Predicting 'outbreak'-level tornado counts and casualties from environmental variables

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ABSTRACT

Environmental variables are routinely used to forecast when and where an outbreak of tornadoes is likely to occur but more work is needed to understand how characteristics of severe weather outbreaks vary with environmental variables. Here the authors propose a method to quantify 'outbreak'-level tornado and casualty counts from environmental conditions. They do this by fitting negative binomial regression models to cluster-level tornado data that estimate tornado counts and associated casualties on days with at least ten tornadoes. Results show that a 1000 J kg^{-1} increase in CAPE corresponds to a 5% increase in tornado counts and a 28% increase in casualties holding the other variables constant. Results also show that a 10 m s^{-1} increase in deep-layer bulk shear corresponds to a 13% increase in tornado counts and a 98% increase in casualties holding the other variables constant. The casualty-count model quantifies the decline in the number of casualties per year and indicates that tornado outbreaks have a significantly larger impact in the Southeast than elsewhere after controlling for population and outbreak size.

1. Introduction

Predicting specific characteristics of severe weather outbreaks is an important but challenging problem. Guidance from dynamical models helps forecasters outline areas of severe weather threats days in advance. Guidance from statistical models help forecasters quantify probabilities for given severe weather events (Hitchens and Brooks 2014; Thompson et al. 2017; Cohen et al. 2018; Elsner and Schroder 2019; Hill et al. 2020). For example, Cohen et al. (2018) develop a regression model to specify the probability of tornado occurrence given certain environmental and storm-scale conditions, and Elsner and Schroder (2019) extend this model by making use of the cumulative logistic link function that predicts probabilities for each damage rating.

These studies put statistical guidance for predicting severe weather outbreak characteristics on a firm mathematical foundation, yet there is room for additional work. For instance, the cumulative logistic regression provides a distribution for the *percentage* of tornadoes within each Enhanced Fujita (EF) rating category, but the regression model is silent concerning the expected overall number of tornadoes. Here we propose a method to model 'outbreak'-level tornado and casualty counts from environmental conditions. The model allows us to quantify the interrelationships between environmental variables and tornado counts. It also helps in extending the available statistical guidance because output from a model that estimates the number of tornadoes together with output from the cumulative logistic model provides a prediction for the expected number of tornadoes by each EF category. Suppose for example that given current environmental conditions a model predicts the distribution for the total number of tornadoes centered on fifteen while the cumulative logistic regression model predicts that for each tornado there is a fifty percent change of it being EF0, a ten percent chance of it being EF1, a five percent chance of it being EF2, and so on. Then a numerical convolution of these two distributions provides an expected number of counts by EF rating as well as the associated uncertainties.

This paper has two objectives: (1) to demonstrate that environmental conditions prior to the occurrence of any tornadoes can be modeled to skillfully estimate the number of tornadoes in a big outbreak (tornado-count model), and (2) to show that these same environmental conditions can be used to estimate the number of casualties if the number of people in harm's way is known (casualty-count model). We accomplish these objects by fitting negative binomial regressions to cluster-level tornado data. The data are environmental variables and tornado characteristics (e.g., number of tornadoes, area of cluster, etc) on 'big' convective days (12 UTC to 12 UTC), when the number of tornadoes is at least ten (see Elsner and Schroder (2019)).

The models show that a 1000 J kg^{-1} increase in CAPE results in a 4.7% increase in the expected number of tornadoes and a 28% increase in the expected number of casualties holding the other variables constant. Further models show that a 10 m s^{-1} increase in deep-layer bulk shear results in a 13% increase in the expected number of tornadoes and a 98% increase in the expected number of casualties holding the other variables constant. The casualty-count model also shows a significant decline in the number of casualties at a rate of 3.6% per year and that expected casualties depend on where the outbreak occurs with more casualties on average over the Southeast all else being equal. The paper is outlined as follows. The data and methods are discussed in section 2 including the mathematics of a negative binomial regression. Statistics describing the response and environmental variables are given in section 3. The modeling results are presented in section 4, and a summary with conclusions are given in section 5.

2. Data and methods

We fit regression models to a set of reanalysis data aggregated to the level of tornado clusters. Here we describe the available data and the procedures we use to aggregate representative values to the cluster level. For our purposes, a cluster is a space-time group of at least ten tornadoes occurring between 12 UTC and 12 UTC. Ten is chosen as a compromise between too few clusters leading to greater uncertainty and too many clusters leading to excessive time required to fit the models (Elsner and Schroder 2019). The number of tornadoes in each cluster is the response variable in the tornado-count regression model, and the number of casualties is the response variable in the casualty-count regression model. Explanatory variables for the models are taken from reanalysis data representing the environment before the occurrence of the first tornado in the cluster.

a. Tornado clusters

First, we extract the date, time, genesis location, and magnitude of all tornado reports between 1994 and 2018 from the Storm Prediction Center [SPC] (`https://www.spc.noaa.gov/gis/svrgis/`). We choose 1994 as the start year because it is the first year of the extensive use of the WSR-88D Radar. Each row in the data set contains information at the individual tornado level. In total, there are 30 497 tornado reports during this period. The geographic coordinates for each genesis location are converted to Lambert conic conformal coordinates, where the projection is centered on 107° W longitude.

Next, we assign to each tornado a cluster identification number based on the space and time differences between genesis locations. Two tornadoes are assigned the same cluster identification number if they occur close together in space and time (e.g., 1 km and 1 h). When the difference between individual tornadoes and existing clusters surpasses 50 000 s ($\sim$ 14 h), the clustering ends. The space-time differences have units of seconds because we divide the spatial distance by 15 m s^{-1} to account for the average speed of tornado-producing storms. This clustering of tornadoes is identical to that used in Elsner and Schroder (2019) who fit a cumulative logistic model to the damage scale at the individual tornado level. Additional details on the procedure as well as a comparison of the identified clusters to well-known tornado outbreaks are available in Schroder and Elsner (2019).

We keep only clusters that have at least ten tornadoes occurring within the same convective day, which results in 768 clusters containing a total of 17 069 tornadoes. A convective day is defined as a 24-hour period beginning at 1200 UTC (Doswell III et al. 2006). The average number of tornadoes (for clusters with at least ten tornadoes) is 22 tornadoes and the maximum is 173 tornadoes (April 27, 2011). There are 80 clusters with exactly ten tornadoes. Each cluster varies by area and by where it occurs (Fig. 1). The cluster area is defined by the minimum convex hull (black polygon) that includes all the tornado genesis locations. The July 19, 1994 cluster with nine tornadoes over northern Iowa and one over northeast Wisconsin had an area of 33 359 km^2 and lasted about four hours. The April 27, 2011 cluster had 173 tornadoes spread over more than a dozen states and had an area of 1 064 337 km^2 with tornadoes occurring throughout the 24-h period (12-UTC to 12-UTC).

