

Predicting Spring Tornado Activity in the Central Great Plains by 1 March

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ABSTRACT

The authors illustrate a statistical model for predicting tornado activity in the central Great Plains by 1 March. The model predicts the number of tornado reports during April–June using February sea surface temperature (SST) data from the Gulf of Alaska (GAK) and the western Caribbean Sea (WCA). The model uses a Bayesian formulation where the likelihood on the counts is a negative binomial distribution and where the nonstationarity in tornado reporting is included as a trend term plus first-order autocorrelation. Posterior densities for the model parameters are generated using the method of integrated nested Laplacian approximation (INLA). The model yields a 51% increase in the number of tornado reports per degree Celsius increase in SST over the WCA and a 15% decrease in the number of reports per degree Celsius increase in SST over the GAK. These significant relationships are broadly consistent with a physical understanding of large-scale atmospheric patterns conducive to severe convective storms across the Great Plains. The SST covariates explain 11% of the out-of-sample variability in observed F1–F5 tornado reports. The paper demonstrates the utility of INLA for fitting Bayesian models to tornado climate data.

1. Introduction

The United States experiences more tornadoes than any country on Earth with an annual average during the 3 years (2009–11) exceeding 1350. According to the National Oceanic and Atmospheric Administration (NOAA) Storm Prediction Center, the annual average number of killer tornadoes since 2009 is 30 with total deaths exceeding 600. Annual statistics are only part of the story. The number of tornado reports varies widely from one year to the next yet we do not know what causes this variation.

We know some of the necessary ingredients on the mesoscale including high values of storm-relative helicity and convective available potential energy (CAPE), surface boundaries, and directional shear of winds with height (Rotunno 1981; Davies-Jones 1984; Rotunno and Klemp 1985; Brooks and Wilhelmson 1993). It is well known that the mesoscale ingredients come together when the synoptic scale includes warm, moist air at low levels, cold, dry air aloft, and a strong jet stream. Missing is a link to the climate scale.

It is also known that a key component to climate predictability is the slowly varying ocean heat content. Here we show that ocean surface temperatures over the western Caribbean Sea and Gulf of Alaska during February provide a small, but statistically significant level of skill in portending springtime tornado activity across the central Great Plains. The model is constructed using a Bayesian formulation. The likelihood on the annual tornado report counts is a negative binomial distribution. The nonstationarity in reporting trends is included as a trend term. Posterior densities for the model parameters are generated using the integrated nested Laplace approximation (INLA) method. The paper is novel in demonstrating a preseason SST link to springtime tornado activity across the central Great Plains and in demonstrating the INLA method for Bayesian computation on tornado data. (The code used in this study is available online at rpubs.com/jelsner/4745.)

The paper is outlined as follows: in section 2 we present the tornado data and our partition of it that focuses on the months of April through June (spring) over the central Great Plains. In section 3 we examine the annual variation in tornado reports using time series plots and histograms. We show that the annual counts are not adequately described by a Poisson distribution. In section 4 we examine the annual variation in SSTs in the Gulf of Alaska (GAK) and in the western Caribbean

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Sea (WCA). While a weak in-phase relationship between the two series is noted overall, the relationship has gone out of phase starting in the early twenty-first century. In section 5 we present the modeling framework mentioned above and in section 6 we present results from the model including posterior densities on the SST covariates and diagnostics related to model fit, calibration, and predictive skill. In section 7 we give a summary and some concluding remarks.

2. Tornado data and study region

The Storm Prediction Center (SPC) maintains a dataset of all reported tornadoes in the United States from 1 January 1950 to the present. Earlier records exist, but there has not been a consistent effort to investigate, document, or maintain a record of these earlier occurrences (Galway 1977). The SPC dataset is the most reliable archive available for tornado studies. (We download the dataset from <http://www.spc.noaa.gov/gis/svrgis/>.)

In this study we consider tornadoes only within a region centered on Russell, Kansas, as defined in Elsner et al. (2013). The region stretches across the central Great Plains from northern Texas to central Nebraska and is bounded by 36.10° and 41.57°N latitudes and 102.37° and 95.34°W longitudes. This is an area with a high concentration of tornadoes and where there are no large spatial gradients in occurrence rates. It corresponds to an area favored by storm chasers. We further restrict our attention to the months from April through June when supercells are common.

Figure 1 shows the distribution of all tornado reports by month. There is a marked peak in activity during May with the main season running from April through June. Here we focus on this three-month period. Of the 6328 tornado reports in this region over the period 1950–2011, 73.8% of them occurred in April, May, or June.

Figure 2 shows a terrain map of the study domain and the touchdown points of the 5932 tornadoes (April–June) during 1950–2011 with a Fujita-scale (F scale) rating. We do not consider further the 6.3% of reports without an F-scale rating.

