Tornado damage ratings estimated with cumulative logistic regression*

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ABSTRACT

Empirical studies have led to improvements in evaluating and quantifying the tornado threat. However more work is needed to put the research onto a solid statistical foundation. Here the authors begin to build this foundation by introducing and then demonstrating a statistical model to estimate damage rating probabilities. A goal is to alert researchers to available statistical technology for improving severe weather warnings. The model is cumulative logistic regression and the parameters are determined using Bayesian inference. The model is demonstrated by estimating damage rating probabilities from values of known environmental factors on days with many tornadoes in the United States. Controlling for distance-to-nearest town/city, which serves as a proxy variable for damage target density, the model quantifies the chance that a particular tornado will be assigned any damage rating given specific environmental conditions. Under otherwise average conditions the model estimates a 65% chance that a tornado occurring in a city or town will be rated EF0 when bulk shear is weak (10 m s^{-1}). This probability drops to 38% when the bulk shear is strong (40 m s^{-1}). The model quantifies the corresponding *increases* in the chance of the same tornado receiving higher damage ratings. Quantifying changes to the probability distribution on the ordered damage rating categories is a natural application of cumulative logistic regression.

1. Introduction

Advances in evaluating and quantifying the tornado threat have recently been made. These advances come from a better understanding of relationships between near-storm regional-scale environmental conditions and the resulting mode of convection [see Smith et al. (2012) and Thompson et al. (2012) for a review of the literature on this topic] and from careful statistical analysis of relationships between radar-based rotational signals at the storm scale and the probability of specific damage rating categories (Smith et al., 2015; Thompson et al., 2017). Cohen et al. (2018) investigated multivariate models as a way to combine various environmental and storm-scale factors influencing the probability of specific enhanced Fujita (EF) ratings. While this approach is an improvement over earlier bi-variate methods (e.g., box-and-whisker plots), more work is required to put the research onto a solid statistical foundation.

The purpose of the present study is to introduce a statistical model to estimate a per-tornado damage rating (and associated uncertainties) directly and to demonstrate features of the model by using it to estimate damage ratings with environmental factors on days with many tornadoes. The aim differs from earlier studies in that the sole focus is on methodology. The goal here is to make researchers aware of modern statistical technology that can be leveraged to help them more effectively improve severe weather prediction.

Mathematically the approach we take is similar to that outlined in Cohen et al. (2018), who fit a linear regression to wind speeds corresponding to midpoints of the EF rating intervals. But our approach differs in that we fit a cumulative logistic regression model to the recorded highest EF rating directly. Statistically the approach we take is similar to the approach used in Thompson et al. (2017) who estimated conditional empirical probabilities of EF ratings by binning various indicators from WSR-88D radar. But our approach differs in that we use a multivariate model and we include estimates of uncertainty on the model output. In short, our approach is unique in that we use damage ratings directly as ordered categorical outcomes and we provide estimates of uncertainty on estimated probabilities.

While our focus in this paper is solely methodological, the application might have some operational relevance. This is because environmental ingredients needed to produce an outbreak of severe convective weather are well known and can be leveraged to make predictions. Considerable skill exists in outlining areas under greatest risk of severe weather on a given day. Outbreaks have large variation in terms of tornado frequency and intensity with much of this variability resulting from the convective mode (Smith et al., 2012; Thompson et al., 2012; Smith et al., 2015). Given a forecast of a severe weather outbreak will conditions favor many violent tornadoes? Dynamical models provide forecast guidance through products like updraft helicity swaths and models that allow for convection can anticipate the convective mode to some degree. But statistical models trained on thousands of tornadoes occurring across dozens of outbreaks can provide a baseline climatology for this risk. The U.S. Storm Prediction Center (SPC) currently uses long-run frequency of two or more tornadoes and long-run frequency of at least one strong (EF2–EF5) tornado as climatology.

In the above sense the present paper is similar to a recent study that employs a model to estimate the probability of at least one significant (EF2+) tornado on days with at least one tornado-warned supercell (Togstad et al., 2011). But it differs in a couple of key ways. First, in demonstrating the approach, we condition our model on the occurrence of a tornado 'outbreak' (at least ten tornadoes occurring within a relatively small area) rather than on the occurrence of a tornado warning. Second, we use cumulative frequency distribution by EF rating as the outcome variable rather than relative frequency of at least one EF2+ tornado. The paper is outlined as follows. The mathematics of cumulative logistic regression are given in §2. The data used to demonstrate the model is described in §3. Model results are presented in §4 and a summary is given in §5.