For each cluster we sum the number of injuries and deaths across all tornadoes to get the cluster-level number of casualties. Further we estimate the total population within the cluster area and the geographic center of the cluster. Population is used as an explanatory variable in place of cluster area when the number of casualties is the dependent variable.

b. Environmental variables

Environmental conditions for producing tornadoes are well known and include high values of convective available potential energy, convective inhibition, and bulk shear (Brooks et al. 1994;

Rasmussen and Blanchard 1998; Tippett et al. 2012, 2014; Elsner and Schroder 2019). We obtain variables associated with these environmental conditions from the National Centers for Atmospheric Research's North American Regional Reanalysis (NARR) which is supported by the National Centers for Environmental Prediction. Each variable has numeric values given on a 32-km raster grid with the values available in three-hour increments starting at 00 UTC. We note that in the severe weather literature these environmental variables are called 'parameters'. However here, since we employ statistical models, we prefer to call them variables to be consistent with the statistical literature where the word 'parameter' denotes unknown model coefficients and distributional moments.

We select environmental variables at the nearest three-hour time *prior* to the occurrence of the first tornado in the cluster. For example, if the first tornado in a cluster occurs at 16:30 UTC we use the environmental variables given at 15 UTC. This selection criteria results in a sample of the environment that is less contaminated by the deep convection itself but at a cost that underestimates the severity in cases where rapid increases in conditions favoring tornadoes occur. We note that roughly 60% of all clusters have the initial tornado occurring between 18 and 00 UTC (Table 1). We also note that there are more tornadoes on average in clusters where the first tornado occurs between 15 and 18 UTC.

The environmental variables we consider in this study include convective available potential energy (CAPE) and convective inhibition(CIN) as computed using the near-surface layer (0 to 180 mb above the ground level) as well as deep (1000 to 500 mb) and shallow (1000 to 850 mb) layer bulk shears (DLBS, SLBS) computed as the square root of the sum of the squared differences between the u and v wind components at the respective levels. We take the highest (lowest for CIN) value across the grid of values within the area defined by the cluster's convex hull. This is done to capture the extremes of the environmental condition. The maximum values within a cluster provide a better representation of the environments since they are not substantially influenced by meso-scale phenomena unrelated to tornado genesis.

c. Negative binomial regression

With the cluster as our unit of analysis we fit a series of regression models to the data having the form

$$
\begin{aligned}
T &\sim \text{NegBin}(\hat{\mu}, n) \\
\ln(\hat{\mu}) &= \beta_0 + \beta_A A + \beta_\phi \phi + \beta_\lambda \lambda + \beta_Y Y + \\
&\quad \beta_{CAPE}\text{CAPE} + \beta_{CIN}\text{CIN} + \beta_{DLBS}\text{DLBS} + \beta_{SLBS}\text{SLBS},
\end{aligned} \tag{1}
$$

where the number of tornadoes (T) (or number of casualties C) is the dependent variable that is assumed to be adequately described by a negative binomial distribution (NegBin) with a rate parameter μ and a size parameter n. The natural logarithm of the rate parameter is linearly related to cluster area (A), cluster center location [latitude (ϕ) and longitude (λ)], year (Y) and the four environmental variables (CAPE, CIN, DLBS, and SLBS). The model is fit using the method of maximum likelihoods carried out in the call to the `glm.nb` function from `MASS` package in R (Venables and Ripley 2002). We do the same for the initial casualty-count model, but we replace cluster area with population (P). We simplify the initial models by single-term deletions as described in §4.

3. Descriptive statistics

The number of clusters decreases exponentially with an increasing number of tornadoes (Fig. 2). There are 80 clusters with ten tornadoes but only ten clusters with 30 tornadoes. The right tail of the count distribution is long with the April 27, 2011 cluster having 173 tornadoes [47 (6%) of the clusters have more than 50 tornadoes and are not shown]. However more clusters have 20 or

21 tornadoes than expected from this exponential decay. This deviation is unlikely the result of physical processes and it appears too large to be sampling variability. The distribution of casualties is also skewed toward many clusters having only a few casualties and a few have many. Thirty-six percent of all clusters (275) are without a casualty and 56% of the clusters have fewer than four casualties.

There is a distinct seasonality to the chance of at least one tornado cluster (Fig. 3). The empirical seven-day probability of at least one cluster is between 20 and 30% for much of the year except between the middle of March and early July. The probabilities approach 80% between mid and late May. The number of tornadoes per cluster is less variable ranging between about 10 and 35 tornadoes per week with no strong seasonality although clusters during July and August tend to have somewhat fewer tornadoes. The casualty rate, defined as the number of casualties per 100,000 people within the cluster area, shows a distinct seasonality with rates being highest between late January through late May.

Across the 768 clusters the mean value of regionally highest CAPE is 2 225 J kg^{-1} and the mean value of regionally lowest CIN is -114 J kg^{-1} (Table 2). The maximum deep-layer bulk shear values range from 5.6 to 47.9 m s^{-1}. Cluster areas range from 361 to 1 064 337 km^2 with an average of 167 990 km^2.

4. Results

a. A model for the number of tornadoes

First we fit a negative binomial regression to the cluster-level tornado counts using the explanatory variables given in Table 2. This is our tornado-count model. We divide the cluster area by 10 million so it has units of 100 km^2. We divide CAPE by 1000 so it has units of 1000 J kg^{-1} and we divide CIN by 100 so it has units of 100 J kg^{-1}. This simplifies interpretation of the model coefficients.

All terms have signs on the coefficient that make physical sense (Table 3). The number of tornadoes in a cluster increases with cluster area, CAPE, and bulk shear (deep and shallow layers) and decreases for increasing values of CIN as expected. The significance of the variable in statistically explaining tornado counts is assessed by the corresponding z-value given as the ratio of the coefficient estimate to its standard error (S.E.). We reject the null hypothesis that a particular variable has no explanatory power if its corresponding p-value is less than .01. Here we fail to reject the null hypothesis for the variables latitude, longitude, and year, which indicates that these non-physical variables have a relatively small impact on tornado counts relative to the physical variables given the data and the model. In particular, there is no significant upward or downward trend over time in the number of tornadoes in these clusters. The only physical variable that is not statistically significant is CIN. We remove all statistically insignificant variables before fitting a final model.

All variables in the final model are significant although the coefficients have changed a bit relative to the initial model. The in-sample correlation between the observed counts and predicted rates is .59 [(0.54, 0.64), 95% uncertainty interval (UI)] (Fig. 4). The model statistically explains almost 60% of the variation in cluster-level tornado counts but tends to over predict the number of tornadoes for smaller clusters and slightly under predict the number of tornadoes for larger clusters. The mean absolute error between the observed counts and expected rates is 8.6 tornadoes or 5.2% of the range in observed counts and 9.3% of the range in predicted rates. The out-of-sample errors are quite similar due to the large sample size (768 clusters). A hold-one-out cross validation exercise (Elsner and Schmertmann 1994) results in an out-of-sample correlation of .58 and a mean absolute error of 8.6 tornadoes.

The β_0 value (Table 3) is the regression estimate when all variables in the model are evaluated at zero. The effect size for a given explanatory variable is given by the magnitude of its coefficient. The coefficient is expressed as the difference in the logarithm of the expected tornado counts for a unit increase in the explanatory variable holding the other variables constant. For example, the scaled units of CAPE are 1000 J kg^{-1}. An increase in CAPE of 1000 J kg^{-1} results in a [(exp(.0459) - 1) $\times$ 100% = 4.7% increase in the expected number of tornadoes. Continuing, units of deep-layer bulk shear are 10 m s^{-1} so an increase in shear of 10 m s^{-1} results in a 13% increase in the expected number of tornadoes. A similar increase in shallow-layer bulk shear results in a 11.1% increase in the number of tornadoes.

