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When do extreme weather events generate attention to climate change?

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Abstract We analyzed the effects of 10,748 weather events on attention to climate change between December 2011 and November 2014 in local areas across the USA. Attention was gauged by quantifying the relative increase in Twitter messages about climate change in the local area around the time of each event. Coastal floods, droughts, wildfires, strong wind, hail, excessive heat, extreme cold, and heavy snow events all had detectable effects. Attention was reliably higher directly after events began, compared to directly before. Financial damage associated with the weather events had a positive and significant effect on attention, although the effect was small. The abnormality of each weather event's occurrence compared to local historical activity was also a significant predictor. In particular and in line with past research, relative abnormalities in temperature (*local warming*) generated attention to climate change. In contrast, wind speed was predictive of attention to climate change in absolute levels. These results can be useful to predict short-term attention to climate change for strategic climate communications and to better forecast long-term climate policy support.

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1 Introduction

Personal experiences with weather events can cause attention to the issue of climate change (Konisky et al. 2015). Previous research on this topic has reported that local abnormalities in temperature (Joireman et al. 2010; Egan and Mullin 2012; Hamilton and Stampone 2013; Myers et al. 2013; Zaval et al. 2014; Li et al. 2011; Lang 2014; Kirilenko et al. 2015), as well as severe rains and associated flooding (Spence et al. 2011; Weber 2013), can increase people's concern about climate change, at least temporarily. When people perceive the present temperature to be warmer than usual, they are more likely to report concern about global warming (Li et al. 2011). This is known as the local warming effect (Zaval et al. 2014). Using similar methods to the current study, Kirilenko et al. (2015) found that relative abnormalities in local temperatures predicted increases in Twitter messages about climate change from those areas. Past experiences with floods correlated with heightened concern about climate change in data from a 2010 survey of UK citizens (Spence et al. 2011). Additionally, Whitmarsh (2016) found that UK citizens who had experienced a damaging flood were more likely to report that the issue of climate change had personal importance to them but were not significantly more likely to be more knowledgeable, concerned, or active in relation to the issue.

Few studies have explored the effects of weather phenomena beyond temperature and flooding. Konisky et al. (2015) found a modest short-term effect of experiencing extreme weather events in general by evaluating data from public opinion polls and historical weather records. Cutler (2016) analyzed the effect of aggregate local damage caused by severe weather on concern about climate change and found an effect of damage that was moderated by individual differences. In another study, New Jersey residents were found to be more likely to support a green politician after experiencing Hurricane Sandy and Hurricane Irene than before each hurricane occurred (Rudman et al. 2013). Lang and Ryder (2016) report that experiences with hurricanes cause interest in climate change measurable using Google search activity in local areas up to 2 months after each event. After a major drought in 1988 in Kentucky, USA, residents living in a county with drought-caused water restrictions had significantly higher environmental attitudes compared to prior levels (Arcury and Christianson 1990).

Our knowledge of how extreme weather experiences affect attention to climate change is increasing, but still scarce. Many extreme weather events such as wildfires, heavy snow, and hail have not been looked at yet to the best of our knowledge. Moreover, previous studies on the effects of hurricanes, droughts, and floods have almost all measured the impacts of these events weeks or months after they occurred. Past research suggests that these time delays may have lessened the observed impacts of the weather experiences. Hamilton and Stampone (2013) found that impacts of temperature changes on beliefs in anthropogenic climate change were strongest for a 2-day period following each event. Similarly, Konisky et al. (2015) found that the impact of experiences with extreme weather events within the last month was far stronger than that of earlier events. In a macro-level study by Brulle et al. (2012), average reported climate concern at the national level was aggregated in 3-month intervals and no significant effects of abnormalities on temperature, precipitation, or droughts were detected. To establish a more comprehensive understanding of how extreme weather experiences affect climate attention and attitudes, we need research on a more comprehensive range of relevant weather events and more studies that examine their immediate impacts.

