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The impact of local temperature volatility on attention to climate change: Evidence from Spanish tweets

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ABSTRACT

Variability in local weather patterns has long been suggested as a major barrier impeding laypeople from recognizing long-term climate trends. However, as humans are able to detect and interpret rapid signal fluctuations, it seems psychologically plausible to assume that they are able to integrate short-term variations of weather variables into their mental representations of climate change. Using a combined analysis of social media and weather station data, here we investigated the impact of the short-term volatility of local temperature on climate change-related tweets from 2014 to 2017. We found a nonlinear hockey stick relationship between weekly temperature volatility and climate change-related tweets, a volatility rise of 1 °C corresponds to an 82% increase in climate change tweets when volatility is above 3.5 °C. This volatility effect was observed from 2016 onwards, suggesting a recent change in people's mental representations of climate change. This study provides empirical evidence illustrating that in the public mind, climate change may not be represented as a mere temperature increase any more, but as a disruption of the climate system in general.

1. Introduction

How do we know that the climate is changing? While the scientific investigation of climate change tracks incremental changes occurring at the timescale of decades (IPCC, 2014), public beliefs and concerns about climate change are largely shaped by immediately accessible local weather information. Perceived or experienced deviations of local temperature averages from normal reference temperatures result in increased climate change concern (Howe et al., 2019). This *local warming effect* reflects heuristic information processing (Kahneman and Frederick, 2012) where boundedly rational humans replace judgments about attributes that are difficult to compute (in this case, global climate trends) with judgments about readily available, more salient information (average local temperatures). Local variability in weather patterns, in contrast, has been suggested as a major cognitive barrier preventing laypeople from recognizing long-term climate trends by adding noise which obscures mean temperatures, impedes the creation of mental representations of climate change, and results in reduced climate change concern (Hansen et al., 2012).

Research investigating the impact of local temperature perceptions on climate change beliefs has so far focused on the high and low ends of the temperature scale, revealing that belief in climate change increases when temperatures are perceived as being warmer or colder than usual (Hamilton and Stampone, 2013; Joireman et al., 2010; Kirilenko et al., 2015; Li et al., 2011; Sisco et al., 2017; Zaval et al., 2014). These studies have privileged a long-term perspective when defining a "normal" climate, frequently relying on deviations from a 30-year reference period (Howe et al., 2013; Kirilenko et al., 2015). Similarly, studies investigating the impact of extreme weather events on public attention to climate change also relied on predefined long-term baselines to identify these events (Sisco et al., 2017). This approach based on the so-called *climate normals*, where reference periods are calculated by only averaging a large number of previous years, is probably informative for elaborating physical climate models but may not optimally reflect how today's temperatures impact climate change perception. For instance, climatic norms could lead to different estimation of anomalies as a function of the chosen reference period (Jarnevich and Young, 2019; Wilks, 2013; Zhang et al., 2011). Moreover, in a changing climate, the perception of what people believe as a normal climate is shifting as well, with the weather experienced in recent years being a crucial

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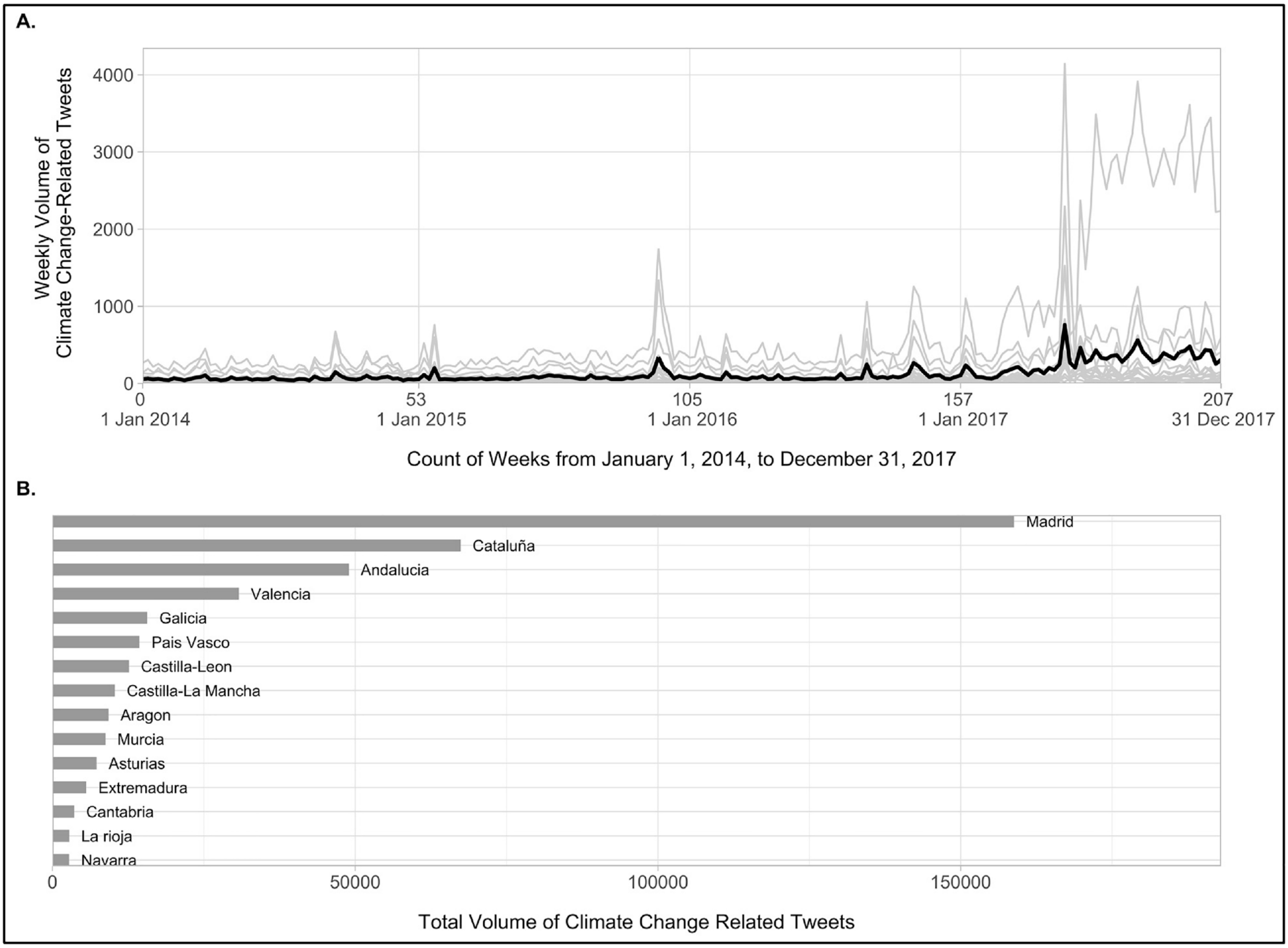