Changes to the expected number of tornadoes given changes in the environmental variables have a large impact on the probability distribution of counts conditional on the cluster area. The negative binomial distribution for the number of tornadoes T with an expected number of tornadoes $\bar{T}$ (obtained from the regression model) has a probability density

$$\Pr(T = k) = \frac{\Gamma(r+k)}{k!\,\Gamma(r)} \left(\frac{r}{r+\bar{T}}\right)^{r} \left(\frac{\bar{T}}{r+\bar{T}}\right)^{k} \quad \text{for } k = 10, 11, 12, \ldots, \tag{2}$$

where $r = 1/n$ and $\Gamma(z) = \int_0^\infty x^{z-1} e^{-x}\, dx$ is the gamma function.

For example, on April 12, 2020 the 12 UTC guidance from SPC outlined a polygon that defined an area with a 10% chance of at least one tornado occurring within 46 km of any location (10% tornado risk). The area of the polygon was approximately 400 000 km^2 (much larger than the average cluster area) centered on Mississippi. With an area of that size, the model estimates the probability of at least 30 tornadoes for a range of deep-layer shear values and conditional on the amount of CAPE while holding shallow-layer shear at an average value (Fig. 5). Given an average amount of shallow-layer shear, a deep-layer shear of 10 m s^{-1} and low CAPE (5th percentile value), the model predicts a 17% [9, 26%, UI] chance of at least 30 tornadoes (given a cluster with at least ten tornadoes). In contrast, given a deep-layer shear of 40 m s^{-1} and high CAPE (95th percentile value), the model predicts a 65% [(56, 71%), UI] chance of at least 30 tornadoes. There were at least 100 tornado numbers on that day.

The procedure quantifies the relationship between CAPE and shear in terms of a probability distribution on the number of tornadoes. The regression model predicts the expected count given values for the explanatory variables. The negative binomial distribution uses the model predicted count and the size parameter to generate a distribution of probabilities. For example, the procedure outputs predicted probabilities across a range of CAPE and deep-layer shear values (holding shallow-layer shear at its mean value) that provides a high resolution picture of the modeled relationship (Fig. 6). The predicted probabilities of at least 30 tornadoes given an outbreak covering an area of 400 000 km^2 increase from low values of both CAPE and shear to high values of both CAPE and shear.

b. A model for the number of casualties

Next we fit a negative binomial regression to the cluster-level casualty counts (direct injuries and deaths) using the same explanatory variables (Table 2) with the exceptions that population (scaled by 100,000 residents) replaces cluster area and C (casualty count) replaces T (tornado count) as the dependent variable. This is our casualty-count model. We find that CIN is the only variable not significant in the initial model (Table 4). We remove it before fitting a final model.

The in-sample correlation between the observed casualty counts and predicted rates is .43 [(.37, .48), 95% UI] (Fig. 7). The mean absolute error between the observed counts and expected rates is 39 casualties or 1.3% of the range in observed counts and 3.4% of the range in predicted rates. The out-of-sample correlation is .36 and the mean absolute error is 40 casualties. The skill is lower than the skill of the tornado-count model as there is additional uncertainty associated with the number of casualties given a tornado.

As expected, based on the model for the number of tornadoes, the number of casualties resulting from a cluster of tornadoes increases with CAPE and with the two bulk shear variables (Table 4). Holding all other variables constant, an increase in CAPE of 1000 J kg^{-1} results in a 28% increase in the expected number of casualties. An increase in deep-layer bulk shear of 10 m s^{-1} results in a 98% increase in the expected number of casualties and a similar increase in shallow-layer bulk shear results in a 76% increase in the expected number of casualties. There is also a significant downward trend (negative value for the β_Y coefficient) in the number of casualties at a rate of 3.6% per year. This is very likely the result of improvements made by the National Weather Service in warning coordination and dissemination leading to better awareness especially for these large outbreak events.

Also as expected the number of people in harm's way is a significant predictor for the cluster-level casualty count. The relationship between population and number of casualties is quantified at the tornado-level in Elsner et al. (2018) and Fricker et al. (2017) so we expect it to hold at the cluster level. But here for the first time, we are able to compare the influence of shear and CAPE on the probability of casualties as modulated by population (Fig. 8). Model results are shown for three levels of population. The probability of a large number of casualties increases with increasing shear and increasing CAPE while keeping the other variables at their mean values and year at 2018.

Importantly, we also find that the location of the cluster has a significant influence on the number of casualties. For every one degree north latitude the casualty rate decreases by 5.5% and for every one degree east longitude the casualty rate increases by 2.9%. Thus cluster-level casualties are highest over the Southeast. This effect is independent of the number tornadoes since location was not a significant factor in the tornado-count model. The result is also independent of the number of people in harm's way since population is included as an exploratory variable in the model.

To visualize the difference the combine effects of latitude and longitude on the difference in the probability of many casualties, we plot modeled casualty probabilities (at least 25) as function of CAPE and deep-layer shear for two *hypothetical* outbreaks that are the same in every way except one outbreak is center on Sioux City, Iowa and the other is centered on Birmingham, Alabama (Fig. 9). The modeled probabilities are lowest (around 5%) for low CAPE and shear values and highest (above 30%) for high CAPE and shear values. The difference in modeled probabilities across these two locations peaks at about +12 percentage points for high CAPE and high shear regimes when the outbreak is centered over Birmingham.

5. Summary and conclusions

Forecasting characteristics of severe weather outbreaks is challenging. Forecasters use a combination of numerical weather prediction and empirical guidance to outline areas of severe convective weather. Machine learning algorithms are now routinely employed for these tasks particularly when the focus is on prediction rather than on explanation. Here we demonstrate how to employ a statistical regression model to take advantage of the large sample of independent tornado-day events as a way to parsimoniously predict and importantly to statistically explain the number of tornadoes and the number of casualties in an outbreak.

We fit negative binomial regressions to observational data aggregated to the level of tornado clusters where a cluster is a space-time group of at least ten tornadoes occurring between 12 UTC and 12 UTC over the period 1994–2018. The number of tornadoes in each cluster is the response variable in the tornado-count model and the number of casualties (deaths plus injuries) is the response variable in the casualty-count model. Environmental explanatory variables for the models are extracted from reanalysis data representing conditions before the occurrence of the first tornado in the cluster. Additional explanatory variables including cluster area, population, location, and year.

The predicted tornado rates explain 59% of the observed tornado counts in-sample, and the predicted casualty rates explain 43% of the observed casualty counts in-sample. Because of the large sample size the out-of-sample skill is lower, but still useful. The models show that a 1000 J kg^{-1} increase in CAPE results in a 4.7% increase in the expected number of tornadoes and a 28% increase in the expected number of casualties holding the other variables constant. The models further show that a 10 m s^{-1} increase in deep-layer bulk shear results in a 13% increase in the expected number of tornadoes and a 98% increase in the expected number of casualties holding the other variables constant. The casualty-count model also shows a significant decline in the number of casualties at a rate of 3.6% per year. And casualty rates depend on where the outbreak occurs with more deaths and injuries, on average, over the Southeast controlling for the other variables.

