



People as sensors: Mass media and local temperature influence climate change discussion on Twitter



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ARTICLE INFO

Article history:

Received 25 July 2014

Received in revised form 29 September 2014

Accepted 10 November 2014

Available online 8 December 2014

Keywords:

Climate change

Temperature

Social media

Twitter

Mass media

ABSTRACT

This study examined whether people living in the US connect their sensory experiences with local temperature to climate change and whether mass media influences the process. We used the volume of Twitter messages containing words “climate change” and “global warming” as the indicator of attention that public pays to the issue. Specifically, the goals were: (1) to investigate whether people immediately notice substantial local weather anomalies such as deviations from long-term mean temperatures and connect them to climate change by contributing to climate change discourse on Twitter and (2) to examine the role of mass media in this process. Over 2 million tweets were collected for a two-year period (2012–2013) and were assigned to 157 urban areas in the continental US. The rate of tweeting on climate change was regressed on the time variables, number of climate change publications in the mass media, and a number of temperature variables. The analysis was conducted at the two levels of aggregation – national and local. The high significance of the mass media and temperature variables in the majority of regression models suggests that both the weather and mass media coverage control public interest to the topic. However, no convincing evidence was found that the media acts as a mediator in the relationship between local weather and climate change discourse. Overall, the findings confirmed that the public recognize extreme temperature anomalies and connect these anomalies to climate change.

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1. Introduction

Public recognition of the existence of climate change and importance of its impacts on the economics and environment is an issue with significant societal and political implications. While the majority of Americans say that global warming is affecting weather (Leiserowitz et al., 2013), a number of studies reported a striking gap between the scientific consensus on the ongoing climate change and the lack of agreement among the general public on the subject (e.g., Doran and Zimmerman, 2009; Oreskes, 2004). Though there are multiple factors contributing to this gap that operate at the individual and societal levels (Lorenzoni et al., 2007), the natural variability of the local climate has long been considered the greatest barrier to the detection of ongoing climate change by the general public (Hansen et al., 2012). Scientific publications study the phenomenon of climate change in terms of changes in the statistical ensemble of long-term weather records, whereas the public tends to use short-term weather phenomena (Bostrom et al.,

1994) such as experiencing today's abnormally hot weather, rather than the changes of regular weather patterns (for a review, see Zaval et al., 2014). Given a tremendous variability of local weather, discerning long-term climate change is problematic for a lay person (Hansen et al., 2012).

In comparison with long-term incremental changes in mean climate variables, weather extremes are more likely to be noticed by the public. For example, Hansen et al. (1998) proposed that the monthly temperature deviations from the climate normal that occur only approximately 15% of the time should be noticeable to the lay person and are likely to be associated with climate change. The assumption that the general public can recognize “abnormal” weather conditions underlies the development of various climate indices, such as the Climate Extremes Index (CEI) (Karl et al., 1996), which was adopted in both the NASA Common Sense Climate Index (CSCI) (Hansen et al., 1998) and the NOAA US CEI. For example, for local temperature, CSCI includes the standard scores of the following observations: seasonal mean temperatures, heating and cooling degree days, and frequency of unusually hot summer days and cold winter days, presenting an aggregate of climate quantities that are, supposedly, noticeable to ordinary people (Hansen et al., 1998). Lasting index values exceeding +1 (which

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e.g., corresponds to air temperature anomaly exceeding the multi-year mean by at least one standard deviation) was suggested to be a perceptible climate change. This suggestion was formulated as a testable hypothesis, but was not in fact tested (Hansen et al., 1998). Therefore, the question remains: are weather extremes indeed recognized by the general public and, consequently, associated with climate change? While the CSCI or similar indices may capture those facets of climate change felt by the lay person, they are “top-down” constructed and reflect scientists’ beliefs, not necessarily the public perceptions. Another important question concerns the mediating role that mass media plays in connecting weather extremes to climate change. For example, Shanahan and Good (2000) posited the following question regarding the abnormally warm weather: could people react to the media cues rather than their own sensory experience in recognizing extreme weather as evidence of climate change?

To date, learning about the weather events that the public associates with climate change has largely been done through surveys, and nearly 300 different surveys of public opinion on climate change were administered since the first Cambridge Reports National Omnibus Survey in 1986 (Brulle et al., 2012). Among the factors contributing toward the detection of climate change by individuals, personal experiences with the natural variability of climate parameters are very important (Weber, 1997). Hence, the population groups with a higher exposure to climate-related hazards are better equipped to detect long-term variations in weather patterns (Weber and Stern, 2011). Indeed, Leiserowitz (2007) observed that residents of developing countries tended to readily accept the idea of risks associated with climate change, as changing weather patterns disrupt their traditional ways of life. Vedwan and Rhoades (2001), from research of apple farmers in the Western Himalayas, found that the respondents perceived the utilitarian aspects of climate change, such as the changes in timing and/or intensity of snowfalls, the hottest time of the year, and precipitation within the growing season; however, they exhibited little awareness of climate changes beyond the end of the harvest season. From a survey of indigenous farmers in Nigeria, Ishaya and Abaje (2008) observed that 3/4 of the respondents reported a multi-decadal trend of increasing temperatures and decreasing rainfall, which affected their crops. From a large survey of farmers from ten countries in different parts of Africa, Maddison (2007, p. 22) found that many of them have already noticed that the temperatures have increased while the rains have become less predictable.