Fig. 1. Weekly (A) and total volume (B) of climate change-related tweets per region. The black bold line in panel A is the time series for the total average of weekly tweets and gray lines are the individual time series for each region.

determinant of people climatic baseline instead of the longer historical periods (Moore et al., 2019).

From a psychological perspective, a mental representation of an abstract state such as a 30-year weather average needs to be constructed in a resource-intensive computational process (Trope and Liberman, 2010; 2003) that is unlikely to be regularly applied by individuals with limited cognitive resources (Weber, 2006). It should rather be expected that individual perceptions of climate change are driven by elements of the current situation, instead of changes relative to historical averages, and consequently should be modelled as a function of the current weather situation. This rationale is more in tune with what we know about the cognitive mechanisms underlying human judgment and decision-making which are based mainly on readily available information without relying on complex mental elaborations (Tversky and Kahneman, 1973). For instance, when suffering a sweltering day, people may think about global warming just because temperatures were very high on that day (i.e., readily available information) and not because it was warmer than the mean of the previous 30 years (i.e., complex mental elaborations).

Climate change being a long-term phenomenon that is happening over a considerable time span, it has been argued that is difficult to directly experience the long-term trend given the variability that exist between years, seasons and months (Hansen et al., 2012). Previous findings suggest that people can actually perceive climate change impacts in changing seasonal temperatures at the local level (Howe, 2018). Therefore, extending the rationale presented above, a short-term index of variability such as the variation of weekly temperatures (or weekly volatility of temperatures) is a piece of available information that may be used to create a representation of the stability or volatility of the climate.

It is moreover questionable to assume that the information of short-term weather fluctuations is not integrated to some extent in people's mental representation of climate change, given that humans evolved to detect rapid changes around them in order to anticipate threats and to cope with risks in a changing environment (Rees, 2008). They are able to detect and interpret rapid signal fluctuations, as for instance illustrated by investor behavior in the stock market, where rapidly fluctuating stocks are considered more unstable and risky (Dimpfl and Jank, 2016; Weber et al., 2005). It is thus entirely plausible to assume that people are also able to process and integrate short-term variations of weather variables into their mental representation of climate change, which in turn should result in increased concern about and attention toward climate change under conditions of high temperature volatility.

Based on this reasoning, we suggest that public attention to climate change is not only influenced by the experience of warmer or colder local temperatures, but that increases in the short-term variation of local temperatures (i.e., increase in temperature volatility), should also increase public attention to climate change. (Hansen et al., 2012). Therefore, here we test the hypotheses that public attention toward climate change is affected by both (i) the short-term volatility and (ii) the mean of local temperatures computed independently of the climatic norm.