2. Cumulative logistic regression

The goal of this research is to put current knowledge about severe convective storms onto a solid statistical foundation. The purpose is to introduce cumulative logistic regression model as a way to estimate damage rating probabilities directly and to demonstrate its features by using it to estimate damage rating probabilities from large-scale environmental variables. We begin with a description of the model in the context of estimating damage ratings from environmental variables.

Let $\Pr(T_i \leq k)$ be the probability that tornado T_i has a maximum EF rating less than or equal to k, where $k = 0, \ldots, 5$. Then the log-cumulative odds (cumulative logit) is defined as

$$\alpha_k = \log \frac{\Pr(T_i \leq k)}{1 - \Pr(T_i \leq k)}, \tag{1}$$

where α_k ('intercept' parameter) has a unique value for each EF rating. Note that the cumulative logit for the highest EF rating (EF5) is infinity since $\log(\frac{1}{1-1}) = \infty$. So for $K = 6$ possible EF ratings, we have $K - 1 = 5$ intercepts that need to be determined.

A rating EF_i is assigned to tornado T_i using an *Ordered* distribution, which is a categorical distribution that takes a vector of probabilities ($\mathbf{p} = \{p_0, p_1, p_2, p_3, p_4\}$) one for each EF rating below EF5. Each probability value p_k in the vector is defined by its link to the intercept parameter value α_k. To include a predictor variable in the model we define the log-cumulative odds as the sum of α_k and a linear model term ($\beta_j x_{ij}$), where x_{ij} is the value of a population-level or group-level variable j (e.g., distance-to-nearest-city/town for a population-level variable and month for a group-level variable) associated with tornado T_i and, where β_j is the coefficient (or coefficient vector for group-level variables) associated with that variable. We determine the α_k's and β_j's using Bayesian inference so the model includes prior distributions on these parameters. We put a flat normal distribution prior on the α_k's and a flat student-t distribution prior on the β_j's.

Following the notation of McElreath (2015), mathematically, we write the model as

$$\begin{aligned}
\mathrm{EF}_i &\sim \mathrm{Ordered}(\mathbf{p}) \\
\mathrm{logit}(p_k) &= \alpha_k - \phi_i \\
\phi_i &= \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_J x_{iJ} \\
\alpha_k &\sim \mathrm{Normal}(0, 10) \\
\beta_j &\sim \mathrm{Student_t}(7, 0, 10)
\end{aligned} \tag{2}$$

The model gives the correct ordering of the EF ratings while allowing for changes in the likelihood for each tornado based on associated environmental conditions and other factors. The negative sign ensures that as the log-cumulative odds of every EF rating below the highest *decreases*, the probability mass shifts *upwards* toward higher EF ratings (McElreath, 2015).

3. Data

We illustrate the utility of cumulative logistic regression for estimating EF rating categories by fitting the model to a set of data. The data consist of the outcome variable [highest (maximum) per-tornado EF rating], predictor variables (environmental factors and distance to nearest city/town), and grouping variables (month and cluster number). Data are filtered to include only tornadoes occurring on days with at least ten tornadoes over the period 1994–2017 within the contiguous United States. Here we describe the procedure that we used to organize the data and provide summary statistics.

First we extract the date, time, genesis location, and maximum EF rating from the tornado record obtained from the Storm Prediction Center. Each row in the record contains information about an individual tornado. The start year of 1994 marks the beginning of extensive use of the WSR-

88D radar. There are 29,372 tornadoes over this period of record. We convert the geographic coordinates of the genesis locations to a Lambert conformal conic projection centered on 107° W longitude.

Next we assign a cluster number to each tornado based on space-time differences between genesis locations. If two tornadoes occur close together in space and time, they are assigned the same cluster number (see Fig. 1 for an example of a tornado cluster). Clustering stops when the difference between individual tornadoes and an existing cluster exceeds 50K seconds ($\sim$14 hours). The differences have units of time because we divide the spatial distance by 15 m s^{-1}. Details of the procedure along with a comparison to a subjective grouping are detailed in Schroder and Elsner (2018). Finally, we filter the tornadoes to include only those occurring as part of clusters with at least ten tornadoes within a single convective day (12 UTC to 12 UTC). This filtering results in 16,501 tornadoes in 742 clusters with the majority of the clusters occurring during April, May, and June (Fig. 2).