Likely the most comprehensive survey-based study connecting public perceptions of climate change to weather variations was attempted by Howe et al. (2013). This research included residents of 89 countries around the globe and demonstrated that people living in regions with objectively increasing temperatures were more likely to notice the local warming of the climate. Krosnick et al. (2006) found local temperature change was a significant factor in a regression model explaining climate change beliefs of the American public. Donner and McDaniels (2013) found a strong link between local temperature trends, media coverage, and the US public opinion polls on climate change. Other scholars, however, found no link between weather conditions experienced by respondents and their climate change perceptions. Brody et al. (2008) investigated multiple physical environment factors that presumably contribute to climate change risk perceptions and found that temperature trend was not significant. Brulle et al. (2012), who focused on the relative role of factors such as extreme weather events, access to scientific information, media coverage, elite cues, and advocacy in forming public opinion of climate change, also found no effect of the weather-related factors, i.e., NOAA CEI and the percentage of the US territory with abnormally high temperatures.

While the results from several studies on the ability of the public to connect weather extremes with climate change are inconclusive, research suggests that mass media coverage, elite cues, and structural economic factors are the most important factors influencing climate change perceptions (e.g., Brulle et al., 2012; Wilson, 1995). The agenda-setting theory defines the role of the mass media in affecting public attitudes as follows: “The news media do not just passively transmit information, repeating verbatim the words of a public official or conveying exactly the incidents at an event. Nor do they select and reject the day’s news in proportion to reality. Through their day-to-day selection and display of the news, editors and news directors focus attention and influence the public perceptions of what are the most important issues of the day” (McCombs and Bell, 1996, p. 93). The factors and conditions that drive media coverage of climate change are not yet fully understood, but there are indications that scientific literature, extreme weather events, and political events play an essential role (Kirilenko and Stepchenkova, 2012; Shanahan and Good, 2000).

The inconsistency of findings regarding the role of environmental factors, media coverage, and their interplay in public perceptions of climate change calls for further investigation. Data collection through surveys primarily relies on recollections and perceptions; real-time responses and behaviors of survey subjects are rarely captured. Recently, the explosive growth of social networks, such as Facebook, Flickr, and Twitter, has enabled “passive” surveying of public opinion. Thus, the early idea of capturing the link between “press attention and public action” by continuous, scientifically grounded monitoring of newspaper content to measure “the “social weather” that is comparable in accuracy to the statistics of the US Weather Bureau” (Tenney, 1912, p. 896) and provide policy insights may finally become feasible. For example, O’Connor et al. (2010) studied the potential of using Twitter data as a substitute for traditional polls and found up to an 80% correlation between estimates of consumer confidence and public political opinion using traditional surveys and Twitter messages.

Twitter is a social networking and microblogging service that allows registered users (twitterers) to interact via short published messages (tweets) up to 140 characters in length (for details, see Leetaru et al., 2013). On average, Twitter generates 500 million unique tweets daily (Costolo, 2012). Since 2009, the focus of Twitter has shifted from a mobile status update service for keeping in touch with friends and other contacts toward posting observations on what is happening “among all the things, people, and events you care about” (Stone, 2009). Consequently, Twitter has become a popular source of observational data for both social and natural scientists. For example, Williams et al. (2013) identified 575 peer-reviewed publications in geography, marketing, natural disaster management, linguistics, and politics that used Twitter data.

A number of scholars have used Twitter as a source of real-time geographically distributed data for monitoring natural and social phenomena, thus, adopting the network of human sensors concept by Goodchild (2007). The concept compares and contrasts people who voluntarily provide various types of geo-information through their online activities to the instrumental sensor networks, both static (e.g., weather stations) and mobile (e.g., portable air quality sensors) (Goodchild, 2007). Following the concept, Twitter users can be regarded as a large, distributed network of mobile sensors that react to external events by exchanging messages (tweets). The subjects of Twitter-based studies are diverse and include early warnings of seismic activity (Sakaki et al., 2013), changes in the Dow Jones Industrial Average (Bollen et al., 2011), monitoring flu cases (Achrekar et al., 2011), and public political sentiment in presidential elections (Wang et al., 2012). Remarkably, we found only a handful of climate-related publications that used Twitter to

study the internal organization of climate change protests (Segeberg and Bennett, 2011), children's understanding of climate change (Satchwell, 2012), or public discourse during the elections (Bruns and Burgess, 2011).

The purpose of this study was two-fold: first, to investigate whether people connect significant local weather anomalies to climate change by contributing to the climate change discourse and, second, to investigate the role that mass media plays in this process. We used the number of tweets discussing climate change at any particular moment as a proxy for climate change discourse among the general public. In more formal terms, the research questions for the study were as follows: (1) Is the number of tweets on the topic of climate change/global warming positively associated with the changes in local weather conditions? (2) Is the number of tweets on the topic of climate change/global warming positively associated with the number of publications on the subject in mass media? To investigate whether people tweet more about climate change during temperature extremes because they discern abnormal temperatures or because they read about the extreme temperatures in national newspapers and analyze the interplay between local weather and media coverage, we added a third question: Does media coverage mediate the relationship between local weather and the rate of tweeting on climate change? The set of weather parameters was chosen based on previous studies (Karl et al., 1996 in particular) and is discussed in the sections below.