Testing hypotheses about the impact of short-term weather variations on human attention to climate change requires data with a high temporal resolution. Previous research on public perceptions of climate change has mostly been conducted using large-scale representative surveys (Howe et al., 2013; Myers et al., 2012). This method is limited by its reliance on respondents' recollections and reconstructions at a single time point. As a consequence, the true temporal dynamics of climate change concerns are not assessed. Social media platforms provide large data sets that can be used to evaluate spontaneous and continuous responses in real-time. Twitter has previously been used as a source of real-time data to investigate psychological and social processes (Zimmer and Proferes, 2014). For instance, changes in the frequency of Twitter messages referring to climate change have been used as an indicator of public attention to climate change (Kirilenko et al., 2015; Moore et al., 2019). However, most of the previous research using Twitter data relied on retrieval methods that do not provide all the available information, but only a small sample representing approximately 1% of the total volume of tweets referring to a specific keyword. These methods are unlikely to yield a valid representation of public reactions to real-world events (Kim et al., 2013; Morstatter et al., 2013). Therefore, in the current study, we rely on the full Twitter data stream (i.e., firehose data) as a proxy for public attention to climate change to test our hypotheses. Given the extensive cost required to analyze the full sample of Twitter data and limited access to the data provider, we focused our analysis on tweets posted in Spain between 2014 and 2017, which can be considered a case study illustrating the predicted effect.

2. Data and methods

The study was approved by the Ethics Committee of the Faculty of Psychology and Educational Sciences of the University of Geneva and conducted following the ethical guidelines of the institution (reference number: PSE.20190604.11). The study did not involve individual participants, no personal information was collected.

2.1. Twitter data

Tweets were collected using Crimson Hexagon (now known as Brandwatch, https://www.brandwatch.com), a Twitter-certified social media analytics company that provides every public tweet posted on Twitter (i.e., Twitter Firehose), in any language, and from any location (Breese, 2015). Crimson Hexagon used the available metadata to assign location to posts. When posts are geotagged, geographic coordinates are used, representing 1% of all posts. For the remaining 99%, statistical models are built with the available contextual information, such as the self-disclosed location in the profile information, to predict the location. This method is able to identify approximatively 70% of all tweets posted in a specific state or province within a country (https://www.brandwatch.com/p/crimson-hexagon-help-resources/). Similar methods have been used in other studies to identify the location of tweets without exact latitude-longitude coordinates (Garcia et al., 2018; Jurgens, 2013; Jurgens et al., 2015).

The lowest spatial resolution provided by Crimson Hexagon for each tweet originating in Spain was the regional level. Therefore, we set the spatial resolution of the study at the regional level. Specific queries were submitted to obtain the daily volume of tweets containing the keywords "climate change," "global warming," or their Spanish equivalent (i.e., "*cambio climatico*," "*calentamiento global*") originated from each Spanish region posted between January 1, 2014, and December 30, 2017 as a proxy for public attention toward the issue of climate change on the Twittersphere during this period. We only took into consideration the regions located on the continent (i.e., Andalusia, Aragon, Asturias, Basque Country, Cantabria, Castile and León, Castile-La Mancha, Catalonia, Extremadura, Galicia, La Rioja, Madrid, Murcia, Navarre, and the Valencian Community). The Balearic Islands, Ceuta, Melilla, and the Canary Islands were excluded. These search parameters led to a total volume of 398'761 tweets referring to climate change posted during the selected period. The temporal resolution of the study was fixed at the week level; we thus computed the weekly volume of tweets for each region. Note that we did not refer to the calendar weeks of the year as reference, we instead summed the number of tweets for seven-day periods beginning on January 1, 2014, resulting in a total of 208 weeks between January 1, 2014, and December 30, 2017 (see Fig. 1).

Table 1
Total number of selected weather stations with the respective amount of observations per region between January 1, 2014, and December 30, 2017.

Region	Total of weather stations	Total of observations
Andalucía	117	16′1458
Aragon	41	56′034
Asturias	23	31′544
Cantabria	18	24′111
Castilla la Mancha	60	80′914
Castilla Leon	116	161′124
Cataluña	73	97′788
Extremadura	50	71′364
Galicia	46	66′695
La Rioja	8	11′606
Madrid	20	26′362
Murcia	23	32′871
Navarra	21	28′631
País Vasco	34	47′237
Valenciana	42	56′663
Total	**692**	**954′402**

2.2. Weather stations data

In total, 825 data files were downloaded from the open data portal of the Spanish state weather agency (https://opendata.aemet.es/). Each file contained historical weather information from each weather station located in the Spanish territory. In order to be able to cross meteorological and social media information, we applied the same spatial and temporal resolution used for the selection of tweets to select the weather stations. We identified and selected 692 weather stations which contained observations between January 1, 2014, and December 30, 2017 and were located within the 15 Spanish regions identified previously, resulting in a total of 954′402 data points (see Table 1). The GPS coordinates of each weather station were used to identify their location within Spain.

We computed an index of weekly mean temperature and an index of weekly temperature volatility for the analysis. For each weather station, we averaged the daily mean temperatures to obtain the weekly mean temperature. We computed the standard deviation of mean daily temperatures as a measure of short-term volatility. Then, we averaged index values for all weather stations located within the geographical boundaries of a specific region. Note that similar to the Twitter data, we did not refer to the calendar weeks of the year as a reference; we instead considered the seven-day periods from January 1, 2014, to December 30, 2017. Therefore, for a given region with w weather stations, let y_{it} be the temperature mean for weather station i at day t. Then the mean temperature for the first week is

$$meantemp = \frac{1}{7}\sum_{t=1}^{7}\frac{1}{w}\sum_{i=1}^{w} y_{it} \tag{1}$$

and the weekly temperature volatility is

$$voltemp = \frac{1}{7}\sum_{t=1}^{7}\frac{1}{w-1}\sum_{i=1}^{w} (y_{it} - y_{i.})^2 \tag{2}$$

where $y_{i.}$ is the average over 7 days at weather station i.