Some of the unexplained variability in cluster-level tornado counts (and thus casualty counts) arises from the uncertainty associated with the preferred storm mode and the evolution of mesoscale convective systems neither of which are captured by a single maximum value in the variable space of CAPE and shear. Also outbreaks associated with tropical cyclones likely add a bit of noise to both models since the number of tornadoes is sensitive to the extent and location of convective bursts within overall evolution of the land-falling storm. In addition, the casualty-count model would be improved by including a skillful prediction of the number of tornadoes. Indeed in a perfect-prognostic setting where we know the number of tornadoes in the outbreak, the out-of-sample correlation between the observed number of casualties and the modeled estimated rate of casualties increases to .79.

A tornado-count model like the one demonstrated here might assist forecast guidance given a convective outlook that highlights an area of elevated risk for tornadoes and a dynamical forecast of CAPE and shear across the elevated-risk area. The statistical model would need to be calibrated for forecast areas and environmental variables but the exact same model equation used here will provide a probability distribution on the future number of tornadoes that should retain some level of skill. Further, a numerical convolution of this probability distribution with a probability distribution for each EF-rating category (Elsner and Schroder 2019) will give a forecast of the expected number of counts by category as well as the associated uncertainties. Similarly the casualty-count model might prove useful for communicating the risk given the population within the elevated risk area.

The casualty-count model can also be employed in a research setting to help better understand the socioeconomic, demographic, and communication factors that make some communities particularly vulnerable to deaths and injuries (Dixon and Moore 2012; Senkbeil et al. 2013; Klockow et al. 2014; Fricker and Elsner 2019). Work along this line has been done at the individual tornado level by identifying unusually devastating events (Fricker and Elsner 2019) but scaling this type of analysis to the cluster-level to identify unusually devastating outbreaks might provide additional insights.

Finally, the model specifications might be improved by adjusting the threshold definition of a cluster. Increasing the threshold on the tornado-count model from 10 to 14 decreases the sample size to 505 clusters and reduces the effect sizes on CAPE and shear by around 25%. Decreasing the threshold from 10 to 6 increases the sample size and thus reduces the standard error assuming the effect size stays the same. The casualty-count model might also be improved by relaxing the assumption that the number of people injured or killed are independent. Casualties counts are typically not independent at the household level where multiple people live under the same roof.

In this case a zero-inflated count model might be provide a better fit to the data compared with a negative binomial distribution count model.

The negative binomial regression models in this paper were implemented with the `glm.nb` function from the `MASS` R package (Venables and Ripley 2002). Graphics were made with the `ggplot2` framework (Wickham 2017). The code to run all the experiments is available on GitHub (https://github.com/jelsner/cape-shear).

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LIST OF TABLES

TABLE 1. Cluster statistics by time of day. Each cluster is categorized by the closest three-hour time (defined by the NARR data) prior to the first tornado.

Time of Day (UTC)	Number of Clusters	Number of Tornadoes	Tornadoes Per Cluster
00	33	523	15.8
03	5	67	13.4
06	2	23	11.5
12	145	3598	12.1
15	124	3222	26.0
18	249	5220	21.0
21	210	4416	21.0

Table 2. Variables used in the regression models. Values include the range and average across the 768 tornado clusters.

Variable	Abbreviation	Range	Average
Explanatory Variables			
Convective Available Potential Energy [J kg^{-1}]	CAPE	[0, 6530]	2225
Convective Inhibition [J kg^{-1}]	CIN	[−668, 0]	−114
Deep-Layer Bulk Shear [m s^{-1}]	DLBS	[5.6, 48]	27.5
Shallow-Layer Bulk Shear [m s^{-1}]	SLBS	[1.1, 33.8]	15.0
Latitude [° N]	ϕ	[27.12, 48.97]	37.20
Longitude [° E]	λ	[−109.9 −72.88]	−92.16
Cluster Area [km^2]	A	[361, 1 064 337]	167 990
Population [No. of People]	P	[0, 38 226 946]	3 387 259
Year	Y	[1994, 2018]	2006
Response Variables			
Number of Tornadoes	T	[0, 173]	22.2
Number of Casualties (injuries plus deaths)	C	[0, 3 069]	29.9

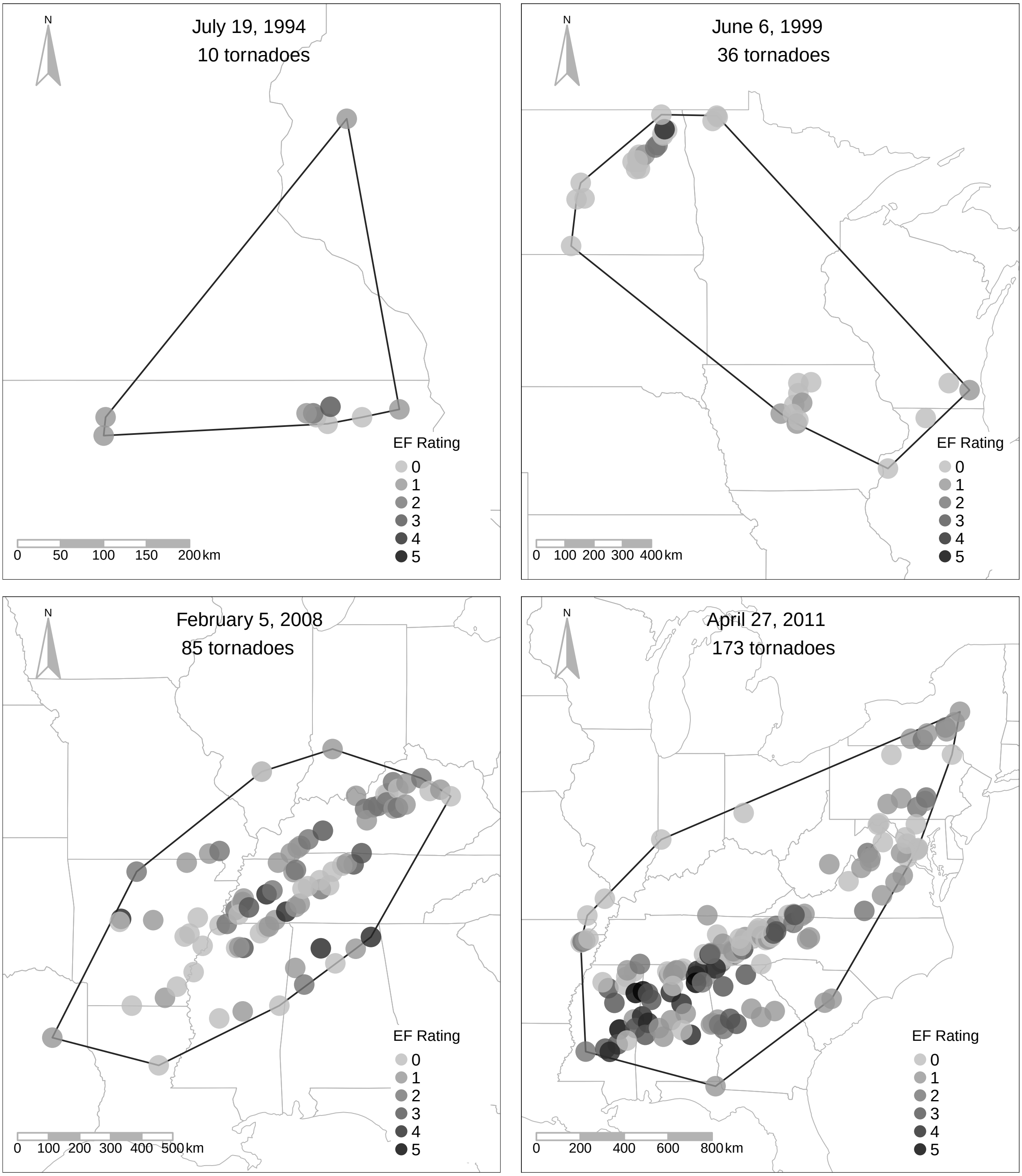
TABLE 3. Coefficients in the tornado-count models. The size parameter (n) is 6.27 ± .393 (S.E.) for the initial model 6.25 ± .392 (S.E.) for the final model.