The F scale, introduced in the 1970s, is the standard measure of tornado intensity. It is based on the maximum damage caused along the tornado path and ranges from F0 (for minimum damage) to F5 (for total destruction). It was replaced by the enhanced Fujita scale (EF scale) in early 2007, using slightly different and more specific criteria for assessment (Potter 2007). The F scale and the EF scale are considered equivalent for climatological applications. The reliability and number of tornado reports have increased over time as a result of better radar coverage, larger population, and greater

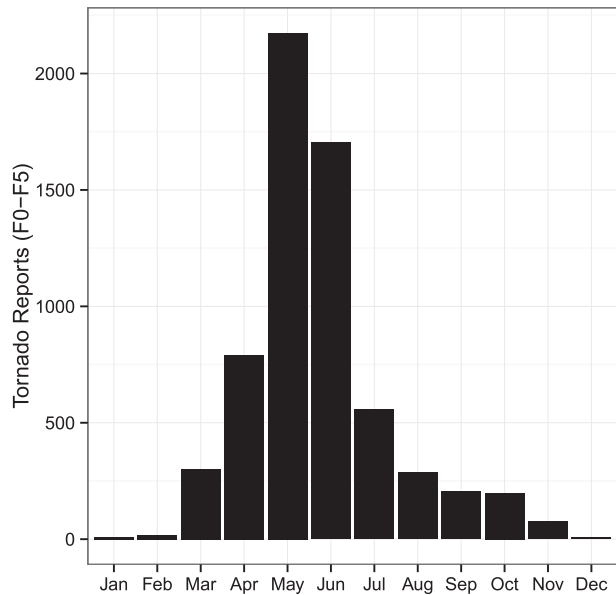


FIG. 1. Tornado reports by month over the study region centered on Russell, KS, for the period 1950–2011. Tornado reports are most numerous during April–June.

public awareness (Doswell et al. 1999; Verbout et al. 2006). Thus, the annual tornado reports are not stationary over time.

3. Annual variation in tornado reports

Figure 3 shows the time series of April–June tornado reports over the study region by F-scale grouping. There is an increase in the reports of all tornadoes (F0–F5) and a slight decrease in the reports of F2 and higher tornadoes. There are some years without F3 or stronger tornadoes. The trend line is shown in gray. It is computed using a local regression fit. For year t_o , the fit is made using reports from all years where the number of tornadoes at each year t is weighted by t 's distance from t_o ($d_{t_o,t}$) using a tricubic weighting proportional to $(1 - d_{t_o,t}/d_{t_o,t_m}^3)^3$, where d_{t_o,t_m} is the distance between year t_o and the year t_m farthest away. The gray band is the 95% confidence interval on the fits. The interval is based on the standard error of the regression coefficient assuming an approximate t distribution. Histograms showing the annual number of tornado reports by F-scale grouping are displayed in Fig. 4.

We propose a parametric statistical model for the annual number of tornado reports. This requires us to specify a distribution for the response variable (annual count). While local tornado counts have been modeled with the Poisson distribution (Anderson et al. 2007; Tippett et al. 2012), the annual springtime counts over the central Plains are not well described by this distribution.

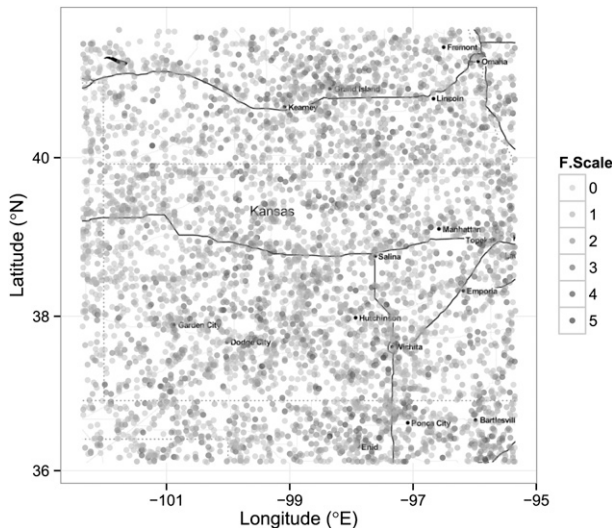


FIG. 2. Tornado reports (F0–F5) over the study region centered on Russell, KS, during April–June for the period 1950–2011. Point grayscale corresponds to the F scale. The points are provided on a Lambert conformal conic (LCC) projection with reference parallels of 33° and 45°N latitudes and the spatial unit is meters.

This is apparent by examining the ratio of the annual variance to the annual mean, which is tabulated by F-scale group in Table 1. For a set of counts described by a Poisson distribution, the ratio is close to 1. Here we see the variance in the counts exceeds the mean for all F-scale groups (the ratio exceeds 1) and by a factor of more than 27 for the group that includes the weakest tornadoes.