Table 2
AIC Model Comparison.

Models	Model df	Residual df	R^2_{adj}	AIC	ΔAIC
Base model	11.89	3107.11	0.145	10344.85	–
Temperature Volatility					
Model 1	15.2	3103.79	0.158	10301.19	43.65
Model 2	27.65	3091.35	0.165	10290.03	11.16
Model 2b	205.99	2913.01	0.923	3027.79	7262.24
Model 3	205.99	2913.01	0.923	3027.78	0.01
Model 4	222.07	2896.92	0.928	2848.81	178.97
Model 5	**294.32**	**2824.68**	**0.935**	**2599.20**	**249.61**
Mean Temperature					
Model 1	30.21	3088.8	0.193	10180.34	164.5
Model 2	36.96	3082.04	0.196	10177.34	3.01
Model 2b	203.83	2915.17	0.925	2941.17	7236.17
Model 3	203.81	2915.19	0.925	2941.18	−0.01
Model 4	219.66	2899.34	0.929	2777.17	164.01
Model 5	**287.33**	**2831.67**	**0.935**	**2556.64**	**220.53**

Degrees of freedom for the Model (Model df), Residual degrees of freedom (Residual df), Adjusted R^2 (R^2_{adj}), Akaike Information Criterion (AIC) and delta AIC (ΔAIC) for the different GAM models tested for each weather variable (i.e., volatility and mean temperature). Models in bold are the best model for each weather variable when comparing models using delta AIC.

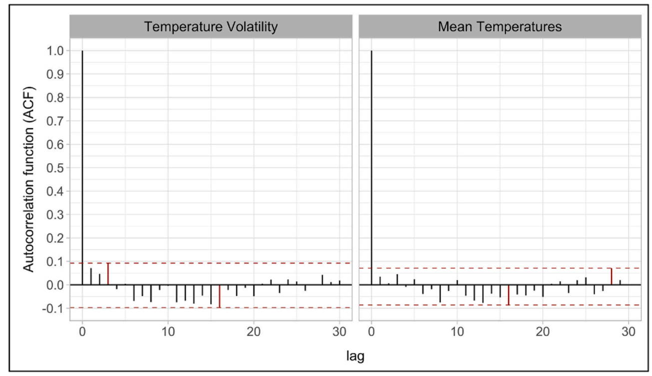

Fig. 2. Autocorrelation function (ACF) for the GAM models used (i.e., Model 5) to quantify the association between the logarithm of the number of climate change tweets, temperature volatility and mean temperature. The dotted line shows the maximum and minimum values of the autocorrelation function for lags superior to 0. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3. Results

Using Generalized Additive Models (GAM; Wood, 2017), we quantified the association between local volume of climate change-related tweets, local temperature volatility (operationalized as the standard deviation of local temperature) and local mean temperature. Each weather variable was modeled separately, a natural logarithmic transformation was applied to the highly skewed weekly tweets counts to better approximate normality and to mitigate the effect of outliers in the data.

3.1. AIC Model comparison procedure

A model comparison procedure based on optimal AIC (Akaike Information Criterion) scores was used to identify the best-fitting model for each weather variable. The time measure was the week count between January 1, 2014, and December 30, 2017 (i.e., from 0 to 207). For both weather variables, data was modelized with a Gaussian distribution and an identity link function. The estimation of coefficients and smoothing parameters was based on the Restricted Maximum Likelihood estimator. All analyses were conducted using the statistical software R (version 3.5.1). The GAM estimation was based on the R package 'mgcv' (Wood, 2017). We used *gam.check()* to improve models by updating the number of basis functions based on its results. Results of the AIC model comparison procedure are shown in Table 2.

We started with the simplest possible model as basis model. We modeled the logarithm of the number of tweets referring to climate change with a single one-dimensional cubic regression spline of time (i.e., referred to as base model in Table 2). We opted for a number of basis functions equal to the number of observations ($k = 208$), but similar results were obtained with a smaller number of knots. Then, the same procedure was followed to model both weather variables separately. Model 1 incorporated a cubic regression spline for the predictor (i.e., temperature volatility or mean temperature). In Model 2, we added a factor smooth interaction for the categorical variable year to calculate specific smooths for each year (i.e., 2014, 2015, 2016, 2017). This model included a separate linear term for the year variable to include a varying intercept allowing these categories to differ in overall means in addition to the shape of the smooths. Then, we added a fixed effect of regions to adjust for different effects possibly linked to the region such as region size (i.e., Model 2b). In Model 3, 4, and 5, we tested the optimal random-effects structure appropriate for the regional factor, that encompasses the fixed effect of region. Therefore, Model 3 incorporated a random effect for the regions to model region-specific intercepts, Model 4 captured by-region variation in linear effects with the integration of random slopes, and Model 5 incorporated random smooths to capture the by-region variation in non-linear effects. As shown in Table 2, the comparison of AIC scores revealed that by incorporating individual curves to each region, Model 5 provided the best fit to model the relation between the logarithm of the number of tweets referring to climate change and both weekly temperature volatility and weekly mean temperature. Additionally, the random smooth incorporated in Model 5 allowed us to deal with the autocorrelation issue in the model. As shown in Fig. 2, visual inspection of the residual autocorrelation plots of Model 5 for each weather variable revealed acceptable levels of autocorrelation with low values, mainly between 0.092 and -0.097.

