classes ($k = 1, 2, \ldots, K$) from a point of observation. Let $N_k, k = 1, \ldots, K$ be the number of animals in each distance class available to be counted. In the vast majority of animal sampling problems, abundance is not observed directly. Instead, one observes a biased count $n_k \leq N_k$, owing to the fact that animals are elusive and may go undetected even if they are present. The most common assumption to express the relationship between the observed counts n_k and the population sizes N_k, is the binomial sampling model

$$n_k \sim \text{Bin}(N_k, p_k(\theta)), \tag{1}$$

where $p_k(\theta)$ is a function of the distance from the point of observation and some parameter θ. More precisely, when counts in discrete distance classes are collected, $p_k(\theta)$ is an integral of some distance function. For example, a common distance function is the half-normal $g(x;\theta) = exp(-x^2/\theta)$, where x is the distance from the point of observation and θ is a scale parameter to be estimated. Thus, the probability that an individual in distance class k is detected is equal to

$$p_k(\theta) = \int_{c_k}^{c_{k+1}} g(x;\theta)dx,$$

where c_k and c_{k+1} are the lower and upper bounds, respectively, of distance class k.

We note that explicit in this development is the intuitive notion that animals are more difficult to observe as their distance from the point of observation increases. The parameter θ determines the relative detectability of animals as a function of distance. Large values of θ indicate less of a decrease in detectability as distance increases, and vice versa. That is, θ is the effect of the covariate "distance from point of observation". Conceptually, however, there is no reason at all that x need be Euclidean distance. In the present application, we suppose that the detectability of tornadoes is primarily affected by population density. Thus, we equate $x = x_k$ to the inverse of population density for the k-th county, N_k to actual (unobserved) tornado abundance in the county, and n_k the respective observed tornado counts. In the present application of adjusting for imperfect detection in estimation of tornado density, the observations are not pooled into distance classes. However, it is reasonable to assume that pooling according to county is analogous, with differing population densities corresponding to distance. Thus, in this case we equate $p_k(\theta) = g(x_k; \theta)$.

Thus far, we have not specified additional model structure on N_k. The assumption made in classical distance sampling applications is that animals are uniformly distributed over the area being sampled. That is, animal locations are a homogeneous Poisson point process. Although clearly not the case with tornado frequency over large spatial domains, this is a reasonable assumption over relatively small spatial areas in which the climatology is the same. Under this assumption, we have that $N_k \sim \text{Poisson}(a_k\lambda)$ where a_k is the area of the k^{th} distance class (in our case, the k^{th} county). Note also that $N = \sum_k N(k)$ is Poisson with mean $\lambda \sum_k a_k$. Then, the distribution of $N_k, k = 1, \ldots, K$ conditional on the total N is multinomial with cell probabilities $a_k\lambda/(\lambda \sum a_k) = a_k/(\sum a_k)$. Finally, the distribution of the sample counts $\{n_k\}_{k=1}^{K}$ conditional on the total population size N, under the binomial sampling assumption, is also multinomial of the form

$$f(\{n_k\}_{k=1}^K|N) \propto \left\{\prod_{k=1}^K \left(\frac{a_k p_k(\theta)}{\sum a_k}\right)^{n_k}\right\}\left(1-\sum_k p_k(\theta)\right)^{N-\sum_k n_k}, \tag{2}$$

where the last cell of this multinomial corresponds to those individuals not detected. This is the distance sampling likelihood when data are recorded into distance intervals (in our case, counties). Estimation of the unknown parameters θ and N may be based on this likelihood.

In some cases, it is convenient to remove N from (2) by integrating over the distribution of N (recall that $N \sim \text{Poisson}(\lambda \sum_k a_k)$). In this case, the n_k are, marginally, independent Poisson random variables with mean $a_k p_k(\theta)\lambda$. A more complete discussion of the integrated likelihood approach to estimation in distance sampling under the Binomial-Poisson model can be found in Royle et al. (2004) (see Dorazio et al. 2005 for a related application). Thus, in our tornado count problem, for county $k = 1, \ldots, K$, we have

$$n_k \sim \text{Poisson}(a_k p_k(\theta)\lambda), \tag{3}$$

with

$$p_k(\theta) = g(x_k; \theta) = \exp(-\theta x_k), \tag{4}$$

where x_k is the inverse of the population density of the k-th county.