Next we extract environmental variables from the North American Regional Reanalysis (NARR) obtained from the National Center for Environmental Predictions (NCEP) North American Regional Reanalysis (NARR) from the National Center for Atmospheric Research (NCAR) (National Centers for Environmental Prediction). Variables are available on a 32.4 km grid and are a blend of modelled and observed data. We use the files that contain environmental data for each day ranging from 12 UTC to 12 UTC in three-hour increments. Variables considered include the 180 to 0 hPa above ground level (AGL) CAPE and CIN (layer 375, 376), the 0 to 3000 m AGL helicity (layer 323), and the 0 to 6000 m AGL u and v components of storm motion (layer 324, 325). Additionally, we compute total storm motion as the square root of the sum of the velocity components squared and bulk shear as the square root of the sum of the squared differences between the u and v winds for the 1000 hPa and 500 hPa levels. We consider these variables because they are well known to be associated with tornado activity (Cheng et al., 2016). For each tornado cluster, we find the closest three-hour time *before* the appearance of the first tornado in the cluster and use the environmental variables from that time. We pick a time before the event starts to have a sample of conditions prior to the appearance of any tornado. We join the environmental variables at the cluster level with the data at the tornado level.

Finally, for each tornado, we compute the distance between the genesis location and the nearest city/town. Population values are based on the 2010 U.S. Census data [obtained from Steiner (2019) and accessed through the `USAboundaries` package (Mullen and Bratt, 2018) in R] and range from a few hundred people to more the eight million people. The distance between a tornado and the nearest city/town serves as a proxy for the potential number of damage targets. All else being equal a tornado occurring within a city or town will have a greater opportunity to impact a damage target, on average, than one that occurs in a rural area. With distance-to-nearest-city/town as a predictor variable we are able to quantify how the potential number of damage targets shifts the distributions for example from EF0 to EF1 and from EF1 to EF2. We know that the chance of getting an EF4+ tornado in the data set increases with the number of targets, but we don't know by how much relative to an EF3. Table 1 list the predictor variables along with the associated extremes and average values. Averages are computed over all tornadoes. We remove tornadoes occurring during the May 30, 2003 cluster since the maximum helicity value for this cluster had an erroneously high value.

4. Results

We begin with a histogram of maximum EF rating per tornado (highest rating given to the tornado as recorded in the SPC data). As expected, the histogram (Fig. 3) shows that the vast majority of tornadoes that occur as part of a big cluster are rated EF0 or EF1 with far fewer rated

EF4 or EF5. But relative to all tornadoes the distribution of tornadoes in big clusters favors higher ratings. For example, 3.5% of tornadoes occurring in big clusters are rated EF3 compared to 2.3% of all tornadoes. And .08% of tornadoes occurring in big clusters are rated EF5 compared to .05% of all tornadoes.

Next, we describe this histogram on the log-cumulative-odds scale by constructing the odds of a cumulative probability and then taking logarithms. The logit function is the logarithm of the odds (log-odds) so the cumulative logit is log-cumulative-odds. Both the logit and the cumulative logit constrain the probabilities to lie in the interval between 0 and 1. Predictor variables are added on the cumulative logit scale (Eq. 2). The link function takes care of converting the parameter estimates on these variables to the proper probability scale (McElreath, 2015). We compute the cumulative probabilities from the histogram, which are the discrete proportions of tornadoes by each EF rating. We then compute the series of intercept parameters to re-describe the histogram in terms of log-cumulative odds (Eq. 1). Each intercept is on the log-cumulative-odds scale and stands in for the cumulative probability associated with each EF rating (Fig. 4). The discrete probability for each EF rating $\Pr(T_i = k)$ is the successive difference between the elements of the vector of cumulative probabilities. These probabilities are the likelihoods that are conditioned on the values of the predictor variables and combined with the priors to complete the model (Eq. 2).

Posterior distributions on the model parameters are obtained using the Stan computational engine (Carpenter et al., 2017) accessed through the `brms` package (Bürkner, 2017). Mildly informative conservative priors are specified to improve convergence of the sampler and to guard against over-fitting. To improve the efficiency of the sampler, predictor variables are scaled by subtracting their respective means and dividing by their respective standard deviations. The environmental variables and year are included as population-level effects (fixed effects). The month of the cluster and the unique cluster identification number are included as group-level effects (random effects).

The model reproduces the distribution of tornadoes by EF rating category as expected (Table 2). It slightly under estimates the proportion of EF0 tornadoes and slightly over estimates the number of EF1 tornadoes and EF3 tornadoes, but overall the proportions from the model match the data very well. Signs on the fixed-effect coefficients (Table 3) are consistent with expectations based on physical reasoning derived from the current understanding of how environmental factors influence tornado activity (Smith et al., 2012; Thompson et al., 2017). The coefficient on cluster year is positive indicating a trend toward higher rated tornadoes as discussed in Elsner et al. (2018). The coefficient on distance-to-nearest-city/town is negative as expected. The closer a tornado occurs to a city/town, the greater the chance it will get rated at the next higher EF rating relative to the same tornado occurring in a rural area. The largest effect occurs with bulk shear. The sign on the coefficient indicates that greater shear results in a better chance of a higher EF rating as we would expect from physical reasoning.