3.2. Mathematical representation of the selected GAM models.

The corresponding mathematical representation of the GAM model used to estimate the relation between weekly temperature volatility and our dependent variable (i.e., Model 5) is as follows:

$$y = \mu + \alpha_j + f(t) + f_r(t) + g\ (v_r) + g_j(v_r) + \mathscr{E} \quad (3)$$

where y is the logarithm of the number of tweets for week t and region r, μ is the overall mean, α_j is the overall year effect for the four years indexed by j. For the smooth parts, $f(t)$ is the spline fit with $k = 208$ nodes along the weeks taking into account all unmodelled effects. As a spline term, it is orthogonalized to the previous terms and has therefore a zero average. $f_r(t)$ is a random effect spline that codes for the difference of fit for a region r compared to the general effect over all regions $f(t)$. The most important term is $g\ (v_r)$, the spline fit with $k = 20$ nodes along the weekly variability, whose estimation is shown on Fig. 1A. $g_j(v_r)$ is the difference of fit for a given year j compared to the general effect. Fig. 1 B, C, D and E represent $g\ (v_r)+g_j(v_r)$ which is the overall effect of weekly variability per year. Finally, $\mathscr{E}$ is the residual error term. Note that each of the above spline functions can alternatively be written as $X\beta$ where X is a matrix that codes the k splines bases, and β are the corresponding coefficients. The corresponding mathematical representation of the GAM model used to estimate the relation between the mean temperature and our dependent variable is the same as expressed in Eq. (3), except that the weekly volatility ν is replaced by the mean temperature.

Table 3
GAM models used to estimate the relation between climate change-related tweets and the weekly temperature volatility.

Model 5				
Parametric coefficients	*Estimate*	*Std. Error*	*t-value*	*p-value*
Intercept	4.272	0.523	8.176	< 0.0001
year2015	−0.312	0.417	−0.749	0.454
year2016	−0.444	0.591	−0.751	0.453
year2017	−0.785	0.723	−1.086	0.278
Smooth terms	*Edf*	*Ref.df*	*F-value*	*p-value*
s(time)	173.853	194.684	14.551	< 0.0001
s(voltemp)	**6.679**	**8.4**	**2.96**	**0.0029**
s(voltemp) : year2014	3.598	4.47	1.779	0.1193
s(voltemp) : year2015	3.844	4.78	2.603	0.0246
s(voltemp) : year2016	3.87	4.786	16.352	< 0.0001
s(voltemp) : year2017	3.966	4.92	14.617	< 0.0001
s(time, region)	94.512	132	252.571	< 0.0001
Model 5b				
Parametric coefficients	*Estimate*	*Std. Error*	*t-value*	*p-value*
Intercept	4.268	0.523	8.167	< 0.0001
year2015	−0.31	0.418	−0.742	0.4584
year2016	−0.439	0.591	−0.742	0.4580
year2017	−0.781	0.724	−1.08	0.2804
Smooth terms	*Edf*	*Ref.df*	*F-value*	*p-value*
s(time)	173.879	194.699	14.577	< 0.0001
s(voltemp) : year2014	**5.468**	**6.847**	**0.437**	**0.8408**
s(voltemp) : year2015	**5.902**	**7.378**	**0.441**	**0.8834**
s(voltemp) : year2016	**5.928**	**7.366**	**18.22**	**< 0.0001**
s(voltemp) : year2017	**6.144**	**7.645**	**11.932**	**< 0.0001**
s(time, region)	94.678	132	252.426	< 0.0001

The table shows the estimated parametric and non-parametric components, with their corresponding standard errors, *t*-values, effective degrees of freedom, *F*-statistic and *p*-values for the GAM models used to estimate the relation between the logarithm of the number of tweets referring to climate change and the weekly temperature volatility using a Gaussian distribution with an identity link function (i.e., Model 5 and 5b). *Voltemp* refers to the weekly temperature volatility. Estimations in bold are reported and discussed in the main text.

3.3. Increased climate change attention in periods of high local temperature volatility

Results supported our central hypothesis in that an increase in weekly temperature volatility predicted public attention toward climate change. The GAM analysis identified a significant nonlinear hockey stick relationship between weekly temperature volatility and logarithmized volume of climate change-related tweets ($p = .0029$; see Model 5 in Table 3). As depicted in Fig. 3A, the main relationship between the weekly volatility of temperatures and climate change-related tweets was relatively invariant, showing no effects when weekly volatility was below approximatively 3.5 °C and rising sharply after that. The estimated linear trend for the increasing section showed a slope of 0.6 [log(#Tweet)/°C] (i.e., dotted segment in Fig. 3A), corresponding to an 82% increase in the volume of climate change-related tweets for each 1 °C increase in temperature volatility.