A goodness-of-fit test for a Poisson distribution gives a p value less than 0.001 for all groups with the exception of the F4–F5. The p value is evidence in support of the null hypothesis that the counts are indistinguishable from Poisson. Even with the group of violent tornadoes we reject the null hypothesis of a Poisson distribution at a significance level of 0.016. The overdispersion (variance larger than the mean) in annual counts results from tornadoes occurring in clusters—defined as an outbreak—on days when synoptic weather conditions are particularly favorable for severe convective storms. Statistically, the occurrence of a tornado on a given day increases the chance of another one on the same day, often in the same general area. The largest outbreak of five F4–F5 tornadoes over this region occurred on 26 April 1991. The negative binomial distribution is an alternative to the Poisson distribution when counts are overdispersed.

4. Sea surface temperatures

As mentioned, an important component to climate predictability is the slowly varying ocean heat content.

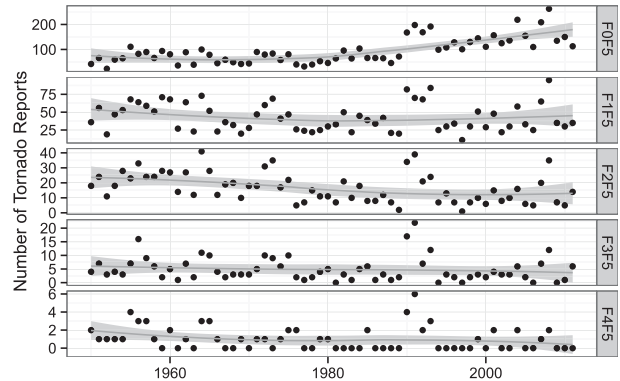


FIG. 3. Time series of spring tornado reports by F-scale groups over the study region centered on Russell, KS. A local cubic polynomial fit to the report counts shows the trends.

Here we demonstrate that ocean surface temperatures over the western Caribbean Sea and Gulf of Alaska during February provide some skill in predicting the amount of springtime tornado activity across the central Great Plains. The tornado region and the two SST regions are shaded in Fig. 5.

The two regions are selected because of the relatively close proximity (on the global scale) to the Great Plains and because the considerable thermal inertia of the ocean can guide the long-term (several months) evolution of the climate patterns. In particular, we might expect lower-than-average temperatures in the Gulf of Alaska to combine favorably with higher-than-average temperatures in the western Caribbean Sea to produce jet stream divergence above the central United States.

We are interested in a model that can be used to predict springtime tornado activity so we obtain SST values for the month of February from both regions (<http://www.esrl.noaa.gov/psd/data/timeseries/>). The series are plotted in Fig. 6. As with the tornado reports, we apply a local polynomial (cubic) fit to the series (gray line) and the gray band is the 95% confidence level. There is year-to-year variation in SST in both regions but no long-term trends.

The correlation between the two SST time series (GAK and WCA) is +0.24 (−0.01, +0.46) [95% confidence interval] over the 62-yr period indicating a weak, in-phase relationship. When the WCA is warmer than average, there is a tendency for the GAK to be warmer as well. Interestingly, this in-phase relationship has gone out of phase since about 2004. Hence, the correlation between the two series is +0.35 (+0.09, +0.56) [95% confidence interval] before 2004 and −0.37 (−0.85, +0.46) [95% confidence interval]. If the out-of-phase relationship continues we might expect to see more years of high tornado activity.