Several studies have shown that individual differences such as gender, political affiliation, and environmental values moderate the effect of extreme weather experiences on climate change concern and attention (for more details, see Brody et al. 2008; Hamilton and Stampone 2013). Howe and Leiserowitz (2013) found that prior beliefs about climate change substantially biased perceptions of local temperatures and, to a lesser degree, biased perceptions of precipitation, replicating similar results observed with Illinois farmers by Weber and Sonka (1994). Similarly, Goebbert et al. (2012) showed that perceptions of temperature changes were substantially more biased contingent on participants' political ideologies than those of floods and droughts. Cutler (2016) found that household income, political affiliation, and beliefs about climate change interact with the effect of local damage from severe weather events to influence individuals' concerns about climate change. These findings further highlight the importance of expanding our knowledge of the effects of extreme weather experiences beyond temperature changes. Experiences with other weather events may be more influential because they may be less politicized; i.e., people may have fewer preconceived notions about them.

The aspects of weather events that predict changes in people's attention and attitudes to climate change also warrant examination. Brody et al. (2008) showed that the amount of financial damage and human fatalities caused by weather events in local areas are marginally predictive of people's perceived risk of climate change. More studies examining these variables and other event characteristics are needed. Little research to date has analyzed the effect of the degree of abnormality of weather events other than temperature changes. In this context, it is useful to ascertain whether attention is guided by the absolute or relative degree of abnormality. A well-known psychophysical law known as Weber's law (Weber 1978) states that the amount of change in a stimulus that is just noticeable by a human is proportional to the magnitude of the original stimulus. In other words, the degree of difference needed for a human to notice a change in a stimulus (such as the loudness of a sound or the temperature in a room) is predicted best by the amount of the change relative to the stimuli's prior state, not the absolute level of the change. Extending this law to the detection of changes in weather predicts that people's sensitivity to extreme weather will be relative, i.e., proportional to normal levels (Weber 2004), but it is also plausible, at least for some events such as those causing substantial damage, that absolute levels of extremeness could drive attention to the event and to climate change.

A better understanding of the effects of extreme weather on climate attention benefits short-term and long-term predictions about climate concern. Accurate short-term predictions can allow policy makers and grassroots organizations to implement climate communications more strategically by capitalizing on time periods when people have heightened attention to climate change such as after recent extreme weather experiences. Long-term predictions about climate concern are more difficult to model with much certainty but can be used by policy makers to forecast the future favorability of climate policies. Such predictions are already being formulated based on models of when changes in weather will be statistically detectable in different locations (Ricke and Caldeira 2014). Similarly, Egan and Mullin (2016) estimate how many Americans will experience subjectively less preferable weather by the turn of the century if emissions are not abated. A more detailed empirical understanding of when and how extreme weather events cause attention to climate change can improve long-term as well as short-term predictions.

In the current study, we examine the immediate impacts of ten different types of extreme weather events on attention to climate change: flash flood, excessive heat, wildfire, heavy snow, tornado, hail, strong wind, extreme cold, coastal flood, and drought events. Each of these event types is linked to projected effects of climate change in the past literature. See

Appendix A for a detailed description of how each weather event type is linked to climate change.

Our analysis uses records of 10,748 weather events from December 2011 to November 2014. We measure attention to climate change using approximately 1.7 million Twitter messages emitted from local areas surrounding the weather events. Changes in frequencies of messages about climate change are analyzed as a proxy for changes in attention to climate change. This is based on the simple assumption that when people's attention to the issue increases, they are more likely to post about it on Twitter. We assess the predictive value of events' financial damages and fatalities, as well as the effects of the abnormality of events' occurrences. We separately model and compare the effects of key weather features (temperature, wind speed, and precipitation) on absolute vs. relative scales.

2 Method

2.1 Data

Twitter messages The full Twitter corpus used for this study includes 5.8 million messages posted between December 2011 and November 2014 that were geocoded as originating from a location within the USA. Only messages (~1.7 million) with locations within 35 miles of each weather event and occurring between 1 month before and 3 days after were included in the analyses. We analyze both original tweets and re-tweets.[1] Each of these messages includes the words *climate change* or *global warming* (case-insensitive).[2] The messages were collected using the Twitter API and the (now deprecated) Topsy Social Data API.