Note that as Model 5 included a smooth term for weekly temperature volatility, the interaction with the categorical variable year shown in Table 3 reflects the difference between the shape of the relationship observed for each year and the main hockey stick relationship observed between weekly temperature volatility and the dependent variable. In order to assess the specific nonlinear relation for each year, we computed an additional model without the main effect of temperature volatility (i.e., see Model 5b in Table 3). Interestingly, this model revealed that the nonlinear hockey stick relationship between weekly temperature volatility and logarithmized volume of climate change-related tweets was only observed in 2016 and 2017 (both $ps < 0.0001$; Fig. 3D and E), not in 2014 and 2015 ($ps > 0.1$; Fig. 3B and C), indicating that a significant association between temperature volatility and public attention to climate change has only recently been established.

3.4. Increased climate change attention in periods of high and low local temperatures

The GAM analysis moreover confirmed that warmer and colder temperatures increase Twitter activity related to climate change. It showed a significant gondola-shaped relationship between weekly mean temperatures and logarithmized volume of climate change-related tweets, which increased when mean temperatures fell approximatively below 5 °C or rose above 26 °C ($p < .0001$; see Model 5 in Table 4). As depicted in Fig. 4A, at the higher end, the slope for the estimated linear trend was 0.4 [log(#Tweet)/°C], corresponding to a 49% increase in the volume of climate change-related tweets for a 1 °C increase in weekly mean temperatures. At the lower end, the slope was −0.35 [log(#Tweet)/°C], corresponding to a 42% increase in the volume of climate change-related tweets for a 1 °C decrease in weekly mean temperatures.

Following the same procedure as for temperature volatility, we computed an additional model without the main effect of mean temperature to assess the specific nonlinear relation for each year (i.e., see Model 5b in Table 4). This model revealed a significant gondola-shaped relationship between weekly mean temperatures and logarithmized volume of climate change-related tweets for the years 2017 ($p < .0001$; Fig. 4E), 2016 ($p < .0001$; Fig. 4D), 2015 ($p < .0001$; Fig. 4C), and a tendency for 2014 ($p = .0588$; Fig. 4B).

4. Discussion

The study reported here demonstrates that readily available information about the weather, such as the mean and the variation of weekly temperatures, impacts climate change attention on social media. We observed an increase in the volume of climate change-related tweets originating in Spain during weeks where the temperature volatility (i.e., weekly variation of mean temperatures) was high, above 3.5 °C. Interestingly, this relationship was only observed in 2016 and 2017 (and not in 2014 and 2015), indicating that the link between temperature volatility and public attention to climate change has only recently been established. Moreover, we observed an increase in climate change-related tweets originating in Spain during periods where the weekly mean temperature was below 5 °C or above 26 °C across the whole measurement period (i.e., from 2014 to 2017).

Our findings contrast with previous conceptualizations of local weather variability as a significant barrier for creating mental representations of climate change (Hansen et al., 2012). To the contrary, we provide empirical evidence illustrating that people can perceive small local variations in temperatures (i.e., local temperature volatility). While this perception may or may not occur at the conscious level, these variations are linked to an increase in Twitter activity related to climate change. This suggests that local temperature volatility is integrated, to some extent, into people's mental representation of climate change.

Note that we are not claiming here that a global increase in temperature volatility is taking place as a direct consequence of global warming. This issue is still the topic of considerable scientific debate (Alexander and Perkins, 2013; Hansen et al., 2012; Huntingford et al., 2013), with different methodologies leading to a disparity of conclusions. Nonetheless, there seems to be a consensus that temperature variability has increased in some regions of the globe (Myers et al., 2012) and that this will have important ecological (Stenseth et al., 2002) and societal impacts (Guo et al., 2016; Katz and Brown, 1992; Shi et al., 2015). These consequences may be even more important than changes in average temperature (Katz and Brown, 1992), assuming that people will relatively easily adapt to changes in average temperatures but may have more difficulty adjusting to increased temperature volatility (Guo et al., 2016; Shi et al., 2015). Independently from the scientific debate on whether an increase of temperature volatility is happening as a