2. Data and methods

2.1. Twitter

To poll Twitter for current entries on climate change, we developed software that ran a search with the terms “climate change” and “global warming” every 10 min (Kirilenko and Stepchenkova, 2014). The search results were filtered for redundancies and errors and were stored. The final database contained 2,100,849 tweets posted within the period of January 1st 2012–January 31st 2014. Then, the geographical locations of the tweets were identified as described below, and only the tweets originating in the US remained in the database. Finally, the daily number of tweets (tweeting rate) was computed and adjusted for data acquisition errors.

The ability to estimate the geographical origin of a tweet is instrumental to connect the tweeting rate to perceived changes in the local climate. Although Twitter has two options (*coordinates* and *place*) to broadcast a twitterer's latitude and longitude, they

Table 1

Validation of the geolocational algorithm: median, top quartile, and top decile of the haversine distances (km) between estimated and reported US locations and the number of observations (N).

Error base on:	Percentile			N
	50%	75%	90%	
<i>Place</i> field	11	88	386	17,182
<i>Coordinates</i> field	10	67	447	12,275

are used infrequently. In our database, 1.05% of tweets had *place* and 0.82% of tweets had *coordinates* fields. The majority of geographically distributed Twitter studies rely on this approximately 1% of tweets with explicitly defined geographical locations (Leetaru et al., 2013); however, due to the relatively low frequency of tweets on climate change, this approach would reduce the size of our database to few dozen tweets per day. Thus, we used a geolocation resolving algorithm based on the verbal description of the locational data contained in the profile of the users. The geolocation results were manually validated. Specifically, we selected the most actively tweeting urban areas, which were defined as places with populations of at least 1000 where at least 100 tweets originated within the study period. Then, the tweets that originated in the continental US were selected. From those, only the tweets resolved with granularity of a county or better were further processed, e.g., the tweets from a user who listed his location as “Florida” were rejected. Finally, we filtered the data for mismatches between the user-listed time zone and the time zone of the resolved tweet location; thus, all tweets with time zone discrepancies greater than 1 h were removed.

We estimated the accuracy of the geolocation resolution algorithm using the tweets that had a *place* or *coordinates* field. For 75% of the tweets with *place* field, the haversine (great-circle) distance between the estimated and real tweet origins was less than 88 km. Similar results (67 km) were obtained for the *coordinates* field (Table 1). The final database contained 1,309,177 georeferenced tweets sent from the continental US during 105 weeks from Monday, January 9, 2012 to Sunday, January 12, 2014. The tweeting locations were assigned to the closest urban area based on the ESRI *Urban Areas* layer (ESRI, 2006), and Voronoi tessellation was applied to divide the entire territory of the conterminous US into 157 polygons, where the urban areas were used as seeds (Fig. 1). For each of these polygons, climate, tweeting, and population data were aggregated. The geography of tweeting on climate change can be found in the Electronic Supplement (Fig. A1).

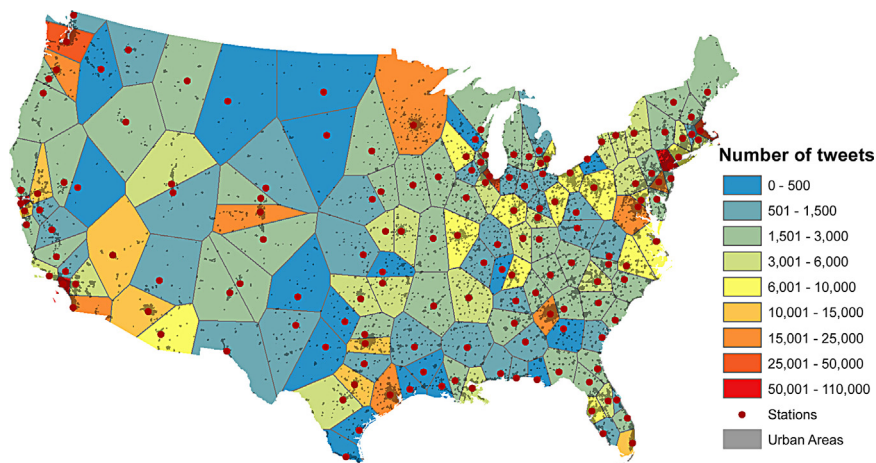


Fig. 1. Voronoi tessellation of the conterminous US territory and locations of the meteorological stations. The number of tweets from each polygon collected over the period of study is color-coded according to the provided scale.

Table 2

Temperature variables. The tilde (\sim) shows that respective variable represents climate norm for the specified day, specified location; σ designates the standard deviation; P_i is population living in a polygon i .