Coefficient	Estimate	S.E.	z value	Pr(>|z|)
		Initial Model		
β_0	4.5489	4.7662	0.9540	0.3399
β_A	0.0146	0.0011	12.80	< 0.0001
β_ϕ	−0.0051	0.0043	−1.17	0.2427
β_λ	−0.0028	0.0031	−0.917	0.3594
β_Y	−0.0012	0.0024	−0.515	0.6068
β_{CAPE}	0.0452	0.0153	2.96	0.0031
β_{CIN}	−0.0110	0.0189	−0.581	0.5612
β_{DLBS}	0.1256	0.0292	4.30	< 0.0001
β_{SLBS}	0.1059	0.0355	2.98	0.0029
		Final Model		
β_0	2.1779	0.0817	26.65	< 0.0001
β_A	0.0149	0.0011	13.85	< 0.0001
β_{CAPE}	0.0459	0.0146	3.13	0.0017
β_{DLBS}	0.1254	0.0288	4.35	< 0.0001
β_{SLBS}	0.1054	0.0314	3.35	0.0008

TABLE 4. Coefficients in the casualty-county models. The size parameter (n) is .261 ± .014 (S.E.) for the initial and final models.

Coefficient	Estimate	S.E.	z value	Pr(>|z|)
		Initial Model		
β_0	76.6908	20.7430	3.70	0.0002
β_P	0.0122	0.0019	6.51	< 0.0001
β_ϕ	−0.0561	0.0187	−3.00	0.0027
β_λ	0.0284	0.0136	2.09	0.0363
β_Y	−0.0364	0.0103	−3.52	0.0004
β_{CAPE}	0.2436	0.0643	3.79	0.0002
β_{CIN}	0.0052	0.0802	0.07	0.9479
β_{DLBS}	0.6853	0.1262	5.43	< 0.0001
β_{SLBS}	0.5650	0.1534	3.68	0.0002
		Final Model		
β_0	76.7677	20.6902	3.71	0.0002
β_P	0.0122	0.0018	6.67	0.0000
β_ϕ	−0.0563	0.0186	−3.02	0.0025
β_λ	0.0287	0.0130	2.20	0.0277
β_Y	−0.0364	0.0103	−3.53	0.0004
β_{CAPE}	0.2440	0.0643	3.79	0.0001
β_{DLBS}	0.6833	0.1253	5.45	0.0000
β_{SLBS}	0.5631	0.1504	3.74	0.0002

LIST OF FIGURES



443 FIG. 1. Example tornado clusters. Each point is the tornado genesis location shaded by EF rating. The black
444 line is the spatial extent of the tornadoes occurring on that convective day and is defined by the minimum convex
445 hull encompassing the set of genesis locations.