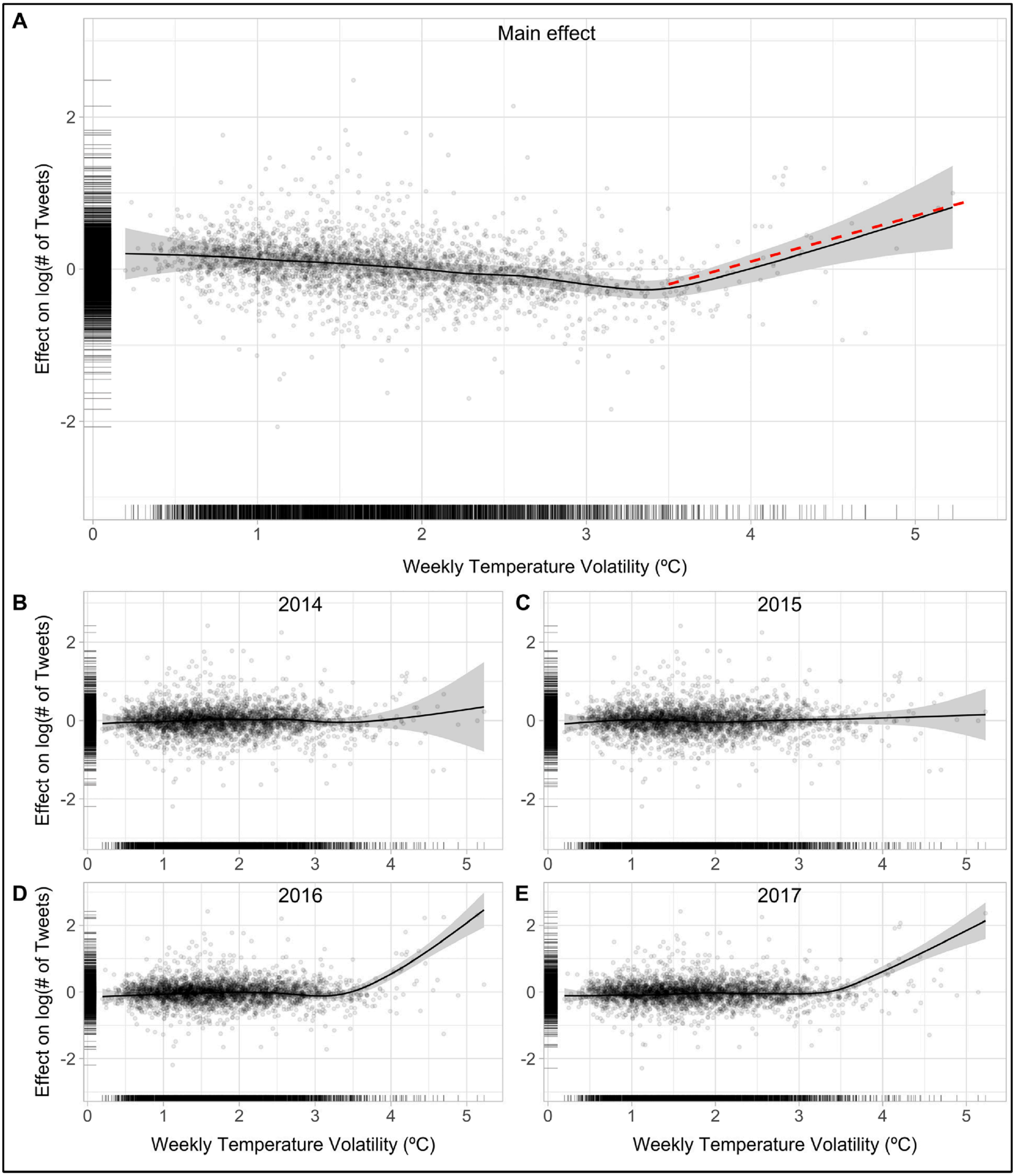

Fig. 3. Main effect (A) and annual effects (B for 2014, C for 2015, D for 2016 and E for 2017) of weekly temperature volatility on logarithmized number of climate change-related tweets, as part of a GAM model with a Gaussian distribution and an identity link function. The other covariates are a smooth effect of time, a linear term for year, and a random smooth of region. The solid line is the GAM smoother, the gray polygon shows the 95% CI, points are raw data, the dotted segment in panel A is a linear approximation of the slope at the higher end. A sensitivity analysis based on an alternative model showed that these results are robust (see Appendix A).

Table 4
GAM models used to estimate the relation between climate change-related tweets and the weekly mean temperature.

Model 5				
Parametric coefficients	*Estimate*	*Std. Error*	*t-value*	*p-value*
Intercept	4.103	0.488	8.404	< 0.0001
year2015	−0.213	0.391	−0.545	0.5859
year2016	−0.329	0.548	−0.6	0.5483
year2017	−0.405	0.669	−0.605	0.5454
Smooth terms	*edf*	*Ref.df*	*F-value*	*p-value*
s(time)	168.727	191.486	12.425	< 0.0001
s(meantemp)	**12.428**	**14.781**	**13.44**	**< 0.0001**
s(meantemp) : year2014	2.568	3.23	0.919	0.4729
s(meantemp) : year2015	2.779	3.504	0.135	0.9646
s(meantemp) : year2016	2.701	3.393	1.024	0.3827
s(meantemp) : year2017	2.762	3.487	0.38	0.6715
s(time, region)	91.365	132	247.242	< 0.0001
Model 5b				
Parametric coefficients	*Estimate*	*Std. Error*	*t-value*	*p-value*
Intercept	4.009	0.49	8.182	< 0.0001
year2015	−0.105	0.394	−0.266	0.79
year2016	−0.18	0.551	−0.327	0.7436
year2017	−0.298	0.673	−0.443	0.6576
Smooth terms	*edf*	*Ref.df*	*F-value*	*p-value*
s(time)	168.737	191.491	12.315	< 0.0001
s(meantemp) : year2014	**9.581**	**11.666**	**1.709**	**0.0588**
s(meantemp) : year2015	**10.574**	**12.814**	**10.839**	**< 0.0001**
s(meantemp) : year2016	**10.077**	**12.29**	**10.373**	**< 0.0001**
s(meantemp) : year2017	**10.583**	**12.874**	**4.405**	**< 0.0001**
s(time, region)	91.146	132	247.068	< 0.0001