Temperature anomalies	Extremes
Anomaly $T^n = t - \tilde{t}$, where t is daily mean temperature ($^{\circ}\text{C}$)	Hot extreme $E^n = \begin{cases} T^s, T^s > n; & n \in \{1, 2, 3\} \\ 0 & \end{cases}$
Standardized $T^s = \frac{t - \tilde{t}}{\sigma(t)}$	Cold extreme $E^{-n} = \begin{cases} T^s, T^s > -n; & n \in \{-2, -1\} \\ 0 & \end{cases}$
Absolute anomaly $T^{abs} = \text{abs}(T^s)$	Population under heat/cold wave stress $P^n = \sum_i E_i^n P_i$

We analyzed the Twitter data on two time scales: daily and weekly. For the weekly analysis, daily tweeting data were summed by treating Monday as the first day of the week. For both time scales, the number of tweets was corrected for the days when the data collection was temporarily disrupted due to Internet connection problems (1.8% of the overall data collection time) using the interpolation described in (Kirilenko and Stepchenkova, 2014). Because the Internet disruptions were randomly distributed throughout the period of study, we did not expect any significant impact of this issue on the results. Finally, the daily distribution of tweets was heavily skewed to the right; in other words, there were disproportionately large number of days with large number of tweets. Thus, the data on the daily number of tweets was subjected to a logarithmic transformation.

2.2. Weather

The daily minimum and maximum temperatures for the 1981–2014 period were obtained from the United States Historical Climatology Network (USHCN) for the station locations closest to the centers of the urban areas that served as the seeds for Voronoy tessellation (Fig. 1). The 1981–2010 30-year temperature mean and standard deviation, which were computed for each urban zone, were used as the climate normals. For the analysis, we computed the following indices: standardized temperature anomaly, absolute standardized temperature anomaly, and extreme cold and hot temperature anomalies for each urban area. The extreme cold and hot temperature anomalies were then transformed into country-level values that represent the number of people living in extreme temperature conditions (Table 2 and Fig. A2 in the Electronic Supplement).

2.3. Mass media

The LexisNexis Academic database (lexisnexis.com) was polled for *Major US Newspapers* source articles containing the words

“climate change” and/or “global warming” published from January 9, 2012 to January 12, 2014. The *Major US Newspapers* source contains English-language newspapers published in the United States that are listed in the top 50 in circulation in the *Editor & Publisher Year Book*. In total, 7,217 articles were extracted. From those, we removed the following articles: (1) articles that appeared in newspapers that were not present in the *The Major US Newspapers* source for any part of the study period; (2) duplicate publications (e.g., an article published in both the morning and evening issues); and (3) those that appeared in newspapers that rarely publish on climate change, i.e., those with fewer than 100 retrieved articles. The last step was done to satisfy step (1) control for sparse data and removed lesser than 5% of articles. This filtering process left 6,421 articles that were published in 14 newspapers; 48% of the articles were published in just two sources: The New York Times and The Washington Post. Other news sources, listed in descending order of the number of climate change publications, included the Pittsburgh Post-Gazette, St. Louis Post-Dispatch, The Christian Science Monitor, USA Today, Star Tribune (Minneapolis), Orange County Register, The Philadelphia Inquirer, Tampa Bay Times, The Atlanta Journal-Constitution, The Tampa Tribune, The New York Post, and Daily News (New York).

3. Results

3.1. Periodicity

Growing popularity of Twitter platform with the number of the US-based monthly active users expanded from 37 million to 57 million within the study period and cyclical changes in the tweeting rate affect the number of daily tweets on climate change. To account for the first factor, we detrended the tweeting rate by subtracting the least-squares-fit straight line representing the regression of the tweeting rate on time. With respect to the second factor, the number of tweets on climate change in the US exhibits a strong increase during the daytime hours: half of daily tweets are published from 9 am to 5 pm (Fig. 2A). This daily cycle is much stronger than the general background variability in the daily tweeting rate, as found by the Sysomos Twitter tool (Sysomos, 2014). While for the background Twitter activity the ratio of the max (1 pm) and min (5 am) tweeting rates is 2.2, the same ratio for tweeting on climate change is 8.0, with maximum and minimum peaks at 10 am and 4 am, respectively. On a weekly time scale, tweeting on climate change has a 7-day periodicity, obtained from a Fourier analysis of the detrended daily number of tweets. Similarly to the daily cycle, the weekly cycle in climate change tweeting is stronger than the background cycle, with more tweets published during the first three to four days of the work week and less tweets from Friday to Sunday (Fig. 2B). Following the outcomes of the periodicity analysis, we included the time variable (days or weeks) into the regression models; additionally, six

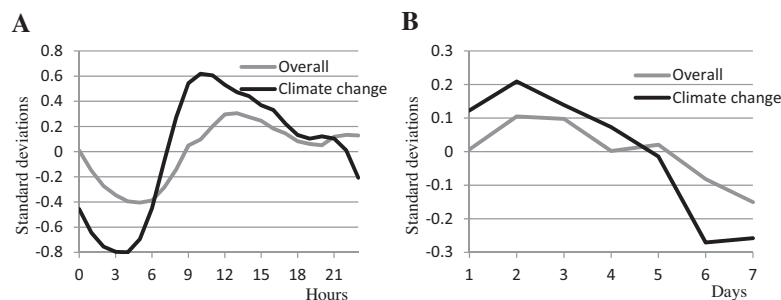


Fig. 2. Normalized number of tweets on climate change over time of the day (A) and day of the week (B) in the US, compared with overall Twitter statistics (June 2009, <http://www.sysomos.com/>).