3.2 Estimation

In this relatively simple case where we have assumed a constant λ and θ, we can determine numerically the maximum likelihood estimates (MLEs) for λ and θ as described in Royle et al. (2004). However, for K relatively small, as in our case, the usual asymptotic theory that provides nice properties of the MLEs no longer holds. A consequence of this is that one does not get good estimates of the variation in the estimates of λ and θ.

Rather than use the MLE approach, we consider the problem from the Bayesian perspective. That is, we simply let θ and λ have prior distributions of the form,

$$\theta \sim logN(\mu_\theta, \sigma_\theta^2), \tag{5}$$

where $logN(\ )$ refers to a log-normal distribution, and the associated mean and variance are μ_β and σ_β^2, respectively. These "hyperparameters" are specified to be .5 and 10000, respectively, corresponding to a non-informative prior (so our prior beliefs do not overly affect the results). Furthermore, we let

$$\lambda \sim Gamma(q, r), \tag{6}$$

where $Gamma$ refers to a gamma distribution with parameters q and r. In our case, we let $q = .001$ and $r = .001$, again corresponding to a non-informative prior distribution.

In this Bayesian case, rather than considering the point estimates of the parameters of interest, we get their posterior distributions. That is, we get the distribution $p(\theta, \lambda | n_1, \ldots, n_K)$. By Bayes' rule, this posterior distribution is proportional to the likelihood (3) times the prior distributions (6) and (5):

$$p(\theta, \lambda | n_1, \ldots, n_K) \propto \prod_{k=1}^{K} p(n_k | \lambda, \theta) p(\theta) p(\lambda), \tag{7}$$

where the proportionality constant is given by the integral of the right-hand side of (7) with respect to 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 Markov Chain Monte Carlo (MCMC) to obtain Monte Carlo samples from this posterior distribution (see Congdon 2001, Gelman et al. 2004, or Robert and Casella 2004 for discussions of Bayesian estimation and numerical approaches).

3.3 Implementation

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

4 Results

4.1 Sensitivity to Data Set

We examined sensitivity of model results to alternative reporting standards by comparing parameter estimates that were obtained from two distinct data sets: SPC severe weather log and Grazulis volumes. We summed tornado reports for the entire period of record 1953-2001. The Grazulis data set 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 compared parameter estimates for the Oklahoma City, OK region.

Comparison of λ (Table 2) reveals higher incidence of F2-F5 reports in the SPC archive compared to significant tornado reports in the Grazulis volumes. This is consistent with results reported in Brooks (2000) that show a higher incidence of national F2-F5 reports in the SPC log compared to Grazulis' frequency of significant tornadoes. Despite this disparity, the probability of detection in high and low population density counties is comparable in the two data sets. These results suggest that inconsistency of reporting standards may have directly influenced overall frequency but had less impact on spatial variability of reports. Thus, we present results derived from the SPC data set only, and, unless otherwise stated, the results are valid for the entire period of record 1953-2001.

4.2 Regional Dependence of Population Effects

The probability of detection may be interpreted as the frequency of tornado occurrences that are reported and classified correctly. 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 things mistaken to be tornadoes, which are unaccounted for in our stochastic model.

It has been argued that, since F2-F5 tornadoes are generally larger and longer-lived than F0-F1 tornadoes, the reported incidence of F2-F5 tornadoes is less affected by unreported tornadoes (Concannon et al. 2000, Brooks 2004). In the context of our model, this effect would be manifested as higher probability of detection in low population density counties for F2-F5 compared to F0-F1 tornadoes. However, in the Oklahoma City and Tulsa regions, the results show the opposite – higher probability of detection in low population density counties for F0-F1 compared to F2-F5 tornadoes. An alternative effect of population density that is consistent with this result is the possibility that some tornadoes were underrated, possibly due to 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.