Textual identifications of users' locations from users' profiles were recoded into geographical coordinates using the Data Science Toolkit geocoder[3] which emulates the Google Geocoding API (but without a rate limit). For any messages that were downloaded with coordinates provided by the Twitter API, this location was used in the analysis instead of the geocoded textual location. We evaluated the distance of the locations of messages downloaded with geographic coordinates from the coordinates of the locations for these messages determined by the geocoder based on the textual locations. The median difference was 17.3 miles. Additionally, we randomly selected a subset of messages ($n = 50$) that were identified as being within the USA (and therefore usable in the analysis) and we manually determined if each geocoded location was correct. We found that 90% of these locations aligned with at least the correct US state of the Twitter user based on the textual location provided. One issue with identifying the geographic origin of Twitter messages is that many users do not provide a precise location beyond what state they live in. Identifying the originating locations of Twitter messages is inherently limited to somewhat coarse geographic precision (Graham et al. 2014). Nonetheless, we believe that the precision achieved by our methods of location identification is

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[1] As a robustness check, we re-ran the analysis excluding all re-tweets. This produced results almost identical to the analysis of all tweets and re-tweets.

[2] Investigating the differences between trends in messages that mention "global warming" versus messages that mention "climate change" is outside the scope of this paper. However, we did re-run the mixed-effects regression using only climate change messages and then only global warming messages. These results can be seen in Appendix I.

[3] http://datasciencetoolkit.org (last accessed on March 10, 2017)

appropriate for the analyses that follow. See Appendix N for robustness checks related to location inaccuracies.

Weather events An archive of significant weather events from 2005 through 2014 was obtained from the National Climatic Data Center's (NCDC) Storm Event Database.[4] Records of weather events occurring before 2011 were used to quantify the abnormality of each event occurring in the time range of our Twitter data. Only events that were deemed by event reporters as causing significant damage or inconvenience were included in this database.[5] For each weather event included, there is a detailed record of its start time, location, event type (e.g., hurricane or tornado), financial damage caused, deaths caused, and other variables. Some weather events recorded are indicated as being part of a larger storm system. For cases where there were multiple events of the same type reported within a single larger storm system, we only analyzed the first event of each type in each larger system. Further, only weather events that had ten or more messages included in the abovementioned Twitter corpus published within 35 miles and within 30 days before or 3 days after the event were included in the analysis (n = 10,748). The ten messages or more criterion was to ensure that there was a sufficient number of Twitter messages to accurately estimate the effect of each event. The median number of messages analyzed for each weather event is 65.[6] Events with missing location information were geocoded using the centroid of the county or the National Weather Forecast Zone that was provided for the events.

Daily weather records Historical daily temperature, wind speed, and precipitation data were accessed through the Weather API maintained by Weather Underground.[7] The Weather API provided historical daily weather records from the National Weather Service ASOS weather station nearest to each event's reported coordinates. The Automated Surface Observing Systems (ASOS) system includes approximately 2000 weather stations located at airports across the country. The ASOS program is partially coordinated by the National Weather Service.[8]

2.2 Measuring attention to climate change

To estimate the attention to climate change caused by each event, we calculate a metric that captures the relative increase in climate change messages emitted from the local area directly after each event begins. The local area is defined as a 35-mile radius from the reported location of the event. Figure 1 illustrates that $C_{-10}, C_{-9}, \ldots, C_{-1}$ are the counts of climate change messages across ten 3-day intervals leading up to the time of each event. C_1 is the count of messages in the 3-day interval directly after the event. C_1 begins precisely at the recorded start time for each event. Our attention measure is the number of messages in the interval directly
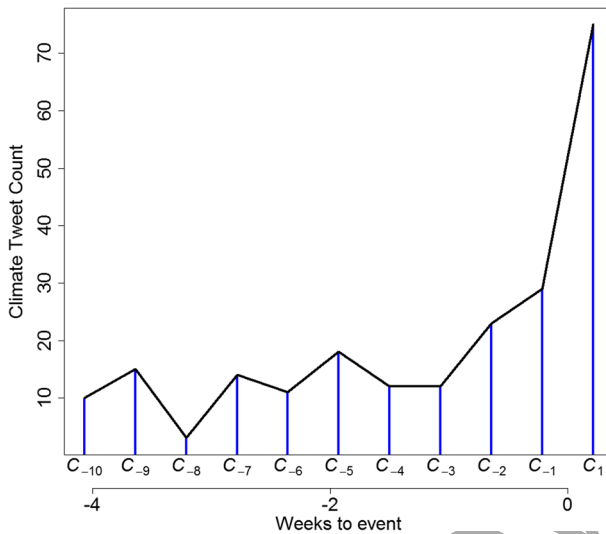
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[4] More information on the NCDC Storm Events Database can be found here: https://www.ncdc.noaa.gov/stormevents/ (last accessed on March 10, 2017).
[5] The instructions for weather event reporters including detailed definitions of each event type can be found here: https://www.ncdc.noaa.gov/stormevents/pd01016005curr.pdf (last accessed on March 10, 2017). See Appendix M for additional information on weather event definitions.
[6] Descriptive statistics on message counts for all event types are shown in Appendix K.
[7] http://www.wunderground.com/weather/api (last accessed on March 10, 2017)
[8] http://www.nws.noaa.gov/ost/asostech.html (last accessed on March 10, 2017)