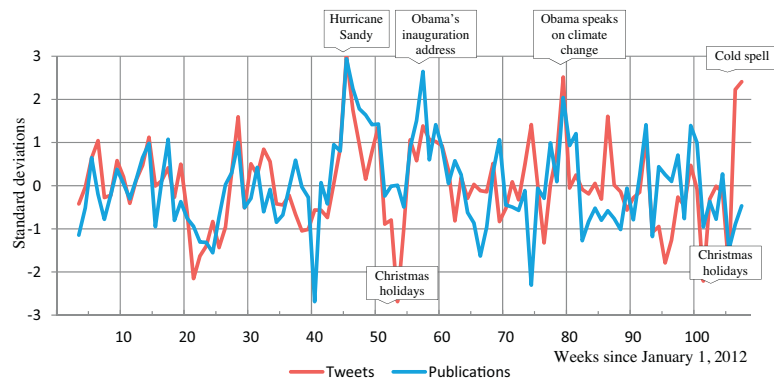


Fig. 3. Detrended normalized weekly number of tweets and weekly number of publications on climate change. The explanatory text boxes are added to spikes in tweeting activity exceeding two standard deviations from mean.

dummy variables representing days of the week (further referred to as “temporal block”) were included in the analysis of the daily data.

3.2. Country-level models

We analyzed the factors contributing to the dynamics of tweeting on climate change by regressing the tweeting rate on variables representing time, mass media coverage and weather conditions. The largest effect on the daily tweeting rate was produced by the mass media. The connection between tweeting and mass media is demonstrated in Fig. 3, which captures the weekly dynamics of the standardized detrended tweeting activity and newspaper publishing on climate change. The major spikes in the tweeting activity tend to coincide with spikes in the mass media driven by major political and climate change discourse events (e.g., the release of the IPCC AR-5 draft summary for policymakers), while major extreme weather events seem to impact tweeting more than mass media publications (Table 3). For example, the January 2014 US cold spell followed by the record low temperatures across the US Midwest (top right of Fig. 3) coincided with a two-standard deviation spike in the tweeting activity, while the number of newspaper publications on climate change remained near average. However, Hurricane Sandy, which was likely the most publicized extreme weather event within the period of study, coincided with the overall high mentioning of climate change in both Twitter and mass media.

The base model (linear regression on the temporal block variables and the number of newspaper publications: adj.

$R^2 = 0.39$, $p < 0.001$) exhibited significant autocorrelation (Durbin–Watson = 0.64). We applied first-differencing to transform the tweeting and publication rate variables; the transformed variables are interpreted as the rate of change in tweeting and publishing on climate change (Table 4, model US₁). With the transformed variables, the autocorrelation effects were virtually absent from the US₁ model (Table 5: adj. $R^2 = 0.49$, $p < 0.001$, Durbin–Watson = 2.14), and no lagged effect of newspaper publications on tweeting was found, with the exception of a one-day lag. At lag 0, the respective standardized coefficient was $\beta = 0.117$; at lag 1, $\beta = -0.075$ (Table 5).

In the US₂ model, variable p^n representing local temperature extremes was operationalized as the overall population living in the areas under extreme cold and extreme hot temperatures (Table 4, model US₂). The introduction of the temperature variable largely reduced the autocorrelation problem in the base model. The p^n variable was significant in the model for negative temperature anomalies at -2 , $+1$, and $+2$ standard deviations (Table 5, models US₂ $n = -2, 1, 2$). For the warm period of June–August taken alone, the variable p^n was significant only for positive temperature anomalies ($n > 0$ – see Table 5, models US₂ JJA $n = 2, 3$). Similarly, for the cold period of December–January taken alone, the variable p^n was significant for negative temperature anomalies ($n < 0$).

3.3. Local-level models

To estimate the effect of local temperature on tweeting about climate change, we regressed the number of tweets that originated from one of the 157 locations on time, the overall number of newspaper publications, and the local temperature variables. To

Table 3
Spikes in tweeting activity that exceed one standard deviation. Possible explanation for the spikes, extracted from content of the tweets, is provided in the Note column. Extreme weather events are shaded.

Approx. date	Week	Twit $\sigma >$	News $\sigma >$	Note
31-Jan-2012	6	1	0	Warm spell in the US
28-Mar-2012	14	1	1	IPCC Special report on managing the risks of extreme weather events
3-Jul-2012	28	1	1	Derecho (severe winds) event
30-Oct-2012	45–46	3	2	Hurricane Sandy
3-Dec-2012	50	1	1	Doha climate conference; historic high temperatures in E US
9-Jan-2013	55	1	1	NASA says Sun drives climate; draft US climate assessment
22-Jan-2013	57	1	2	Multiple events including Obama's inauguration address
30-Jan-2013	58	1	1	Tornado outbreak
9-Feb-2013	59	1	1	Winter Storm Nemo
20-May-2013	74	1	0	Oklahoma EF5 tornado event
25-Jun-2013	79	2	2	President Obama speaks on climate change
13-Aug-2013	86	1	0	Severe storms in US East Coast
27-Sep-2013	92	1	1	IPCC AR-5 draft summary for policymakers released
3-Jan-2014	106–107	2	0	Record cold temperatures over the US

Table 4

Regression models. For the entire-country models US₁ and US₂, the data is per day; for local-level models L₁ and L₂, the data is integrated on a weekly basis. Variables: time: D₀ – time (day or week); D₁...D₆ – dummy binary variables representing days of the week; Tweets on climate change: dTweets and LnTweets – first difference and logarithm of the overall US daily number of tweets, respectively; LnTweets_j – normalized weekly number of tweets from a location j; Publications on climate change: nPublications and dPublications – the daily number of newspaper publications and its first differencing; weather: Pⁿ – population under n-temperature stress (see Table 2).