Coefficients on the fixed effects and on the month random effect are plotted in Fig. 5. Magnitude of the departure from zero indicates the importance of the variable to the model for estimating damage ratings as discussed above. The monthly variation in the distribution of tornadoes by EF rating is an important model component with May and June having a significantly lower proportion of most damaging tornadoes after accounting for the fixed effects. January and November have a larger than average proportion of most damaging tornadoes.

To get an idea how much a particular variable statistically influences the distribution of EF ratings while holding the other variables constant we examine marginal effects (Fig. 6). A variable's marginal effect is computed by holding the other variables at their respective mean values. Consider the marginal effect of bulk shear. For tornadoes occurring in environments of low shear (less than 10 m s^{-1}) the model estimates the probability that a tornado gets rated EF0 at nearly 75%. This probability drops to 40% for tornadoes occurring in environments of high shear (greater than

40 m s^{-1}). There are compensating increases in the chance of EF1 and higher ratings across the range of bulk shear values. Further, we see that CAPE and helicity have less of an effect on the probability distribution of EF ratings compared to bulk shear (posterior means on the respective coefficients are farther from the zero line). We also quantify the trend toward higher EF ratings and the relative changes over time depending on where the tornado occurs (near a city/town or outside a city/town; Fig. 7).

Importantly we can use the model to get an estimate of the probability distributions for any *particular* set of predictor values. Since the model uses Bayesian inference, we get *posterior predictive samples* of the EF probability distribution for any set of values. As an example, we show the posterior predictive samples across a range of bulk shear values setting the variables to their respective averages except distance-to-nearest-city/town, which we set to zero (Fig. 8). Bulk shear is illustrated because it has the largest influence on the outcome (distribution of EF ratings) as noted above. Individual samples (100 of them) of the cumulative proportion of tornadoes for different EF ratings are shown.

When bulk shear is 10 m s^{-1} the posterior mean relative percentage of an EF0 tornado is 65% [(56%, 79%), interquartile range (IQR)] but when bulk shear is 40 m s^{-1} the posterior mean relative percentage of an EF0 tornado drops to 38% [(25%, 50%), IQR]. This decrease in percent is compensated by increases in the relative percentage of tornadoes rated higher. For example, when bulk shear is 10 m s^{-1} the posterior mean relative percentage of an EF3 tornado is 2.0% [(.9%, 2.5%), IQR] but when bulk shear is 40 m s^{-1} the posterior mean relative percentage of an EF3 tornado rises to 6.1% [(2.9%, 8.2%), IQR]. This quantification of the effect of bulk shear on EF ratings is possible with a cumulative logistic regression model.

We can use the model in a similar way to quantify a well-known (but not well quantified) EF rating bias. We find that under average environmental conditions when a tornado occurs near the center of a city or town 47% [(31%, 59%), IQR] of the time it will get rated EF0. This compares with 56% [(41%, 70%), IQR] of the time when the same tornado occurs 50 km from the center. This increase in the percentage of EF0 tornadoes going from city to rural areas is compensated by corresponding decreases in percentages of tornadoes getting rated higher. For example, the chance that a tornado gets rated as EF3 or higher is 5% in the city compared with 3.6% at a distance of 50 km from the city/town and only 2.4% at a distance of 100 km from the city/town. This quantification of an EF rating bias is possible with a cumulative logistic model. By including an interaction between year and distance to nearest city/town in the model we determine that this bias is not diminishing over time. This differs from the decreasing population bias on the tornado reports as documented and quantified elsewhere (Elsner et al., 2013; Jagger et al., 2015).

5. Summary

We introduced the cumulative logistic regression model to estimate damage rating probabilities directly and we demonstrated features of the model by using it to estimate probabilities from environmental variables for tornadoes occurring in large clusters (ten or more tornadoes). Model parameters were determined by Bayesian inference using the method of Hamiltonian Monte Carlo with the Stan language. Stan code was generated from R through the `brms` package. The flexibility of this approach makes it straight forward to adjust the model to estimate other outbreak characteristics (e.g., overall number of tornadoes) and to include domain-specific knowledge. Results show that the chance of higher damage ratings can be explained statistically by increasing values of bulk shear, CAPE, and helicity by decreasing values of distance to nearest city/town.

Coefficients on the environmental variables are consistent with expectations based on physical reasoning derived from the current understanding of how environmental factors influence tornado activity. There is a trend toward higher rated tornadoes with time as inferred in Elsner et al.