Brooks and Craven (2002) find evidence of an abrupt change in 1973 of proximity sounding indices associated with F2-F5 tornadoes. This year is the first in which the National Weather Service was responsible for tornado verification. They found F2-F5 tornado reports prior to 1973 were sometimes associated with environments that are more like environments of F0-F1 reports submitted since 1973. This implies the reports were misclassified such that more F2-F5 tornadoes were reported prior to 1973 than might have been expected given the meteorological environment and contemporary reporting standards. This could influence the results from our model such that the disparity between high and low population density counties of probability of detection for F2-F5 tornadoes may be smaller than it is for F0-F1 tornadoes during 1953-1973. We examined this possibility by estimating model parameters using two subperiods: 1953-1973 and 1974-2001. Higher probability of detection in low population density areas for F0-F1 compared to F2-F5 tornadoes occurred in both periods.

Parameter values for Champaign, IL, Atlanta, GA, and Des Moines, IA reflect the expected relationship between population density and probability of detection. It is possible that tornado statistics in Oklahoma might be different than elsewhere in part because of the activities of the National Severe Storm Project, which sent scientific teams in search of tornadic storms beginning in the late 1950's (NSSP 1963). The results from Omaha show almost no difference of (very high) probability of detection for F0-F1 and F2-F5 tornadoes. The tornado density λ for the Omaha region is much lower than in all other regions. This implies the report sample size may be too small to estimate the effect of population density.

The primary purpose of statistical adjustment of tornado counts for unreported tornadoes has been to improve estimates of tornado risk in hazard models (Tescon et al.

1983, Schaefer et al. 1986, Nixon et al. 2000, 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. An advantage of our approach, in which model parameters are considered random, is that a range of possible adjusted tornado counts is generated for each county, reflecting uncertainty in both probability of detection and natural (meteorological) variability. 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. Nixon et al. (2000) developed a population density adjustment of tornado counts that suggests the ratio ranges 0.37 to 0.73 in the southern plains. A kriging method developed by Ray et al. (2003) suggests the risk of tornado occurrence at any given location in the central United States is only 62 percent of the expected value. Thus, different statistical approaches have resulted in similar ranges, lending confidence that our modeling approach provides a reasonable estimate of the actual range.

5 Conclusion

We have evaluated the relationship between probability of detection of tornadoes and 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 main conclusions are:

- In Oklahoma, probability of detection in rural areas of F0-F1 tornadoes exceeds that of F2-F5 tornadoes. It appears that in rural areas F2-F5 tornadoes have been underestimated on the Fujita scale, inflating the incidence of F0-F1 tornadoes in rural areas. The ratio of reported to actual number of tornadoes varies between 0.97 to 1.00 in Oklahoma county and 0.33 to 0.54 in Major county, within the range reported elsewhere.

- Near Atlanta, GA, Des Moines, IA, and Champaign, IL, probability of detection in rural areas of F2-F5 tornadoes is greater than F0-F1 tornadoes, consistent with the hypothesis that F2-F5 tornadoes are more faithfully detected due to their comparatively large size and long duration.

- Near Omaha, tornado reports are too infrequent to estimate a population effect.

The results indicate that some of the spatial variability of 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 could reasonably presume 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 probability of detection and population density lays the groundwork for more ambitious study of population and meteorological effects in all regions. An extension of this work might use climatological information of indices relevant to tornado frequency, such as those identified in Brooks and Craven (2002), and examine alternative indices of human density. It is a challenge to estimate statistical model parameters given the spatial and temporal variability of climatological data. However, hierarchical Bayesian 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).

We find a population density effect that runs counter to results in Brooks and Craven (2002) that suggest an effect possibly due to changes in reporting standards. Whereas Brooks and Craven (2002) hypothesize from meteorological evidence that some F2-F5 tornado reports in 1953-1973 may have been overrated if contemporary rating standards were applied, we hypothesize from report data that some F2-F5 tornadoes in rural Oklahoma were underrated. The hypotheses are not necessarily at odds with one another. They might simply reflect differences of samples, since our analysis is of regional rather than national tornado reports. It would be interesting to adjust simultaneously for meteorological conditions and underreporting due to variations in population density to better understand regional variations in relative importance of both factors. Furthermore, an adjusted tornado count that reflects both population density effects and meteorological conditions should provide a more realistic estimate of climatological tornado frequency for tornado hazard models.