Fig. 1 Example of climate change tweet counts for ten 3-day intervals prior to an extreme weather event and one 3-day interval after the event

after the event, centered and standardized by the mean and standard deviation of the baseline values from approximately 1 month before the event (excluding the 3-day interval directly before the event as counts in this interval are sometimes also increased by the weather event).

Our *attention* variable is similar to a z-score, except that the counts of messages near the time of each event (C_{-1} and C_1) are not included in the calculation of the mean and standard deviation used to center and standardize the score. This is done to prevent the C_{-1} and C_1 counts from dominating the standardizing mean and standard deviation values. In Appendix B, you can see the formulas for the *attention* metric. In Appendix C, you can see the results of the *attention* metric vs. calculated z-score values in a simulation where the counts directly before and after the event linearly increase as the baseline values are held constant. The z-score does not linearly increase with the simulated increase in attention while the *attention* metric does.

2.3 Measuring abnormality

We calculate a score representing abnormality in frequency for each event by first dividing the number of weather events (of the same type, E) that occurred in the same US state (s) in the same month (m) in the same year (Y) by the average number of events that occurred in the same calendar month and state historically since 2005.

$$\text{abnormality}_{\text{raw}}(E_{smY}) = \frac{E_{smY}}{\overline{E_{sm(2005;\ Y-1)}}}$$

For example, imagine (fictitiously) that 20 hail events occurred in March in the state of New Jersey in 2014 and the historical average for occurrences of hail events in March in New Jersey is 10. The raw abnormality ratio would be 20/10 = 2. If only five hail events occurred in 2014 instead of 20, then the raw abnormality ratio would be 5/10 = 0.5. When the denominator was

equal to zero for any event, we replaced that value with 1 to avoid producing an infinite or undefined raw abnormality score. Only 2% of events had a zero in the denominator of the raw abnormality ratio.

We next subtract 1 from the raw abnormality ratio so that zero means that the number of event occurrences in the current month is identical to the historical average ($1/1 \rightarrow 0$), i.e., zero abnormality. This also makes events that had a fractional raw abnormality score (indicating that the current month had abnormally fewer events than the average) now have a negative score (e.g., $5/10 \rightarrow -0.5$). The negative or positive difference of the raw abnormality score from $1/1$ reflects the level of abnormality due to a higher or lower frequency compared to the historical average. We then take the absolute value so that both types of abnormality, less than and greater than the historical average, have a positive score and increase as the raw abnormality score decreases or increases away from $1/1$.[9] This produces an abnormality variable with a highly skewed distribution, so we log transform the abnormality score to achieve an abnormality variable that is more normally distributed. We added 1 to each value directly prior to the log transformation to avoid taking the logarithm of zero, and also, so that when the value to be transformed is zero, the transformed version of it is also zero (as $\log(1) = 0$).[10]

$$\text{abnormality}_{\text{final}} = \log(|\text{abnormality}_{\text{raw}} - 1| + 1)$$