(2018). The closer a tornado occurs to a city/town, the greater the chance it will get rated at the next higher EF rating. Bulk shear has the strongest relationship to damage rating proportions. Under otherwise average conditions, the model estimates a 65% [(53%, 78%), IQR] chance that any tornado occurring near a city or town will be rated EF0 when the bulk shear is weak (10 m s^{-1}). This probability drops to 38% [(26%, 50%), IQR] when the bulk shear is strong (40 m s^{-1}) but with compensating *increases* in the chance of *higher* ratings. This quantification is only possible with a cumulative logistic regression.

This study makes the case that cumulative logistic regression is the right tool for quantifying the combined role environmental factors play on the distribution of tornadoes by EF rating. It might be tempting to fit a simpler model to these data as was done in Cohen et al. (2018) who suggested that simulated tornado wind speeds from their model can be scaled within the context of the damage ratings. But it is unclear how this can be done while preserving the relative frequency of ratings given that the model residuals are assumed to be described by a normal distribution centered about the conditional mean wind speed. Cumulative logistic regression makes no such assumption and estimates probabilities directly.

Finally, although the results from applying the model for demonstration purposes are consistent with past research on this topic, there are limitations to the inferences that can be made with them. In particular, our exclusive focus on days with at least ten tornadoes is a type of selection bias meaning that the sample of data used to fit the model does not represent the population of all tornadoes, which limits what we can say in general about the effect of convective environments on the probability of a particular EF rating. Further, no attempt was made to assess model skill in the context of its potential value in actual forecast situations. At a minimum a cross-validation exercise [see Elsner and Schmertmann (1994)] would be needed.

Acknowledgments

The code and data to produce all the figures and results of this paper are available at `https://github.com/jelsner/EF-dist`.

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Variable Name	Abbreviation	Minimum	Maximum	Average
Year	YR	1994	2017	2006
Nearest distance to city/town (km)	D	.019	137	19.2
Convective available potential energy (J kg^{-1})	CAPE	0	6530	2134
Helicity (m^2 s^{-2})	HLCY	23	1027	350
Bulk shear (m s^{-1})	BS	5.7	45.5	28.5
Convective inhibition (J kg^{-1})	CIN	−651	0	−176

TABLE 1. Variables used in the model to estimate damage ratings. The values are based on 16,483 tornadoes in 741 clusters.

Damage Rating	Observed	Estimated
EF0	.5325	.5220
EF1	.3183	.3489
EF2	.1057	.0945
EF3	.0348	.0279
EF4	.0079	.0061
EF5	.0008	.0006

TABLE 2. Observed and estimated proportions of tornadoes by EF damage rating. The estimated proportions are from a cumulative logistic regression model.

Coefficient	Estimate	Error	95% UI
β_{YR}	0.10	0.03	(0.03, 0.16)
β_{D}	-0.13	0.02	(-0.17, -0.09)
β_{CAPE}	0.10	0.04	(0.02, 0.18)
β_{HLCY}	0.12	0.05	(0.03, 0.21)
β_{BS}	0.28	0.04	(0.20, 0.38)

TABLE 3. Estimated coefficients on the population-level effects. Abbreviations in the subscripts refer to the variables listed in Table 1

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FIG. 1. Tornado locations (origin) during one tornado cluster used in this study.

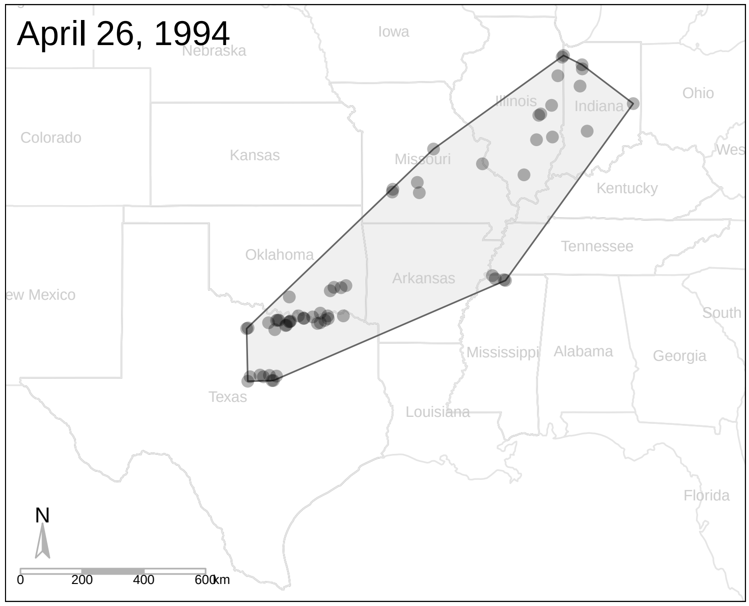
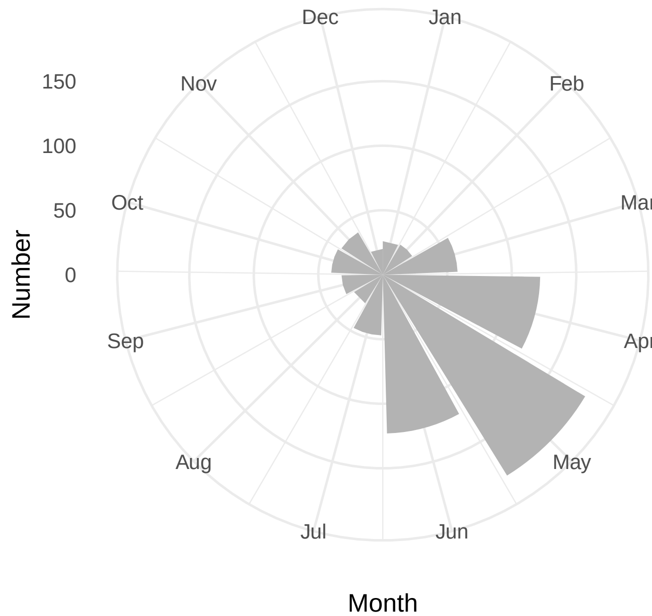