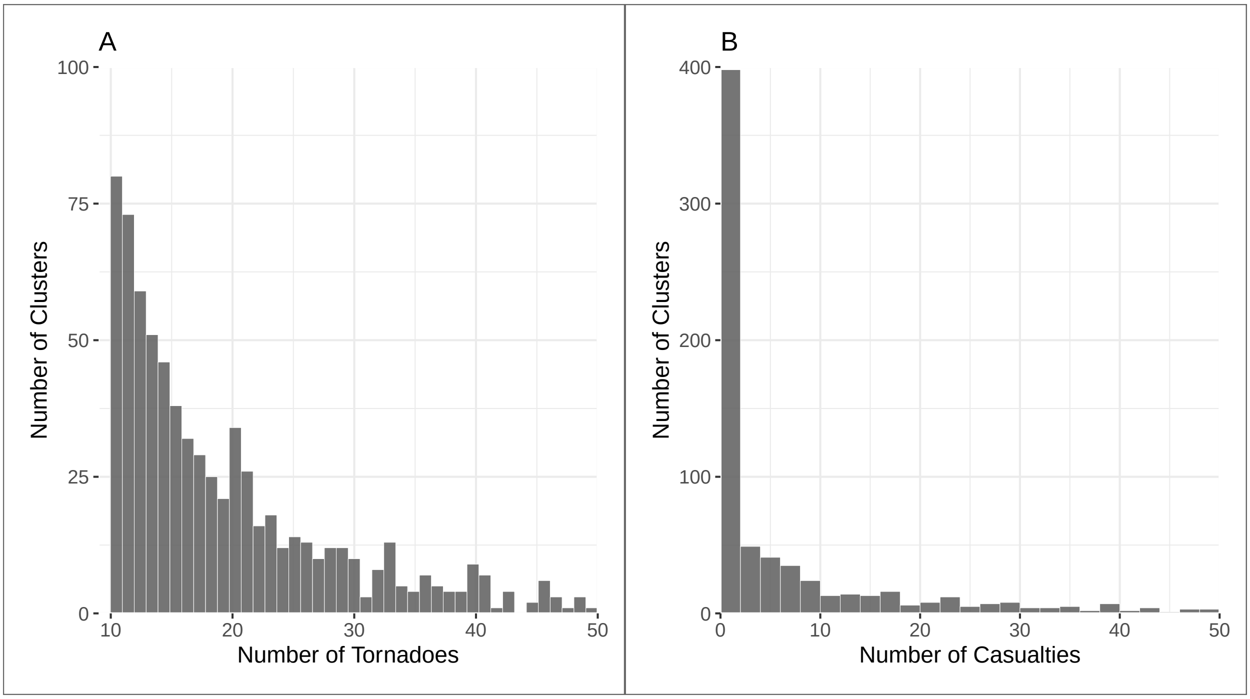
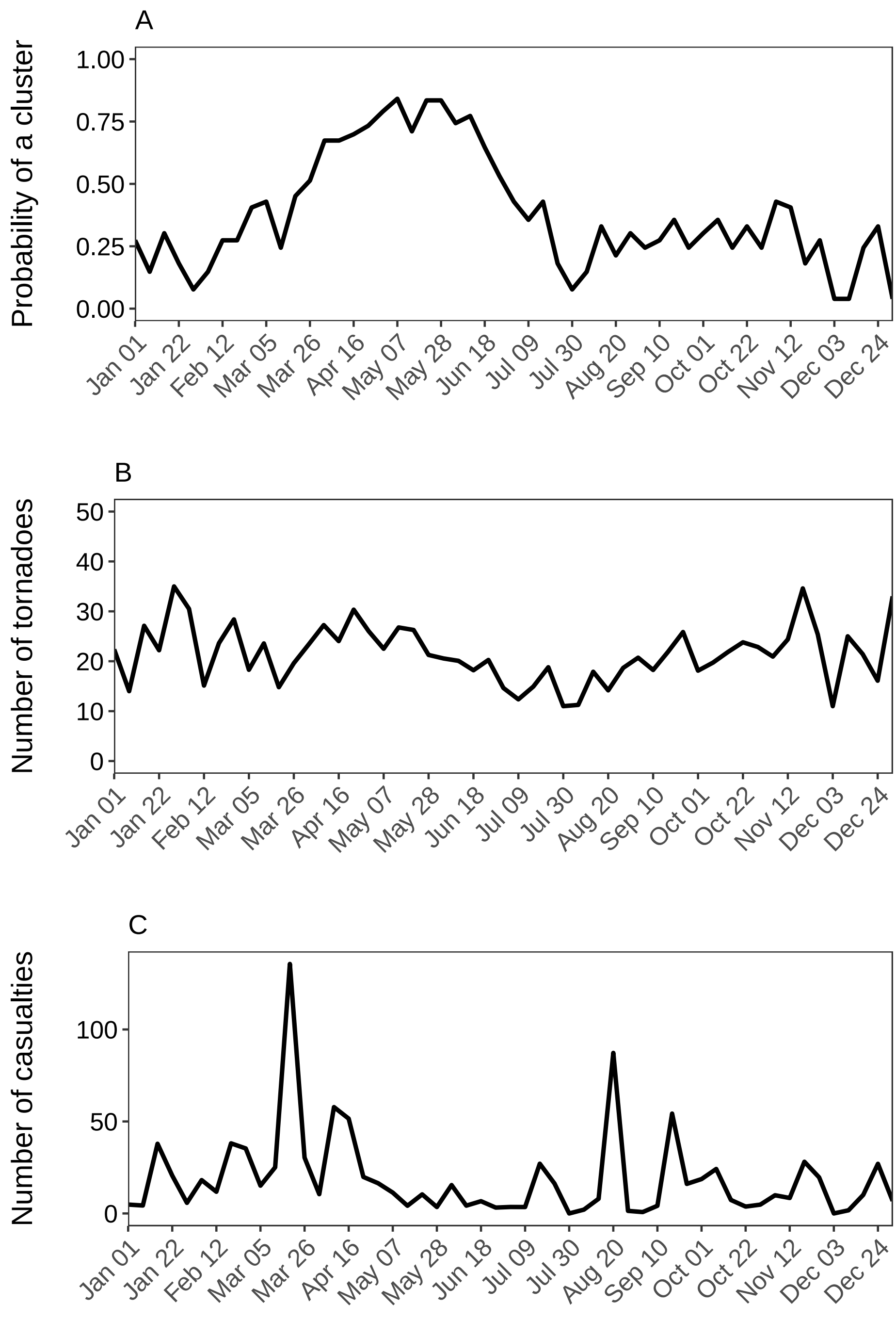


FIG. 2. Histograms of the number of clusters by number of tornadoes (A) and number of clusters by number of casualties (B). The histograms are right-truncated at 50 to show detail on the left side of the distributions. Only clusters with at least ten tornadoes are considered in this study.



449 Fig. 3. Probability of a cluster, average number of tornadoes per cluster, and average number of casualties per
450 million people per cluster by week of the year.

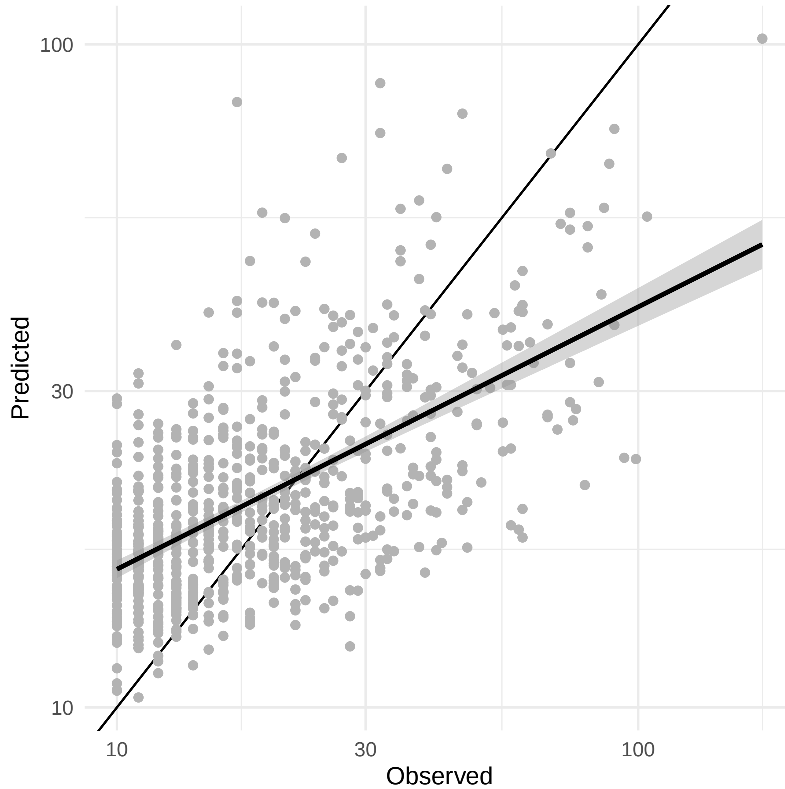


Fig. 4. Observed cluster-level tornado counts versus predicted rates from a negative binomial regression.