2.4 Estimating the null distribution

The average frequency of messages posted on Twitter increased consistently over the time range of this analysis. Therefore, the *attention* metric can be expected to be slightly and consistently positive even when there is no real effect of any target event. This is because it quantifies the relative increases in message counts after the event compared to the average from 1 month prior. Another reason the *attention* metric may be positive when there is no true effect of a measured event is the chance that some other event (such as a film release or climate speech) unrelated to the target event caused an increase in attention to climate change at the same time and place as the target event. Both of these considerations mean that the true null value of *attention* for which the effects of weather events should be compared should not be assumed to be zero. In order to estimate an appropriate distribution of our *attention* measure under the null hypothesis, we calculated *attention* scores for a set of locations and dates where there were no occurrences of any recorded extreme weather events occurring within one week before or after. These *null* events were matched to the locations and calendar dates of our target weather events and therefore serve as a distribution of geographically and seasonally comparable control observations. For each target weather event, we matched one control event in the same location shifted 1 year before or after the target weather event and within 30 days of the original calendar date.[11] About 91% of these control events had enough surrounding Twitter messages ($>=10$) to be included in the analysis.

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[9] When the events with a raw abnormality score of <1 (indicating negative abnormality) are removed from the analysis, the effect of abnormality is essentially unchanged.

[10] A visualization of the transformation from the raw abnormality scores to the final abnormality scores can be seen in Appendix D.

[11] The algorithm for this matching procedure can be found in the electronic supplementary material "control_matching_algorithm_ESM2."

The distribution of the *attention* scores for the control events is shown in Appendix E. The mean of the null distribution of *attention* is 0.20 and is shown by the dotted vertical gray line. The distributions of *attention* for the ten weather event types analyzed can be seen compared to the null distribution in Appendix F.

3 Results

3.1 Comparing attention before vs. after each event

We examine the effects of the control events and ten different types of extreme weather events with varying sample sizes: control (9769), flash flood (2381), excessive heat (304), wildfire (295), heavy snow (584), tornado (807), hail (4299), strong wind (1177), extreme cold (245), coastal flood (130), and drought (526).

Our measure of attention to climate change (described above) quantifies the relative number of climate change messages occurring in the local area directly *after* each weather event. In Fig. 2, we compare this attention variable to a modified version that quantifies the effect directly *before* each event hits.

$$\text{attention}_{\text{before}} = \frac{C_{-1} - \mu_{\text{baseline}}}{\sigma_{\text{baseline}}} \; ; \; \text{attention}_{\text{after}} = \frac{C_1 - \mu_{\text{baseline}}}{\sigma_{\text{baseline}}}$$

The dotted gray line in each graph represents the average before and after values for all of the null event control cases. Across the ten event types examined, attention to climate change is usually greater directly after each extreme weather event hits compared to directly before.
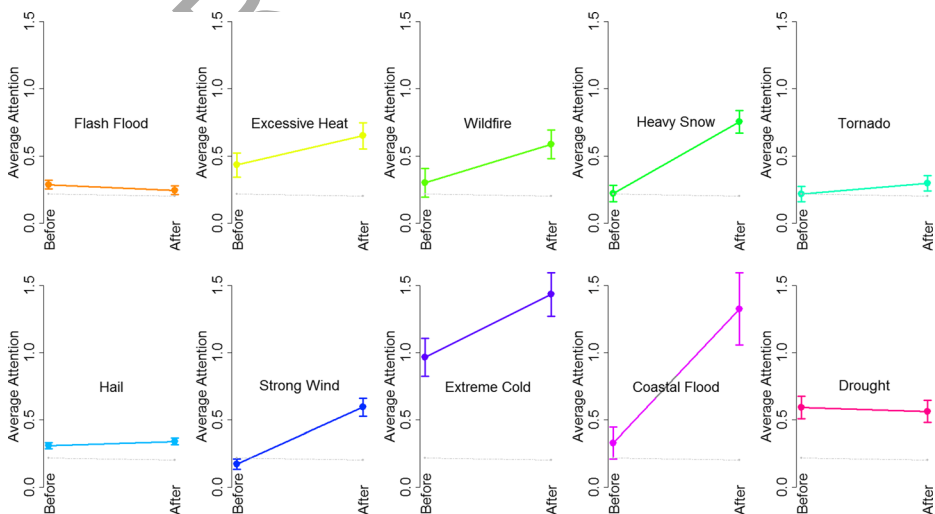
Fig. 2 Average *attention* before vs. after different weather events. *Error bars* depict 1 standard error