Name	Model	Purpose
US ₁	$dTweets = A + \sum \alpha_i D_i + \beta dPublications + \epsilon$	Effect of newspaper publications on tweeting
US ₂	$LnTweets = A + \sum \alpha_i D_i + \beta dPublications + \gamma P^n + \epsilon$	Effect of extreme temperatures
US ₃	$nPublications = A + \sum \alpha_i D_i + \gamma P^n + \epsilon$	Effect of extreme temperatures on news
L ₁	$LnTweets_j = A + \alpha_0 D_0 + \beta nPublications + \gamma T_j^a + \epsilon$	Effect of local temperature anomaly
L ₂	$LnTweets_j = A + \alpha_0 D_0 + \beta nPublications + \gamma T_j^{abs} + \epsilon$	Effect of local temperature extremes

compensate for a smaller number of tweets from a particular location, we used the weekly aggregated data. Consequently, we did not include the dummy variables representing days of the week in the model. Note that the weekly aggregation of the data reduced the autocorrelation problem in the regression models (Durbin–Watson ~ 1.5–1.7 in models L₁–L₂, Table 4).

A direct introduction of a variable representing temperature anomalies to the regression model showed that the temperature has minimal influence on tweeting on climate change (model L₁, Table 6). However, when the absolute value of the temperature anomaly was included in the model, the temperature becomes highly significant (model L₂, Table 6). We interpret this effect as evidence that both the lower-than-usual and higher-than-usual temperatures are linked to climate change by the public. Supporting this interpretation, in both the L₁ and L₂ models, the standardized coefficient for the temperature anomaly becomes significant at the p < 0.001 level when the days with positive or negative temperature anomalies were separately included in the model (Table 6, models L₂ T_a > 0, T_a < 0).

The effect of positive and negative temperature anomalies on the tweeting rate is stronger in colder regions with annual

temperatures below 10 °C (γ = 0.156 for positive anomalies and 0.158 for negative anomalies, p < 0.001), while in the warmer regions with annual temperatures above 15 °C, the influence of temperature anomalies on the tweeting rate is smaller (γ = 0.082 for positive anomalies and 0.097 for negative anomalies; p < 0.001). Similarly, we found that wetter locations tend to have a higher temperature response: compare γ = 0.128, p < 0.001 and γ = 0.043, p < 0.05 for locations with precipitation above 1000 mm and below 500 mm, respectively (Table 6). The effect of temperature on the tweeting rate also differ seasonally, with a higher effect observed in the cold season of December–February (DJF) and the warm season of June–August (JJA); lower effects are observed in the shoulder seasons (γ = 0.112 vs. γ = 0.064, see Table 6), particularly in the fall.

4. Discussion

To explain the observed variability of the Twitter activity related to climate change, we tested three groups of variables: time (in days and weeks), media coverage, and temperature anomalies. The most important variables influencing the dynamics of

Table 5

Country-level models: regressing daily number of tweets (models US₁ and US₂) and newspaper publications (model US₃) on time (α₀), day of the week (α₁...α₆), newspaper publications (β), and population living under temperature stress (γ). Intercept is not shown; coefficients are standardized; for γ, both standardized and not standardized (in parenthesis) coefficients are reported. Columns represent the models defined in Table 3.

	US ₁	US ₁ , lag 1	US ₂ n = -2	US ₂ n = 1	US ₂ n = 2	US ₂ JJA n = 2	US ₂ JJA n = 3	US ₃ n = -2	US ₃ n = 2	US ₃ n = 3
Adj R ²	.493	.483	.471	.466	.471	.509	.505	.214	.214	.209
α ₀	.001	-.001	.440***	.478***	.478***	.513***	.501***	.121**	.118**	.108**
α ₁	.431***	.480***	.244***	.251***	.252***	.266***	.260***	.193***	.189***	.190*
α ₂	.090	.114	.323***	.324***	.326***	.387***	.373***	.076	.073	.074
α ₃	-.172***	-.128**	.293***	.290***	.290***	.360***	.357***	.108*	.105*	.108*
α ₄	-.177***	-.149***	.216***	.211***	.215***	.230***	.255***	.207***	.207***	.210*
α ₅	-.139***	-.110**	.235***	.227***	.232***	.198**	.204**	-.122**	-.120**	-.120***
α ₆	-.430***	-.364***	-.136**	-.131**	-.129**	-.095	-.095	.419***	.421***	.421***
β	.148***	-.075*	.281***	.262***	.262***	.212***	.230***			
γ			.100*** (4.63)	.106*** (1.44)	.122*** (3.86)	.166*** (8.19)	.150*** (48.4)	-.074* (-33.1)	.075* (27.7)	.018 (30.1)

* p < 0.05.
 ** p < 0.01.
 *** p < 0.001.

Table 6

Local-level models: a regression of weekly number of tweets on time (α₀), newspaper publications (β), and temperature variables (γ). Intercept is not shown; all coefficients are standardized; for γ, both standardized and not standardized (in parenthesis) coefficients are reported. Columns represent models defined in Table 2. Seasons: December–February (DJF), March–May (MAM), June–August (JJA), and September–November (SON).