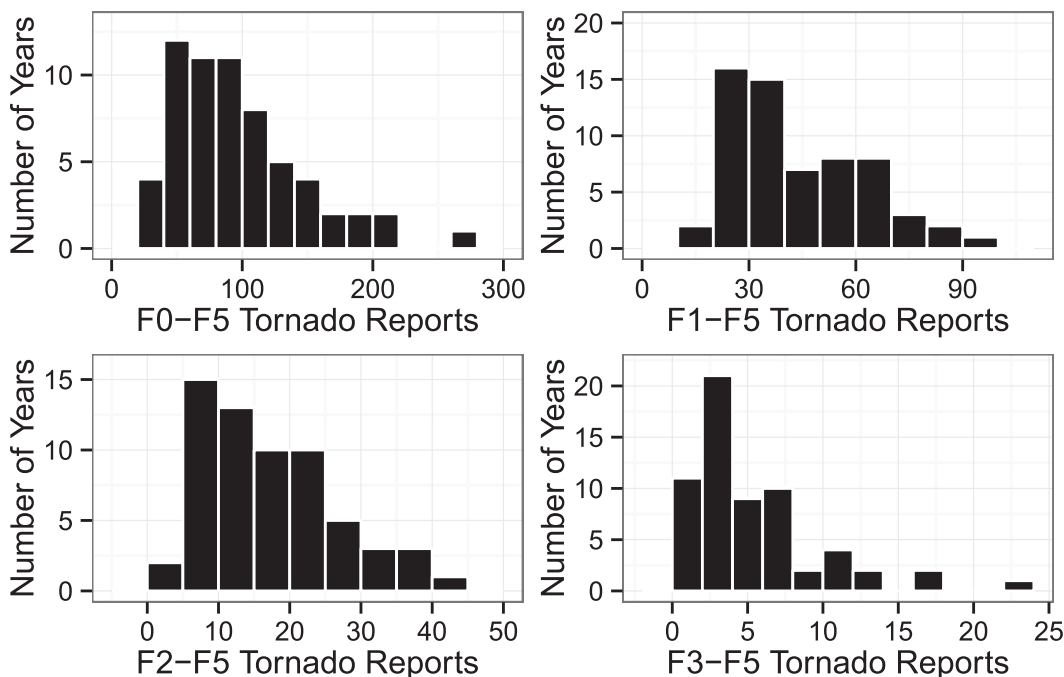


FIG. 4. Histograms of annual tornado reports by F-scale groups. The number of years is on the vertical axis and the number of tornado reports in nonoverlapping intervals is on the horizontal axis. The bin width varies by F-scale group.

5. Seasonal prediction model

We seek a prediction model for annual tornado reports. While hurricane counts are successfully modeled using Poisson regression (Elsner and Schmertmann 1993; Elsner and Bossak 2001), the Poisson distribution is not appropriate for tornado counts as explained above. To account for improvements in tornado reporting over time, we include a trend term. A linear trend might not be optimal because changes to reporting practices are not necessarily uniform over time (see Elsner et al. 2013).

Modeling is done using a Bayesian approach (see Elsner and Jagger 2006). Here the reported number of tornadoes each year T_t is assumed to belong to a negative binomial distribution where the mean μ_t is linked to a structured additive predictor ν_t through the link-function $\log(\mu_t) = \nu_t$. The likelihood model is controlled by the dispersion parameter n (size). The predictor ν_t accounts for the SST effects on tornado counts (β_{WCA} , β_{GAK}) and trend (β_{YEAR}) in an additive way.

The model equation is

$$T_t | \nu_t \sim \text{NegBin}(\mu_t, n) \quad (1)$$

$$\begin{aligned} \nu_t = & \beta_0 + \beta_{\text{WCA}} \times \text{WCA}_t + \beta_{\text{GAK}} \times \text{GAK}_t \\ & + \beta_{\text{YEAR}} \times \text{YEAR}_t + f(u_t), \end{aligned} \quad (2)$$

where $\text{NegBin}(\mu_t, n)$ indicated that the conditional tornado counts ($T_t | \nu_t$) are described by a negative binomial distribution with mean μ_t and dispersion parameter n . The covariates WCA_t and GAK_t are the western Caribbean and Gulf of Alaska SST values for year t , respectively, and where YEAR_t is year t to account for trend in the tornado reports. Note that YEAR_1 is 1950. We assign vague Gaussian priors with known precision to the β s. The first-order autoregressive term $f(\mu_t)$ is given by

$$u_1 \sim \mathcal{N}\{0, [\tau(1 - \phi^2)]^{-1}\} \quad (3)$$

$$u_t = \phi u_{t-1} + \varepsilon_t; \quad \varepsilon \sim \mathcal{N}(0, \tau^{-1}). \quad (4)$$

To complete the model the hyper-parameter (parameter of a parameter) n is written as $\theta_1 = \log(n)$ and assigned

TABLE 1. Annual tornado report statistics by F-scale grouping. The ratio is defined as the variance divided by the mean. The p value is from a likelihood ratio test under the null hypothesis that the counts are adequately described by a Poisson distribution.

Group	Mean	Variance	Ratio	p value
F0-F5	95.7	2660	27.8	<0.001
F1-F5	42.9	372.9	8.70	<0.001
F2-F5	16.7	95.76	5.74	<0.001
F3-F5	4.87	19.33	3.97	<0.001
F4-F5	1.00	1.672	1.67	0.016