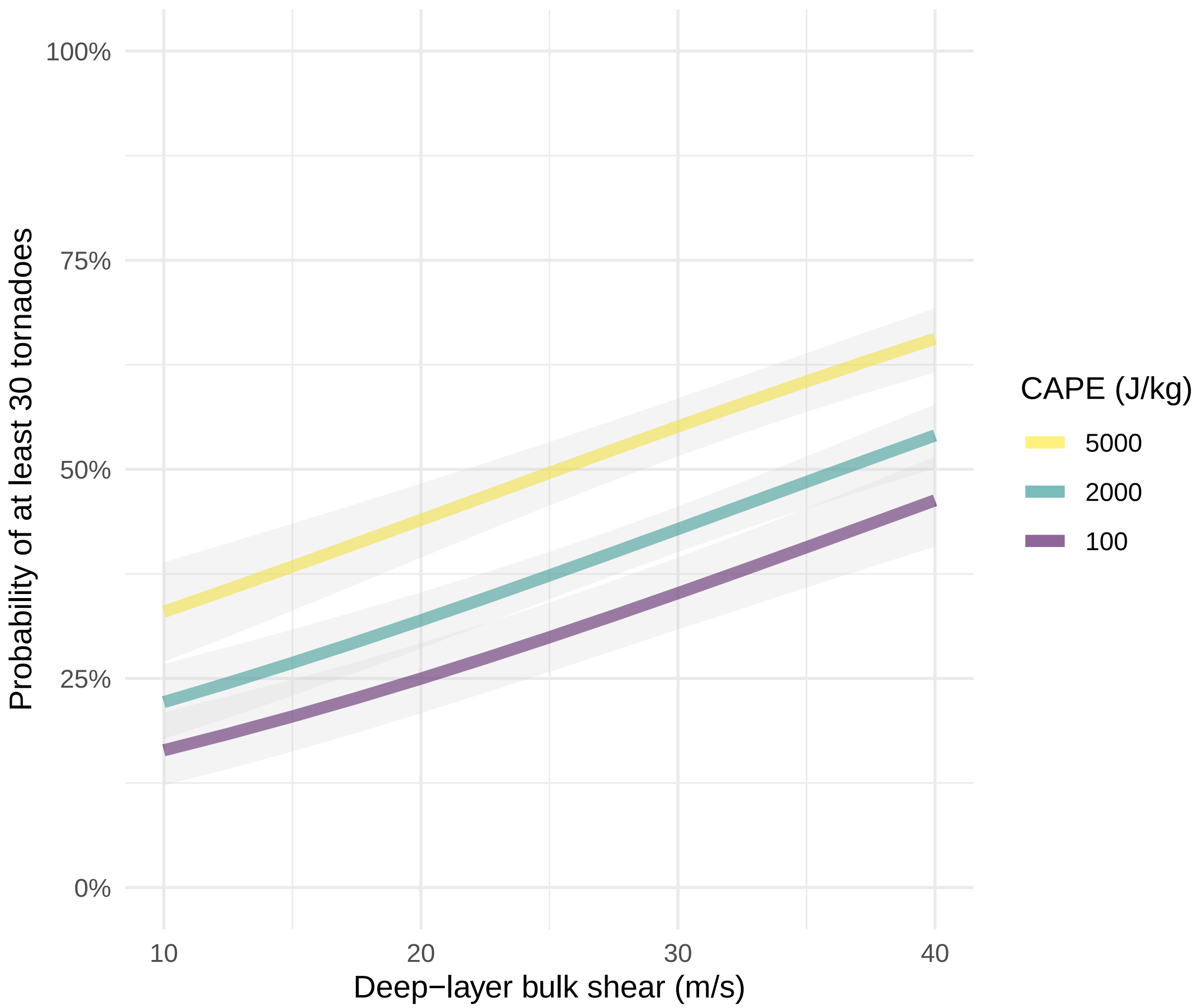


Fig. 5. Estimated probability of at least 30 tornadoes given an outbreak of at least ten tornadoes and the regression model. The predicted count from the model is a parameter in a negative binomial distribution with cluster area set at 400 000 km^2 and shallow-level bulk shear is set to its mean value.

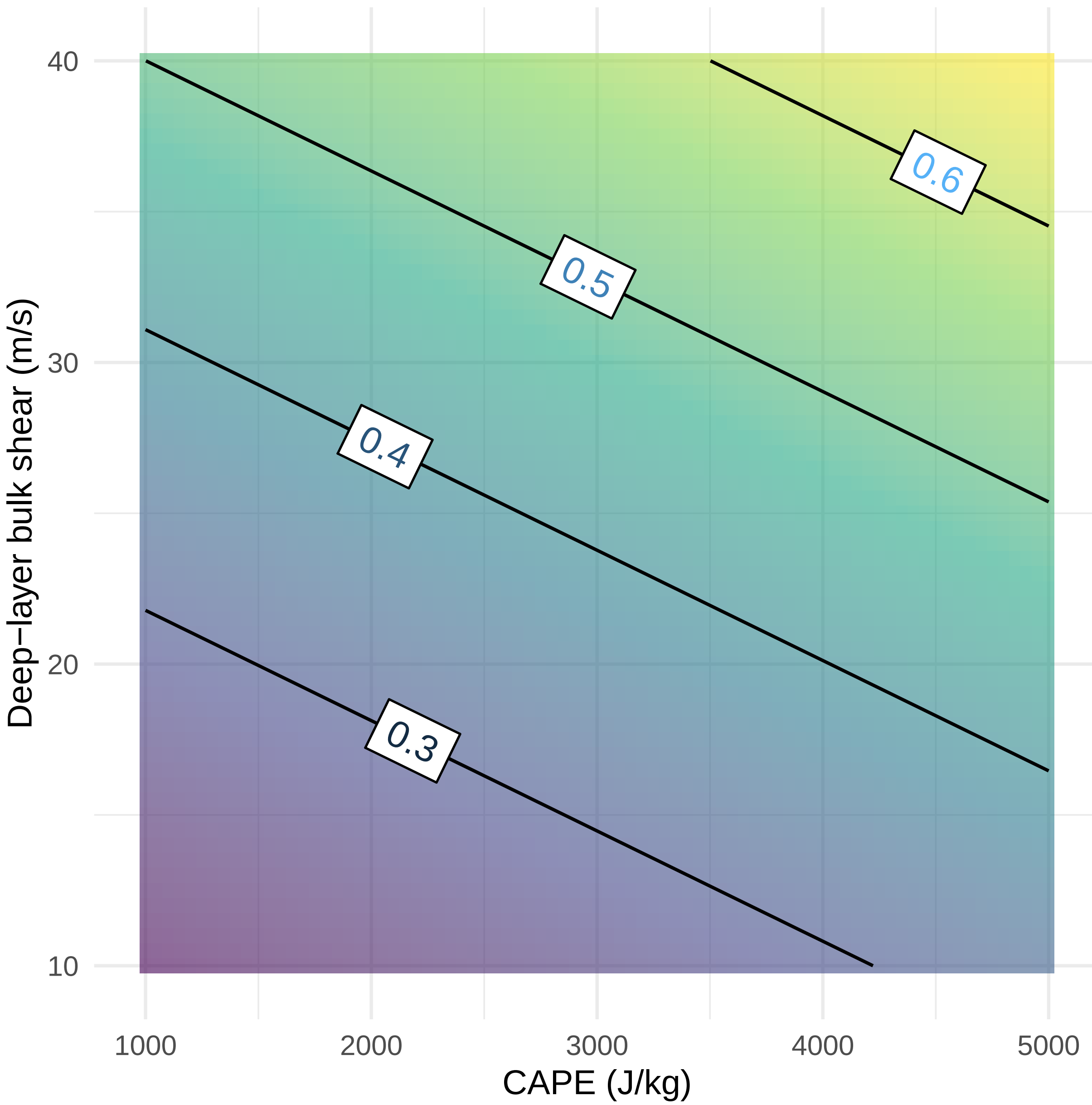


Fig. 6. Estimated probability of at least 30 tornadoes given an outbreak of at least ten tornadoes and the regression model across a range of CAPE and deep-layer bulk shear values holding the shallow-layer bulk shear at a mean value.