	L ₁	L ₂	L ₂ , T ^a > 0	L ₂ , T ^a < 0	L ₂ , T ^a > 0 t̄ < 10	L ₂ , T ^a < 0 t̄ < 10	L ₂ , p̄ < 500	L ₂ , p̄ > 1000	L ₂ , DJF and JJA	L ₂ , MAM and SON
Adj. R ²	.270	.284	.298	.267	.303	.305	.264	.306	.350	.229
α ₀	.388***	.386***	.368***	.390***	.282***	.354***	.417***	.394***	.429***	.340***
β	.283***	.282***	.315***	.254***	.399***	.324***	.223***	.297***	.273***	.297***
γ	.017* (.008)	.119*** (.093)	.120*** (.093)	.110*** (.088)	.156*** (.101)	.158*** (.123)	.043* (.039)	.128*** (.101)	.134*** (.112)	.087*** (.064)

* p < 0.05.
 ** p < 0.01.
 *** p < 0.001.

tweeting are time and day of the week. The time variable accounts for the fast expansion of the Twitter user base, from 117 to 241 million active users worldwide within the period of the data collection (Statistica, 2014). The day of the week variable reflects the weekly cycle of Twitter publishing on climate change. The tweets on climate change are more likely to appear on a weekday, similar to all the messages comprising the background Twitter activity. However, variability of tweeting on climate change within a week is twice as large as that of for background tweeting. On an hourly scale, the tweets are more likely to be published during the work hours (9 am–5 pm). Compared with the background tweeting, the range of variability of climate change tweeting within a day is twice as large as the background variability. We speculate that this periodicity indicates that a significant proportion of climate-related tweets are published by organizations, professional journalists, and elite bloggers as part of their job responsibilities.

Two other groups of factors, the media coverage on climate change topics and temperature, are significant in the majority of the models we considered. Our finding on the prevalent role of mass media in tweeting on climate change is consistent with Brulle et al. (2012, p. 185): “the greater the quantity of media coverage of climate change, the greater the level of public concern.” We also found that the public does connect extreme temperatures, both negative and positive values, with climate change. For the country-level models, where temperature was operationalized as the population living under heat/cold stress, the temperature variable was significant at the $p < 0.001$ level. For the local-level models, where temperature was operationalized as the size of deviation from the 30-year average, the temperature was significant at the $p < 0.01$ level. These findings indicate that people do notice extreme weather events and connect them with climate change.

The country-level models (US₂) explain 47% to 51% of the total variance, and the local-level models (L₂) explain 23% to 31% of the variance. For example, in the US₂, $n = 1$, the model time, day of the week, media, and temperature explain 24.0%, 15.9%, 5.7%, and 1.1% of the variance, respectively. With the increasing temperature stress, the respective temperature variable becomes responsible for a larger percentage of the variance, while the significance of the media coverage decreases. For example, in the warm-season US₂ JJA $n = 2$ model, where the population experiences a summer heat wave with a temperature anomaly above 2 standard deviations, the temperature and media variables are responsible for 2.5% (up from 1.1%) and 4.4% (down from 5.7%) of the total variance, respectively. In contrast, in the lower-stress model US₂ JJA $n = 1$, the temperature predictor is responsible for only 1.4% of the variance. Because a 30-year weather average was used for computing the climate anomaly, low-stress temperature anomalies are getting closer to what is frequently experienced today in many regions of the US: what has been observed during recent heat waves as extreme, highly uncommon conditions will soon be the new normal, with common occurrences of even more extreme conditions (Hansen et al., 2012). In the local-level models, the time variable predicts a smaller percentage of the variance compared with the country-level models; however, both the media and temperature predictors are significant. For example, in the L₂ DJF and JJA model (where a summer heat wave occurs with a temperature above 2 standard deviations from the norm), the media and temperature predictors explain 9% and 2.1% of the total variance, respectively.

Model results indicate that the effect of strong negative temperature anomalies on the tweeting rate is as high as the effect of positive temperature anomalies. The significance of negative temperature anomalies is consistent with a recent study that found more people in the Northeast, Midwest, and the South reported extreme cold weather during 2013 (Leiserowitz et al., 2013). Our findings may also indicate that people experiencing

cold waves consider them a contradiction to “global warming” phenomenon, and tweeting, in fact, represents skeptical attitudes in action.

The temperature variables are weaker in their explanatory power compared with the media influence. Connecting personal experience of weather events to climate change may be difficult. In accordance with the “two-step flow” communication theory (Katz, 1957; Lazarsfeld et al., 1948), Weber and Stern (2011) suggested that the American public experience climate change almost entirely indirectly through the opinions of leaders and the media, so that the media mediates the exposure of the American public to concerns about climate change. Therefore, the more the media writes about climate change, the more the public pays attention to the issue; this effect is also consistent with the Quantity of Coverage Theory (Mazur and Lee, 1993). Thus, the present study posited and answered the third question: Do people blog more about climate change during temperature extremes because they discern abnormal temperatures or because they read about the extreme temperatures in national newspapers?