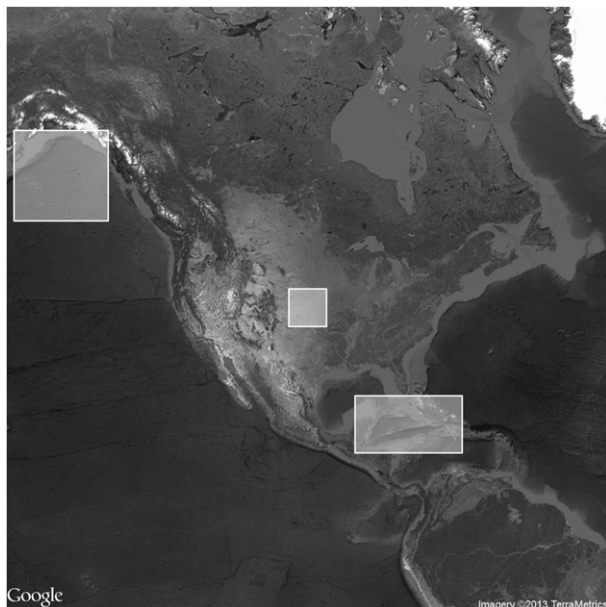


FIG. 5. Tornado activity and SST regions. The tornado activity region is a small square in the central United States. The Gulf of Alaska (GAK) region is bounded by 50.36° and 59.95°N latitudes and 153.66° and 136.08°W longitudes and the western Caribbean (WCA) region is bounded by 15° and 25°N latitudes and 90° and 70°W longitudes.

a vague log-gamma prior. A prior is a probability distribution for a parameter that comes before examining the data. Here it is the natural logarithm of a gamma distribution with a large variance (small precision—vague). For convenience, the hyper-parameters τ and ϕ are written $\theta_2 = \tau(1 - \phi^2)$ and $\theta_3 = \log[(1 + \phi)/(1 - \phi)]$ and assigned vague log-Gaussian and Gaussian prior distributions, respectively.

The priors and the likelihood are combined in accord with Bayes rule to obtain the posterior distributions for the model parameters. Since the integrals cannot be solved analytically, a common solution is to use a Markov chain Monte Carlo (MCMC) algorithm to obtain samples from the posterior distributions. Here we use the INLA method, which provides a faster alternative for models that have a latent Gaussian structure (Rue et al. 2009a). This is done with functions from the INLA package (Rue et al. 2009b) from the open-source R computing environment (see rpubs.com/jelsner/4745 for the complete set of code).

6. Results

Models are fit separately for each of the five F-scale groups (F0–F5, F1–F5, F2–F5, F3–F5, and F4–F5). The model for the F4–F5 tornado reports is not well calibrated (the predictive distribution does not match the observed

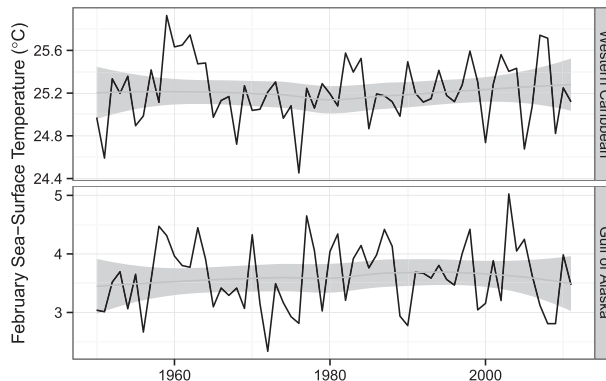


FIG. 6. Time series of February SST across the western Caribbean (WCA) and the Gulf of Alaska (GAK) regions.

distribution) so we present results only for the first four groups. Model output statistics are given in Table 2.

a. SST effects

The question of whether the SST variables are significant in explaining at least some of the annual variability in tornado report numbers is answered in the rows of Table 2, labeled β_{WCA} and β_{GAK} . The posterior mean for the WCA SST influence on F0–F5 tornado reports is +0.41, which translates to an increase of 51% $[(e^{0.41} - 1) \times 100\%]$ °C⁻¹ increase in WCA SST. In contrast, the posterior mean for the GAK SST influence is -0.163, which translates to a decrease of 15% °C⁻¹ increase in GAK SST. The uncertainty on these estimates is available as a posterior standard deviation and credible interval (CI). The CI is the smallest width interval where the probability that the estimate is below the interval is the same as the probability above the interval. The CI indicates a 95% chance that the true WCA SST effect on the tornado reports lies between +0.041 and +0.781 (4%, 118%). The CI on the GAK SST effect for the set of F0–F5 tornadoes includes zero percent indicating it is not significant. However, for stronger tornado categories (those where the F0 counts are removed), the CI does not include zero indicating the GAK SST effect is statistically significant.

Posterior densities for the two SST parameters are plotted in Fig. 7. The black line is the posterior density for the GAK SST parameter and the gray line is the posterior density for the WCA SST parameter. The WCA SST effect is larger than the GAK SST for all F-scale groups with the effect peaking between 50% and 120% increase per degree Celsius depending on the group. The statistical significance of the effect is judged by the area under the density curve to the left of the zero change line, which is a minimum for F2–F5 reports. In contrast, the GAK SST effect is negative for all tornado report groups and peaks

TABLE 2. Model statistics. Models are run separately for tornado reports in the F-scale groups of F0–F5, F1–F5, F2–F5, and F3–F5. The mean is the posterior mean and the CI is a 95% credible interval from the posterior density; β_{WCA} and β_{GAK} are the SST fixed effects and β_{YEAR} is the trend term, n is the size of the dispersion, ϕ is the first order autoregression parameter, DIC is the deviance information criterion, AD p value is from the Anderson–Darling goodness-of-fit test, and $r(o, p)$ is the correlation between the observed and predicted tornado reports. The out-of-sample estimates are from a hold-one-out cross validation.