3.2 Linear mixed-effects models

In each of the regressions summarized below in Sections 3.3 and 3.4, we estimated a linear mixed-effects model specified as follows. The dependent variable is *attention*, which quantifies the relative increase in climate change messages directly after each event occurs as described above.[12] We control for baseline differences in how people in different locations regularly respond to weather events by adding a random effect variable indicating the county or zone that each event was reported in. We include a random effect variable for year to account for gradual increases in Twitter activity. To account for the potential dependence between some observations originating from the same larger weather event, we include a random effect variable for each week and US state pair. We also control for the geographic size of the state each event was located in with a fixed effect variable for state size. We *winsorized* any outliers above the 99.9th percentile of the distribution of *attention* (Wilcox 2014). The 99.9th percentile of *attention* across all observations was equal to 14.32, so any observations above this value were kept in the analysis but transformed to 14.32.[13] All of the following regressions were computed using the *lme4* package in the statistical software R (Bates et al. 2015).

3.3 Examining event type and event characteristics

In the regression displayed in Table 1, we included the null events' average effect as the intercept term and the other ten event types as dummy variables. This allows the coefficient for each event type to be interpreted as the increase in attention compared to the average control event. We then sequentially add financial damage, deaths, and abnormality as predictors. Coastal floods, droughts, wildfires, strong wind, hail, excessive heat, extreme cold, and heavy snow events all had detectable effects. Damage is a significant predictor but has a relatively small effect size. Abnormality is also a significant predictor. Interestingly, adding abnormality in the regression and thereby controlling for it attenuates the coefficient of each of the weather event types, which suggests that abnormality plays an important role in various types of events. As a robustness check, we re-ran the full model, removing outliers above the 99th percentile. The results were nearly identical after the top 1% of all *attention* scores were excluded from the analysis. In Appendix H, we illustrate that messages containing random keywords do not systematically increase after weather events as messages about climate change do. This rules out the possibility that increased Twitter activity after a weather event is common to all topics.

3.4 Absolute vs. relative effects of temperature, wind speed, and precipitation

We also compared the effects of absolute vs. relative levels of the weather variables temperature, wind speed, and precipitation on *attention*, shown in Table 2. The relative scales were generated by transforming each raw value (temperature degrees, wind speed miles/hour, and precipitation inches) into a z-score using the mean and standard deviation from 10 years of

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[12] We also ran this analysis with the attention before as the dependent variable. These results are included in Appendix G.
[13] We also evaluated a model excluding the outliers from the regression instead of winsorizing them, which produced almost identical results as the winsorized regression.

Table 1 Mixed-effects regression results

	Dependent variable: $attention_{after}$			
	Weather events	+Damage	+Deaths	+Abnormality
Control (intercept)	0.216***	0.212***	0.212***	0.210***
	0.021	0.021	0.021	0.021
Flash flood	0.024	0.027	0.027	−0.037
	0.036	0.036	0.036	0.039
Excessive heat	0.305***	0.309***	0.293***	0.182*
	0.088	0.096	0.099	0.103
Wildfire	0.341***	0.342***	0.343***	0.242**
	0.09	0.094	0.094	0.098
Heavy snow	0.502***	0.547***	0.547***	0.474***
	0.068	0.073	0.073	0.076
Tornado	0.093*	0.067	0.066	−0.005
	0.053	0.056	0.056	0.059
Hail	0.089***	0.121***	0.121***	0.076**
	0.03	0.032	0.032	0.034
Strong wind	0.268***	0.263***	0.263***	0.179***
	0.049	0.05	0.05	0.054
Extreme cold	0.716***	0.770***	0.761***	0.593***
	0.107	0.116	0.117	0.125
Coastal flood	0.389***	0.575***	0.576***	0.457***
	0.133	0.143	0.143	0.146
Drought	0.197***	0.203***	0.202***	0.062
	0.069	0.076	0.076	0.084
Damage (in millions)		0.009***	0.009***	0.009***
		0.002	0.002	0.002
Deaths			0.035	0.038
			0.043	0.043
Abnormality				0.110***
				0.028
Observations	20,517	18,919	18,919	18,919
AIC	73,639	67,924	67,930	67,922

SE is shown below each coefficient estimate. An identical regression model using attention (before) as the dependent variable is shown in Appendix G