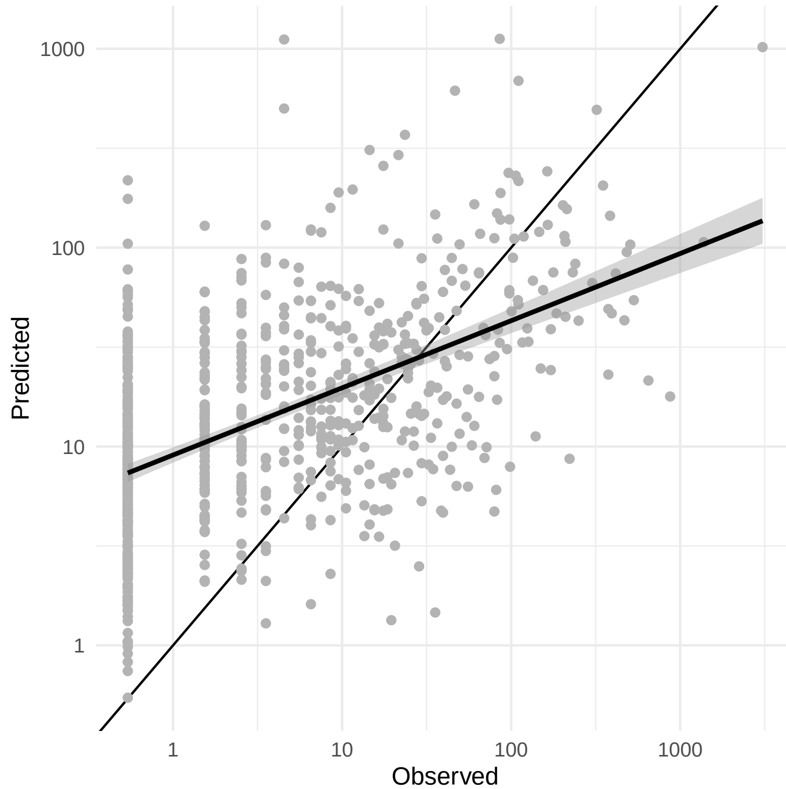


FIG. 7. Observed cluster-level casualty counts versus predicted rates from a negative binomial regression. Clusters without casualties are plotted at the far left.

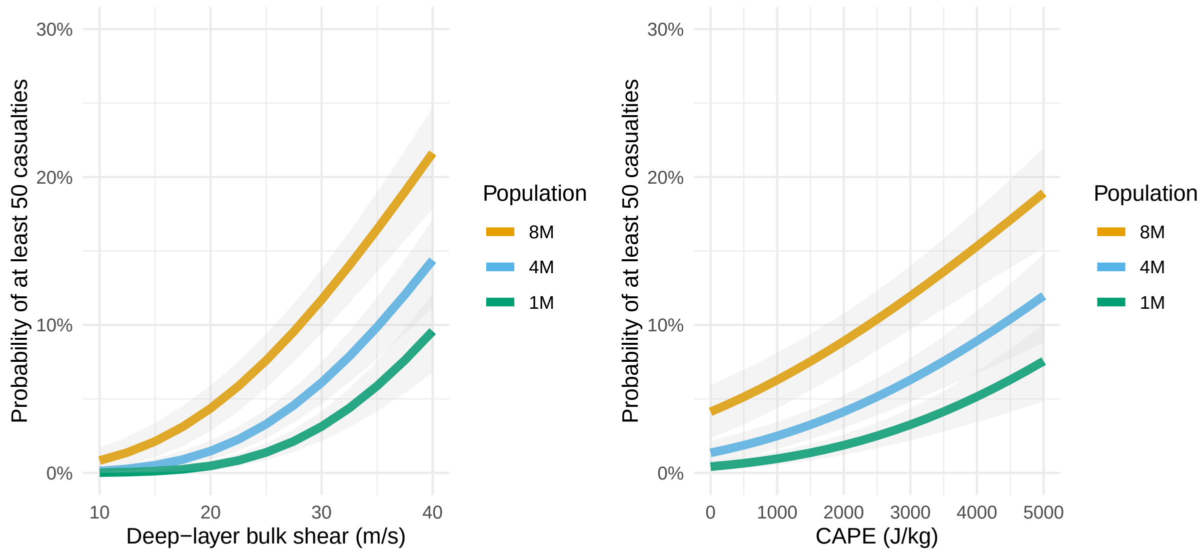


FIG. 8. Probability of at least 50 tornado casualties as a function of deep-layer bulk shear and CAPE and modulated by the number of people in harms way. The other variables are set at their mean values and year is set at 2018.

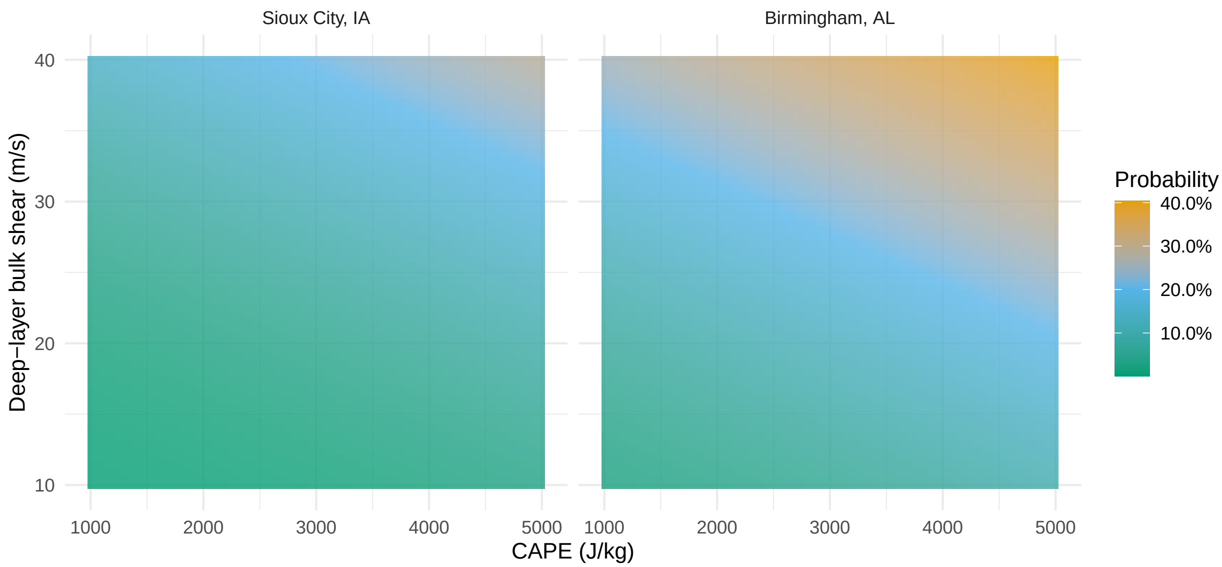


FIG. 9. Probability of at least 25 tornado casualties as a function of deep-layer bulk shear and CAPE and modulated by location for two *hypothetical* outbreaks, one centered over Sioux City, Iowa and the other centered over Birmingham, Alabama. The shallow-layer bulk shear is set to its mean value, year is set to 2018, and population is set to 4M.