FIG. 2. Monthly frequency of tornado clusters (convective days with at least ten tornadoes), 1994–2017.



362 FIG. 3. Histogram of tornadoes by maximum EF rating. Only tornadoes occurring in big clusters are consid-
363 ered (see text).

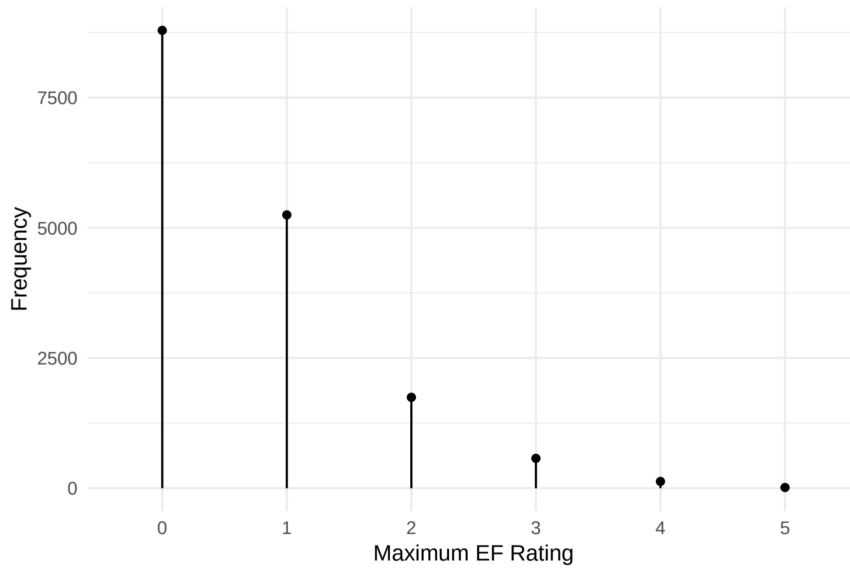


FIG. 4. Cumulative proportion (A) and log-cumulative odds (B) of a tornado by maximum EF rating for all tornadoes (gray) and for tornadoes occurring in big clusters (black). Note the cumulative logit for the EF5 rating is infinity.

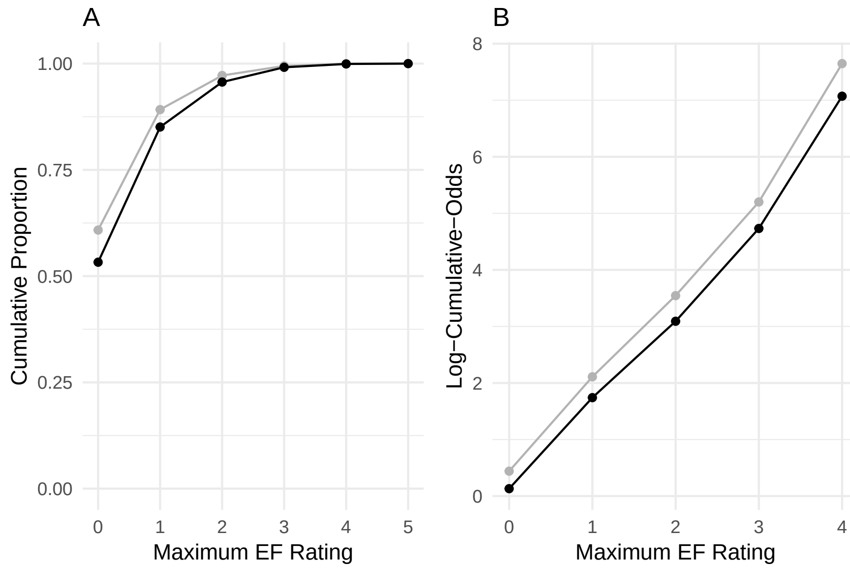


FIG. 5. Posterior median (circle) and highest posterior probability intervals [66% (thick line) and 95% (thin line)] for (A) the fixed effects and (B) the random effect of month.