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

historical observations for each variable at the same location and calendar day of each target observation. We compare these relative variables to absolute versions of each. The absolute variables are globally (using all observations in the data set) z-scored versions of the raw values to make the scale of their coefficients comparable to the relative variable coefficients. We regressed the relative and absolute weather variables on *attention* using all observations in our data set, controlling for the type of weather event, damage, deaths, and abnormality as well as the control variables we included in the regressions above. As a robustness check, we run the same regression, excluding all observations for which there was a reported weather event, only including control observations (where no extreme events were reported). The fact that the results are similar in the control-only analysis suggests that the effects also exist outside the context of large extreme weather events. In both sets of results, the same pattern is seen: wind speed is most predictive of attention in absolute terms and temperature is most predictive in relative terms. Precipitation is not strongly predictive of attention in either form.

Table 2 Mixed-effects regression results

| | Dependent variable: $attention_{after}$ | | | |
| | All cases | | Control only | |
	Relative	Absolute	Relative	Absolute
Control (intercept)	0.179***	0.223***	0.172***	0.204***
	0.026	0.03	0.027	0.032
Wind speed	0.012	0.026**	0.016	0.029*
	0.007	0.013	0.011	0.015
Temperature	0.048***	−0.01	0.038*	0.003
	0.015	0.025	0.019	0.029
Precipitation	0.001*	−0.006	0.0001	−0.021
	0.0003	0.011	0.001	0.014
Observations	16,372	18,043	8455	8455
AIC	58,634	64,662	28,634	28,628

SE is shown below each coefficient estimate

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

4 Discussion

We found that the effects of extreme weather experiences are usually larger directly after weather events hit compared to directly before. This finding could be due to the actual experiences of the events being more impactful than the purely descriptive information about the events which is often made available by the weather forecasts directly before each event hits. Alternatively or in addition, it could be that when media attention increases after an event hits, this drives up the event's effect on attention to climate change. Future research could help tease apart the underlying mechanisms. Coastal floods, strong winds, extreme cold, excessive heat, drought, wildfires, hail, and heavy snow events all had detectable effects on attention to climate change.

In considering the effects of extreme cold and heavy snow, it is important to keep in mind that we did not distinguish between messages expressing belief or disbelief in climate change. We considered developing an automated text analysis algorithm to code for belief and disbelief in messages but expected that such a method would be inherently low in accuracy, largely because of the common use of sarcasm in climate messages. We believe that to accurately code messages automatically or by hand for expressing belief or disbelief in climate change, it would be necessary to know the context of each message such as personal characteristics of the user, other messages the user has written, and messages recently written to him or her. The sizable task of developing such an algorithm is beyond the scope of this paper but could be a fruitful direction for future research.

We feel for two main reasons that it is not essential to differentiate between belief and disbelief in order for our results to be informative. Firstly, messaging of both types is likely to be correlated with the other. If climate skeptics increase the frequency of their messaging, we would expect climate activists to increase their frequency in response and vice versa. As a result of this, if we did distinguish between belief and disbelief climate messages, we would not expect to see dramatic differences across event types. We would expect a difference in which type of messages initiated attention, but not necessarily which type was ultimately more abundant. Secondly, it is easy to logically sort out which weather events likely increase Twitter

messages because of climate skeptic reactions. We feel the increases in attention in our US sample caused by extreme cold and heavy snow are most likely initiated by disbelief messages, although positive climate messages probably also increased in response. However, in contrast, in a study of UK citizens by Capstick and Pidgeon (2014), three times as many people saw recent severely cold winters as evidence of climate change than those who saw the events as disconfirming it. Thus, these assumptions might not apply in regions outside of the USA.

The nonsignificant effects of flash floods and tornados are interesting to consider. In the case of flash floods, it could be that their immediate physical impacts such as flooded basements and roadways need to be physically attended to promptly and, therefore, climate messaging does not increase because affected people are preoccupied with responding to the events practically. The nonsignificant effect of tornados may be because all tornados that are included in the extreme weather event database are not necessarily intense or destructive. The definition of a tornado in the instructions for the personnel who submitted the weather events to the archive is a "violently rotating column of air, extending to or beneath a cumuliform cloud and with some visible ground-based effects" (National Weather Service 2007). Alternatively, it could simply be the case that flash floods and/or tornados are not associated with climate change in most people's minds. Future research should investigate the public's mental associations between different types of weather events and climate change.