Statistic	F0–F5 mean (CI)	F1–F5 mean (CI)	F2–F5 mean (CI)	F3–F5 mean (CI)
β_{WCA}	0.410 (0.041, 0.781)	0.508 (0.118, 0.899)	0.776 (0.290, 1.27)	0.517 (–0.260, 1.30)
β_{GAK}	–0.163 (–0.363, 0.037)	–0.242 (–0.451, –0.032)	–0.336 (–0.587, –0.085)	–0.604 (–0.999, –0.217)
β_{YEAR}	0.018 (0.012, 0.025)	–0.003 (–0.010, 0.003)	–0.015 (–0.023, –0.007)	–0.007 (–0.019, 0.005)
n	7.83 (4.71, 12.0)	5.52 (3.66, 7.93)	4.38 (2.73, 6.57)	2.18 (1.27, 3.53)
ϕ	0.81 (0.40, 0.97)	–0.00 (–0.99, 0.99)	0.00 (–0.99, 0.99)	–0.00 (–0.99, 0.99)
DIC	617	532	432	324
AD p value	0.712	0.833	0.557	0.158
Log score	4.92	4.27	3.48	2.61
In sample $r(o, p)$	0.78	0.46	0.58	0.42
Out of sample $r(o, p)$	0.77	0.33	0.52	0.29

near 50% decrease per degree Celsius for the F3–F5 group. The GAK SST is most significant for the group of strongest tornadoes.

The SST effects on springtime tornado activity make physical sense. Warmer-than-normal SST in the waters of the western Caribbean during February portends a deeper, richer source of low-level moisture into the southern and central Great Plains during spring. The cold GAK and warm WCA couplet implies stronger vertical wind shear by thermal wind considerations. The warm WCA would be supportive of larger values of CAPE to support strong thunderstorms and the shear

associated with strong temperature gradients would make tornadic supercells more likely. One interpretation of the differential in magnitude of the SST effects is that CAPE is more important to tornado activity. The difference in significance going from F0–F5 to F3–F5 tornado counts suggests that shear might be more important than CAPE in modulating violent tornado activity (Brooks 2013; Grams et al. 2012).

b. Trend and dispersion

Significance and magnitude of the trend term is indicated by the posterior statistics of β_{YEAR} . For the set

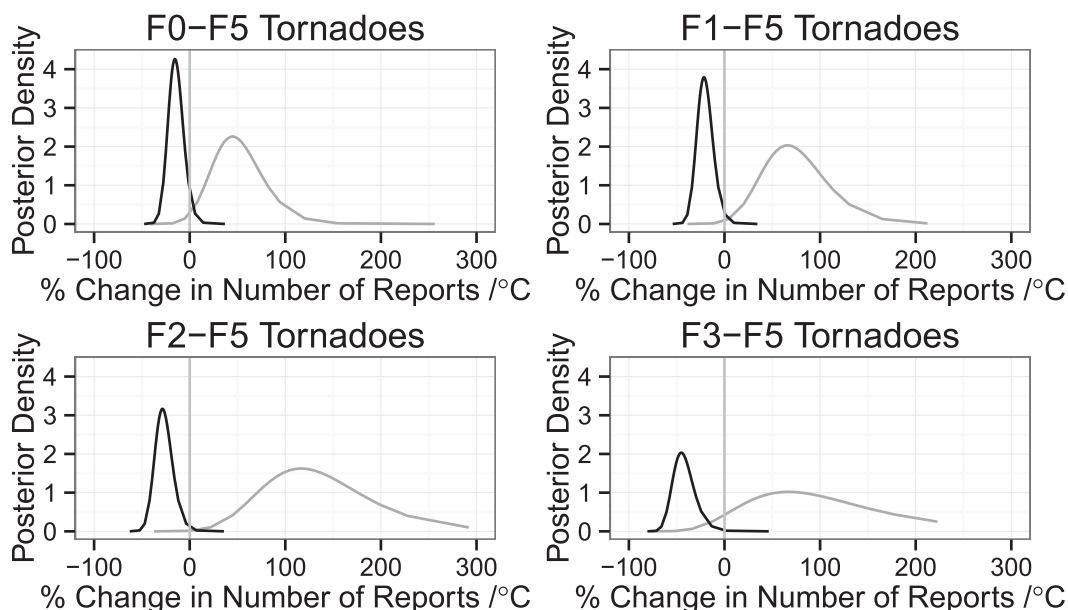


FIG. 7. Posterior densities for the fixed SST effects by F-scale group. The black line is the parameter for the Gulf of Alaska (GAK) SST covariate and the gray line is the parameter for the western Caribbean (WCA) SST covariate. Densities are plotted for the percent change in the number of reports per degree Celsius.