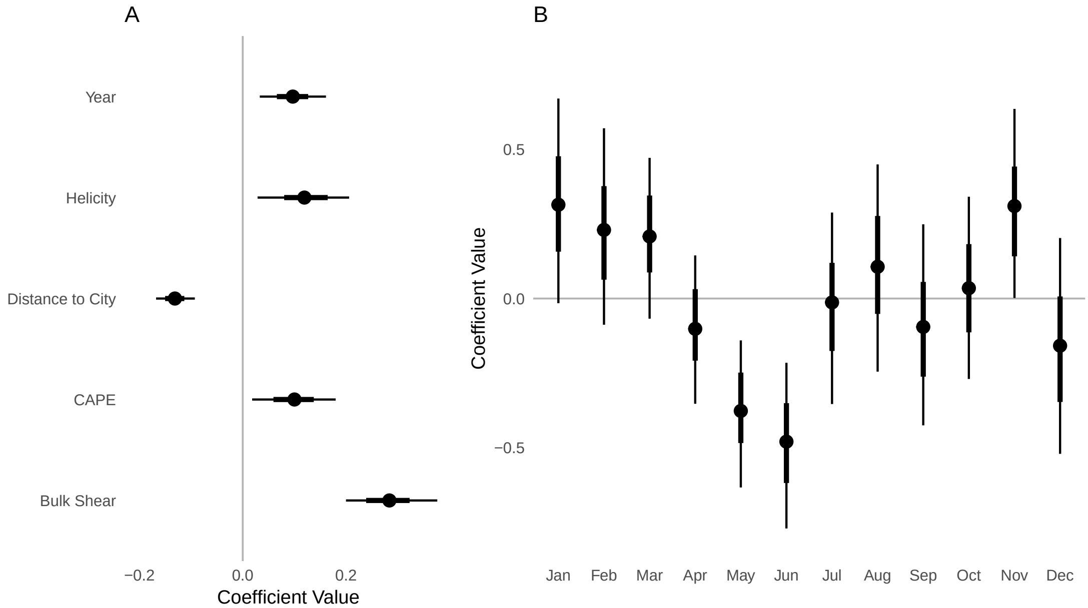


FIG. 6. Marginal effects of the environmental variables on the distribution of EF rating. (A) Bulk shear, (B) CAPE, (C) distance to nearest city/town, and (D) storm relative helicity.