Financial damage had a small positive effect, and the effect of fatalities caused by each event was also small and positive, but nonsignificant. These results echo findings reported by Brody et al. (2008). The abnormality of each event had a significant effect on attention to climate change across events. Once abnormality was added to the model, the coefficients for the effects of the event types all lessened and, in some cases, became nonsignificant, such as in the case of droughts and excessive heat. This suggests that abnormality is generally relevant to the effects of weather events on attention to climate change and, in some cases, may be essential for an effect to occur. It appears that the psychophysical law (Weber 1978) that relative changes in stimuli are more readily perceived by humans than absolute changes is relevant to the domain of extreme weather.

The results in Table 2 show a replication of past findings (Li et al. 2011; Kirilenko et al. 2015) that temperature is more predictive in relative terms than in absolute terms. We interestingly found that wind speed is more predictive in absolute terms. This pattern was found in the regressions with all cases and with only control cases. This finding is also reflected in the results reported in Table 1. When abnormality is added to the regression, the main effect for excessive heat becomes nonsignificant while the main effect for strong wind lessens but remains significant. The predictive value of absolute wind speed could be due to the damage caused by winds at objectively high levels. We controlled for financial damage in our analyses, but strong winds can cause damage in natural surroundings that do not have financial consequences, such as felled trees in forests. The finding that precipitation was not predictive could mean that it is more difficult for people to detect short-term abnormalities in precipitation than in temperature and wind speed. Longer-term trends in precipitation are evidently more detectable. Droughts, for example, had a positive and significant effect.

One limitation of this research is the fact that some weather events tend to co-occur with others. We quantified the tendency of our weather events to co-occur with other types of weather events and determined that the levels of co-occurrences with the event types we analyzed are not high enough for concern that this may be a confounding factor.[14]

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[14] The weather event "co-occurrence" matrix can be seen in Appendix J.

Nonetheless, this is a fundamental aspect of weather events which should be kept in mind while interpreting our results. Another limitation of these findings is that our sample of Twitter users has an unknown demographic distribution, for example, in terms of ethnicity, gender, political ideology, and age. It is not entirely clear how representative our sample is of the US population on all of these dimensions.[15] There may be some differences in effects of extreme weather on our sample compared to the entire US population. For example, if our sample is younger than the US population, our subjects might respond more strongly to extreme weather events and may have somewhat different conceptions of how connected climate change is to different types of events. Also, it should be kept in mind that not all tweets originate from profiles representing individuals. Many tweets are also emitted by people in charge of Twitter profiles representing various organizations. This is another reason why our sample is likely not representative of the US population. Lastly, it should be noted that our method of measuring attention is not equally sensitive to different types of weather events because of differences in the time courses of different types of events. Droughts, for example, can develop gradually over several months. In our analysis of droughts, the reported start time for each event is the time the drought conditions passed a threshold to be considered a severe drought, but the drying period may have begun weeks or months before that. This means that our attention measure is less sensitive to the effects of droughts because our measure uses the month prior to the reported start of each event as the baseline to gauge the amount of increased attention caused by the event after the start time.

5 Conclusion

We report several findings that can be incorporated into short-term predictions about climate attention for strategic communications and long-term forecasts for policy use. We find that more weather events than previously examined can cause immediate attention to climate change. This information could be useful for strategic climate change messaging. Additionally, we find that financial damage is less predictive of increased attention than one might intuitively expect but that abnormality, or degree of unexpectedness, is consistently predictive. We find that wind speed is most predictive in absolute terms, while temperature is most predictive in relative terms.

One key direction for future research is to explore what other factors predict the effects of weather events. For example, do emotions caused by weather events mediate events' effects on attention to climate change? We mentioned above how our knowledge in this domain can enable more strategic communications about climate change. However, it is important to keep in mind that past research also suggests that attention to climate change caused by weather experiences may fade rapidly (Hamilton and Stampone 2013; Konisky et al. 2015). More research is needed to determine how best we can strategically leverage experiences with extreme weather to encourage long-lasting effects on attention and concern about climate change.

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[15] See Appendix L for an analysis of the mix of political ideologies in our sample.

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