of F0–F5 tornado reports, the trend is significantly upward at an average rate of $1.8\% \text{ yr}^{-1}$. For the sets of F1–F5 and F3–F5 reports, there is no significant trend and for the set of F2–F5 reports, there is a significant downward trend of $1.5\% \text{ yr}^{-1}$. The amount of overdispersion n decreases from a posterior mean of 7.8 for F0–F5 reports to 2.2 for the F3–F5 reports, which is consistent with the variance to mean ratios shown in Table 1. The CI on this parameter does not overlap the value of one for any of the categories consistent with the goodness-of-fit tests performed in section 3, where the counts were found to be overdispersed relative to a Poisson distribution.

c. Model diagnostics

The INLA function in R computes the model's deviance information criterion (DIC) as an indicator of the trade-off between model fit and model complexity. DIC is defined as the posterior mean of the model deviance plus the effective number of model parameters with a smaller value indicating a better trade-off. The DIC values decrease with increasing F-scale threshold.

The predictive quality of the model is assessed by the cross-validated log score. A smaller value of the score indicates better prediction quality (Gneiting and Raftery 2007). The log score is minimized for the model of F3–F5 tornado reports as is the DIC.

Model calibration is checked by examining the distribution of the probability integral transform (PIT) values. A well-calibrated model has PIT values that are adequately described by a uniform distribution (Czado et al. 2009). We check this distribution using histograms (not shown) and the Anderson–Darling (AD) goodness-of-fit test (Table 2). The p values from the test exceed 0.15 for all sets of reports indicating little (in the case of F3–F5) to no evidence of problems with calibration.

d. Observed versus predicted reports

Figure 8 shows the observed versus predicted number of tornado reports by F-scale group. The point shows the posterior mean and the line indicates a 95% credible interval. A regression line of the predicted counts onto the observed counts is shown in gray with a 95% confidence band about the line shown in light gray. All four models indicate a significant relationship between the observed and predicted counts. With all models, the predicted counts are under dispersed relative to the observed counts. The underdispersion is most pronounced with the F3–F5 tornado reports. This is indicated by the lowest p value from the AD good-of-fit test on the PIT values across all F-scale groups.

The in-sample correlation between observed and predicted (see Table 2) ranges from a high of 0.78 for the F0–F5 model indicating the model accounts for 61% of

the observed annual report variability to a low of 0.42 for the F3–F5 model (the model accounts for 18% of the observed variability). As expected, the two models that have a significant trend component (F0–F5 and F2–F5) show a better correspondence between the observed and predicted. The models are rerun 62 times using a hold-one-out cross-validation procedure to obtain an estimate of the out-of-sample skill. The correlations are smaller with the F1–F5 and F3–F5 models, which explain 11% and 8% of the out-of-sample variability in tornado reports, respectively. The out-of-sample skill level of 59% and 27% for the F0–F5 and F2–F5 models, respectively, are somewhat inflated because of the trend term. A hold-two-out cross-validation procedure provides an out-of-sample skill level of 54% and 26% for the F0–F5 and F2–F5 models, respectively, with practically no change in skill level for the F1–F5 and F3–F5 models. Although this level of predictive skill is modest, it represents a quantitative benchmark against which future seasonal predictions can be gauged.

7. Summary and conclusions

We demonstrate a strategy for seasonal prediction of tornado activity using observations. The strategy is detailed using tornado reports from the central Great Plains during springtime and SST data from the Gulf of Alaska and the western Caribbean Sea. The modeling is done using a Bayesian formulation where the likelihood on the tornado report counts is a negative binomial distribution and where the trend is modeled as a covariate. Posterior densities for the model parameters are obtained using the INLA method.

The principal findings of the study include the following:

- SST from the Gulf of Alaska (GAK) and western Caribbean Sea (WCA) regions during February have a statistically significant relationship to springtime tornado activity across the central Great Plains.
- On average, the WCA influence amounts to a 51% increase in the number of F0–F5 tornado reports per degree Celsius increase in SST. On average the GAK influence amounts to a 15% decrease in the number of reports per degree Celsius increase in SST.
- The statistical relationships between SST and tornado activity are consistent with our physical understanding of the large-scale atmospheric patterns conducive to springtime convective storms across the Great Plains.
- SST in the WCA is more significant than SST in the GAK for all tornadoes but less significant for the strongest tornadoes.
- The SST covariates explain 11% of the out-of-sample variability in observed F1–F5 tornado reports.