We specifically tested for the mediating effect of the media and did not find significant correlation between the P^n and $nPublications$ variables on a daily or weekly basis for any value of n , except for a weak negative correlation at $n = 1$ (weekly) and at $n = -1$ (daily) for the full dataset. The mediation analysis (Baron and Kenny, 1986) did not show the mass media mediating effect at various ranges of temperature extremes. While the presence of the media variable in the model does account for some variance of the temperature variable, the effect of the temperature variable is nevertheless distinct. Table 3 shows that the climate change topics covered by the media are not limited to extreme events, but also include political events. Our study did not find a strong evidence for mediating effect of mass media for temperature and we conclude that temperature has an effect on the public’s recognition of climate change beyond the influence of the mass media.

The gap between scientific and public concerns about climate change has highlighted the problem of communicating climate change science. The main driver of this study was to examine a proposition that the personal experiences of people living under temperature anomalies are influential in their recognition of climate change phenomenon. While personal experience is susceptible to detection failure and interpretation biases, it is powerful in calling attention to the problem and to climate change discourse in general (Weber and Stern, 2011). It is important to note that this study did not test *what* was tweeted about climate change, e.g., whether extreme weather conditions contributed to acceptance or rejection of climate change or whether the changes in the climate were interpreted as negative. For example, Corbett and Durfee (2004) observed that when talk-show hosts and television reporters in the US asked lay persons about their opinion on climate change, a typical response was that a few degrees warmer might not be so bad. Using the Natural Language Toolkit platform (www.nltk.org), we attempted an automated sentiment analysis on a small subset of the collected tweets to extract the attitudes on climate change and found the results encouraging for further research in this direction. Note, however, that sarcastic messages and jokes may be difficult for automated interpretation; e.g., we found large number of such sarcastic messages in tweets originated from Russia.

Our models explained no more than half of the Twitter data variation. As we already mentioned, it may be difficult to detect the long-term climate trend amid high-frequency weather variations, especially because the younger population (according to the social media analytics provider sysomos.com, over 90% of Twitter users are younger than 40) may not remember the temperatures of 30 years ago (Hansen et al., 2012). Similarly, the mobility of the American population may present a problem. Even if the climate

trend is successfully recognized by an individual, posting on Twitter constitutes behavior and, possibly, relatively strong attitudes toward climate change, which are subject to demographic, attitudinal, and social contextual variables (Brody et al., 2008; O'Connor et al., 2002). Our study did not collect variables such as gender, socioeconomic status, or political orientation, which are believed to affect climate change perceptions the most (Bord et al., 1998; O'Connor et al., 1999).

Overall, Twitter messages have high utility for research on climate change perceptions by the public. The large volume of Twitter communications (over 500 million Tweets per day on average, with spikes up to 0.15 million per second, Krikorian, 2013), high penetration (15.1% of the American population are Twitter users (eMarketer, 2014)) and relatively mature user base (e.g., while on Facebook the percentage of 12–17 year olds is 15% higher than the percentage of 35–44 year olds, on Twitter the representation of these groups is nearly equal, eMarketer, 2014) make Twitter data attractive for public opinion research. The internal architecture of the Twitter messaging system, such as brevity, highlighting of key words, references to other messages, Twitter users, and external sources, as well as information about tweets' authors, their location, number of followers, etc. provide ample auxiliary data (Kirilenko and Stepchenkova, 2014).

Social network data also lead to research limitations. Social networks tend to appeal to the younger generation. Income, race and educational profiles of users of social networks also differ from those of the general population (Webster, 2010). Further, an explosive growth of this audience causes their socioeconomic profile to change over time. Another important issue is data collection. The archive of Twitter messages is unavailable to researchers, aside from extremely limited data grants (e.g., only six research proposals out of 1300 were granted free data in the 2014 Twitter #DataGrants pilot program, Krikorian, 2014), which complicates longitudinal studies. In our research, we had to restrict the study to only two years of data collection period, limiting the number of extreme events covered by the data. Another important limitation is the set of the weather parameters that the public might relate to climate change; these parameters had to be identified based on existing studies. While we described the results of the model that included extreme temperature anomalies, our findings involving liquid and solid precipitation were inconclusive and thus were not reported. Further, on a longer time scale, weather variables other than temperature may be equally important.

In conclusion, the study demonstrated the utility of social network data for “passive” survey of public opinion, specifically on public climate change perceptions. Twitter users were considered a distributed network of sensors who translated their physical experiences of temperature anomalies and extreme weather conditions to engagement in climate change discourse on Twitter. Operationalization of temperature anomalies as the number of standard deviations from the long-term mean, allowed testing a hypothesis that postulates that people are able to recognize local weather variability if this variability is “large enough”. Specifically, the study addressed the role of temperature variables and mass media in influencing public perceptions of climate change and, in addition, investigated whether mass media mediates the relationship between temperature and tweeting about climate change. The analysis conducted at the two levels of aggregation, national and local, confirmed the high significance of the mass media and temperature variables in the majority of regression models, suggesting that both the weather and mass media coverage control public interest to the topic. However, no convincing evidence was found that the media acts as a mediator in the relationship between local weather and climate change discourse. Overall, the findings confirmed that the public recognize extreme

temperature anomalies and connect these anomalies to climate change.

Acknowledgements

The support for this study was provided by NASA Applied Sciences Program Grant #NNX10AH20G and 2014 UND Faculty Seed Money Award.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.gloenvcha.2014.11.003.

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