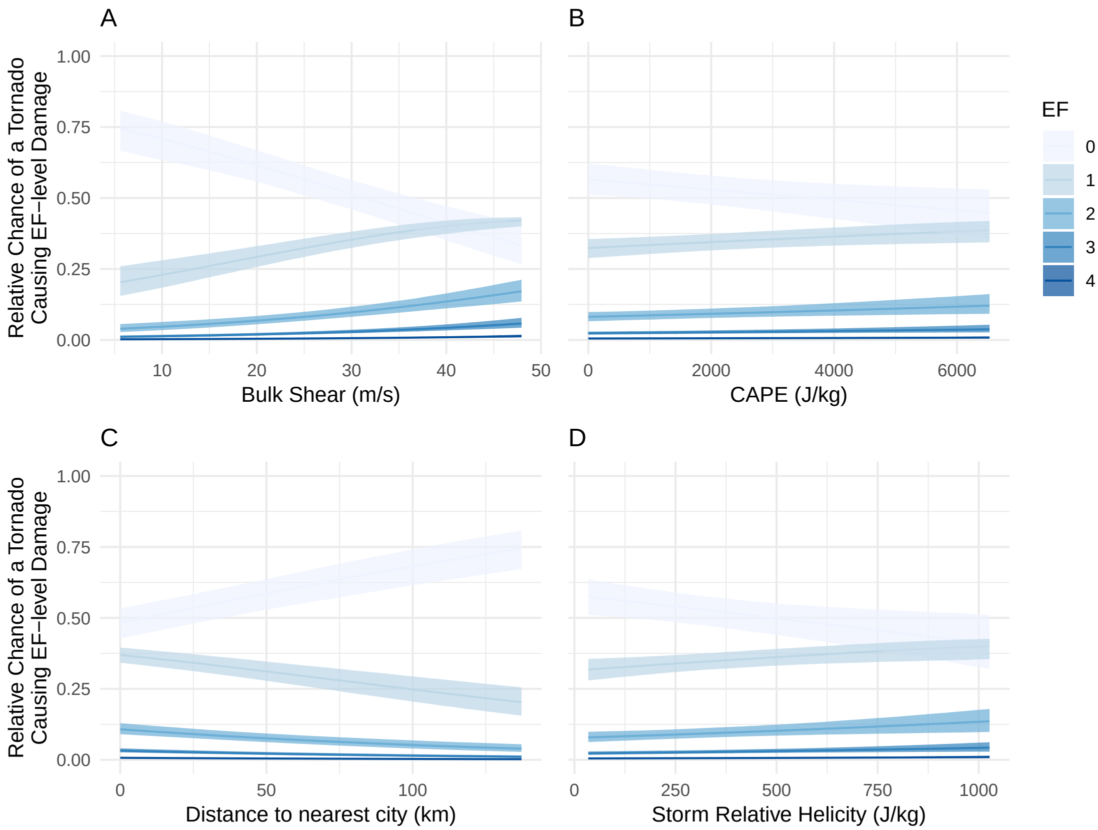


FIG. 7. Marginal trends in the distribution of EF rating (EF0, EF1, and EF2). Trends are estimated by setting the distance to 135 km for remote areas and 0 km for inside a city or town.

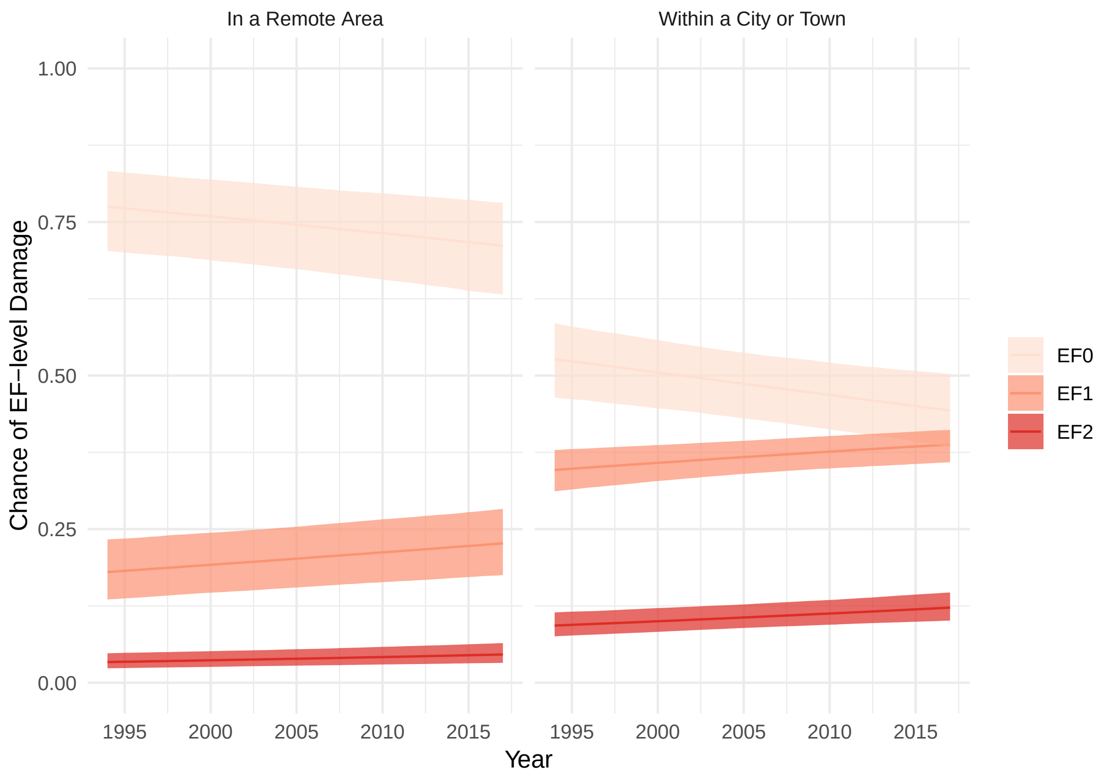


FIG. 8. Posterior predictions over a range of bulk shear values. (A) Cumulative proportion by EF rating for 100 random samples, and (B) Probability of EF-level damage by EF rating. The white line indicates the posterior average and the band indicates the inter-quartile range over the samples. Values for other variables are set to their respective averages except for distance-to-nearest-city/town whose value is set to zero.