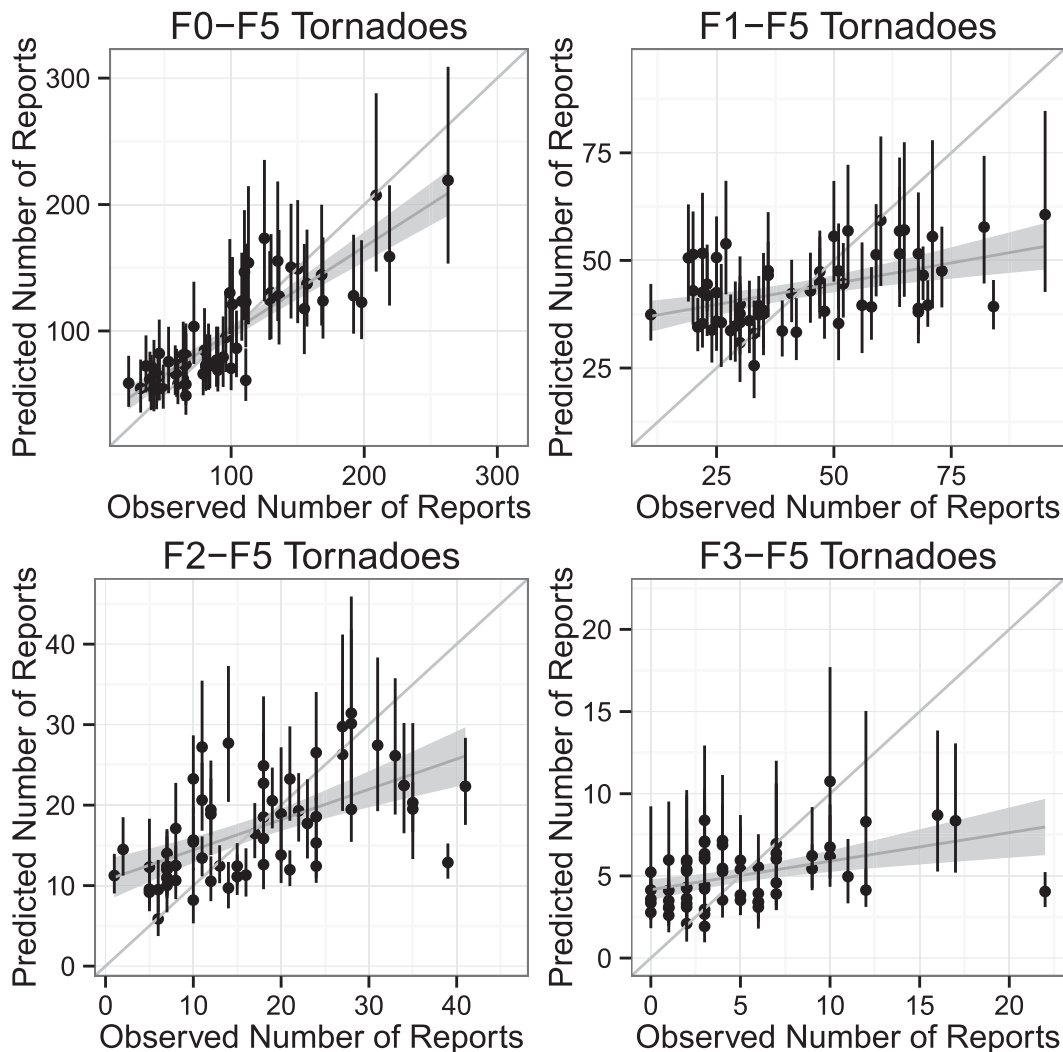


FIG. 8. Observed vs predicted annual tornado report counts by F-scale group. The point shows the posterior mean and the line indicates a 95% CI. The calibration line is the diagonal and a regression line of the predicted counts onto the observed counts is shown in the center of the gray shaded area with a 95% confidence band shown in gray.

- The INLA method is a valuable resource for modeling statistical relationships between tornadoes and climate.

We find that the models are not improved by adding a preseason covariate for the El Niño, the Pacific decadal oscillation, the North Atlantic Oscillation, or soil moisture conditions. Although some modifications to the size and placement of the study area and regional definitions of SSTs were examined, we made no systematic effort to maximize the skill of the models. Results are not overly sensitive to small changes in the regional definition of SSTs.

Although predictive skill is modest, it represents a benchmark against which future improvements can be gauged. The model might be improved by including

a term to explicitly account for the greater uncertainty in the tornado reports from the earlier years and not as a trend as was done here. The model might also be improved by including covariates that more precisely portend the synoptic weather patterns conducive to springtime convective outbreaks like antecedent low-level moisture conditions.

Finally, all the code used in this study along with the links to the datasets are available online (rpubs.com/jelsner/4745). It will be interesting to see if similar (or better) skill can be obtained by examining tornado occurrences elsewhere across the country. In that regard, it would be helpful to develop a spatial model for tornado activity as an extension to the latent Gaussian models used here.

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