Acknowledgments We gratefully acknowledge Thomas Grazulis, who provided his data set of significant tornado reports, and Harold Brooks for comments on an early draft. Wikle and Zhou acknowledge the support of NSF grant DMS 0139903. Anderson acknowledges the support of NSF grant ATM-9911417.

Appendix: WinBUGS Code for Oklahoma City Counties

```
model
{
   alpha~dnorm(0.5,0.0001)
   theta<-exp(alpha)
   lambda~dgamma(0.001,0.001)
   for (i in 1:19) {
     p[i]<-exp(-theta/x[i])
     lambda1[i]<-lambda*area[i]
     sn[i]~dpois(lambda1[i]*area[i]*p[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, 100)
  )
```

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City	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, McIntosh, Hughes, Seminole

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

City	θ	λ	p_{max}	p_{min}
Oklahoma City: F0-F1	4.161	0.0414	0.9947	0.6180
Oklahoma City: F2-F5	13.060	0.0314	0.9836	0.2164
Oklahoma City: Sig.	11.960	0.0176	0.9849	0.2558
Tulsa: F0-F1	9.920	0.0406	0.9880	0.2800
Tulsa: F2-F5	14.060	0.0260	0.9830	0.1700
Atlanta: F0-F1	22.010	0.0189	0.9880	0.4000
Atlanta: F2-F5	0.080	0.0080	1.0000	0.9970
Champaign: F0-F1	24.150	0.0644	0.8910	0.3400
Champaign: F2-F5	0.010	0.0099	1.0000	0.9950
Des Moines: F0-F1	17.410	0.0410	0.9687	0.3600
Des Moines: F2-F5	0.007	0.0115	1.0000	0.9960
Omaha: F0-F1	0.003	0.0253	1.0000	0.9998
Omaha: F2-F5	0.003	0.0193	1.0000	0.9998

Table 2: Population effect parameter (θ), tornado density parameter (λ), and maximum and minimum probability of detection (p_{max}, p_{min}) for each combination of population center and F-scale grouping.

County	Population Density	County Area	Reported Tornadoes	Posterior		
				Mean	Std. Dev.	(2.5, 97.5)
k	x_k^{-1}	a_k	n_k	N_k	N_k	N_k
Oklahoma	788.298	709	74	74.49	0.7105	(74, 76)
Cleveland	240.537	536	45	46.22	1.1360	(45, 49)
Payne	83.630	686	38	42.33	2.2820	(39, 47)
Pottawatomie	67.049	788	47	53.14	2.7830	(48, 59)
Canadian	61.236	900	61	67.64	3.1960	(63, 76
Creek	57.205	956	46	54.62	3.4420	(49, 62)
Garfield	53.984	1058	56	66.07	3.7960	(60, 74)
Pontotoc	43.856	720	41	49.29	3.3310	(44, 57)
Seminole	41.419	632	40	47.68	3.1630	(42, 55)
Logan	34.414	745	37	47.64	3.9140	(41, 56)
McClain	34.307	570	35	43.18	3.2840	(38, 50)
Grady	33.732	1101	52	68.03	5.0990	(59, 79)
Lincoln	26.322	959	57	74.40	5.3700	(65, 86)
Caddo	23.179	1278	88	113.90	7.0880	(101, 129)
Okfuskee	18.207	625	29	44.46	4.8530	(36, 55)
Noble	14.877	732	28	49.11	5.9430	(38, 62)
Kingfisher	14.354	903	45	71.77	7.0100	(59, 87))
Blaine	13.086	929	33	62.49	7.4890	(49, 78)
Major	8.300	957	30	71.29	9.0340	(55, 90)

Table 3: County population density (x_k^{-1}, $persons\ mi^{-2}$), county area (a_k, mi^2), reported number of tornadoes (n_k), and mean, standard deviation, 2.5 and 97.5 percentiles from posterior distribution of adjusted number of tornadoes (N_k).