The table shows the estimated parametric and non-parametric components, with their corresponding standard errors, *t*-values, effective degrees of freedom, *F*-statistic and *p*-values for the GAM models used to estimate the relation between the logarithm of the number of tweets referring to climate change and the weekly mean temperature using a Gaussian distribution with an identity link function (i.e., Model 5 and 5b). *Meantemp* refers to the weekly mean temperature. Estimations in bold are reported and discussed in the main text.

consequence of global warming (Alexander and Perkins, 2013; Huntingford et al., 2013; Lenton et al., 2017), understanding whether and how public attention towards climate change is shaped by the experience of short-term variability in local temperatures may contribute to developing more successful communication and education strategies.

Interestingly, the relation between temperature volatility and public attention to climate change was observed only from 2016 onwards, indicating a recent change in the way people mentally represent climate change. In 2014, a seminal paper on the local warming effect concluded that "weather variability will need to become better associated with heightened belief in climate change, though this new association will need to be accomplished through education" (Zaval et al., 2014; p. 34). Our results indicate that this association is now beginning to show in large-scale public communication patterns. The public may begin to represent climate change not just as an increase in temperatures but rather as a disruption of the climate system in general.

One possible explanation for this is that increased media coverage has improved societal awareness, shaping climate change attention and improving knowledge about climate change mechanisms. Moreover, the rise of climate change on the political agenda may contribute to a better-informed public. For instance, one may speculate that the intense coverage of the United Nations Climate Change Conference COP21, which occurred at the end of 2015, was one of the triggering moments that led people to update their mental template of climate change and its manifestations. Newspapers worldwide increasingly devote reporting space to climate change issues (Schmidt et al., 2013). Therefore, the more the media writes about climate change, the more the public pays attention to this issue. A recent study has also established a clear relation between short-term weathers anomalies and media coverage of climate change, analyzing online news articles covering climate change in 28 European countries from 2014 to 2019. Their results show that positive deviations from short-term averages temperatures are a strong determinant of climate change media coverage (Pianta and Sisco, 2020). However, there is no convincing evidence that media coverage acts as a mediator in the relationship between local weather events and the climate change discourse in social media (Kirilenko et al., 2015).

Independently of the effects of short-term temperature volatility on climate change twitter activity, our findings also revealed that high and low weekly mean temperatures increase public attention to climate change. This finding relates to what researchers refer to the *local warming effect*, where belief in climate change increases when temperatures are perceived as being warmer or colder than usual (Hamilton and Stampone, 2013; Joireman et al., 2010; Kirilenko et al., 2015; Li et al., 2011; Sisco et al., 2017; Zaval et al., 2014). By conjointly tracking the development of these two effects over time between 2014 and 2017, we demonstrate that warmer and colder temperatures contributed to public attention toward climate change across the whole measurement period, but that local volatility contributed only from 2016 onwards.

Three features of the study limit the conclusions we can draw about the impact of short-term volatility and mean temperatures on climate change attention. First, we collected data only from a restricted geographical zone (i.e., Spain) reducing our ability to generalize our findings to other countries. For instance, a representative survey conducted across Europe in 2016 put Spain on top of 23 European countries believing that climate change will have negative impacts (Poortinga et al., 2018), making them potentially more aware of subtle changes in the weather patterns. A comparative study should investigate if these findings are consistent across countries, and if country-level variables mediated this effect. Second, as our data collection spanned four years only, we were not able to investigate it the observed effects follow a cyclic pattern across time. This adds some uncertainty to the interpretation of our findings, particularly for the volatility effect, which was observed only for half of the time period. Third, there is an inherent limitation to using social media data to investigate public climate change perception; we cannot assume that the sample is representative of the general population. Moreover, depending on the method used to extract the information from Twitter, the data obtained may not represent Twitter activity on a particular topic (Kim et al., 2013; Morstatter et al., 2013). In this study, we relied on a data provider to get access to the full Twitter data stream (i.e., firehose data) and get a valid representation of public attention to climate change in Spain.

More generally, by estimating how public attention toward climate change is affected by both recent mean temperature and temperature volatility, and without relying on historical averages as a reference period, this study adds considerable evidence to a significant association between the experience of current weather events and the manifestation of public attention toward climate change.

5. Data and materials availability

The data reported in this paper are available on the Open Science Framework (https://osf.io/rwcdy/).

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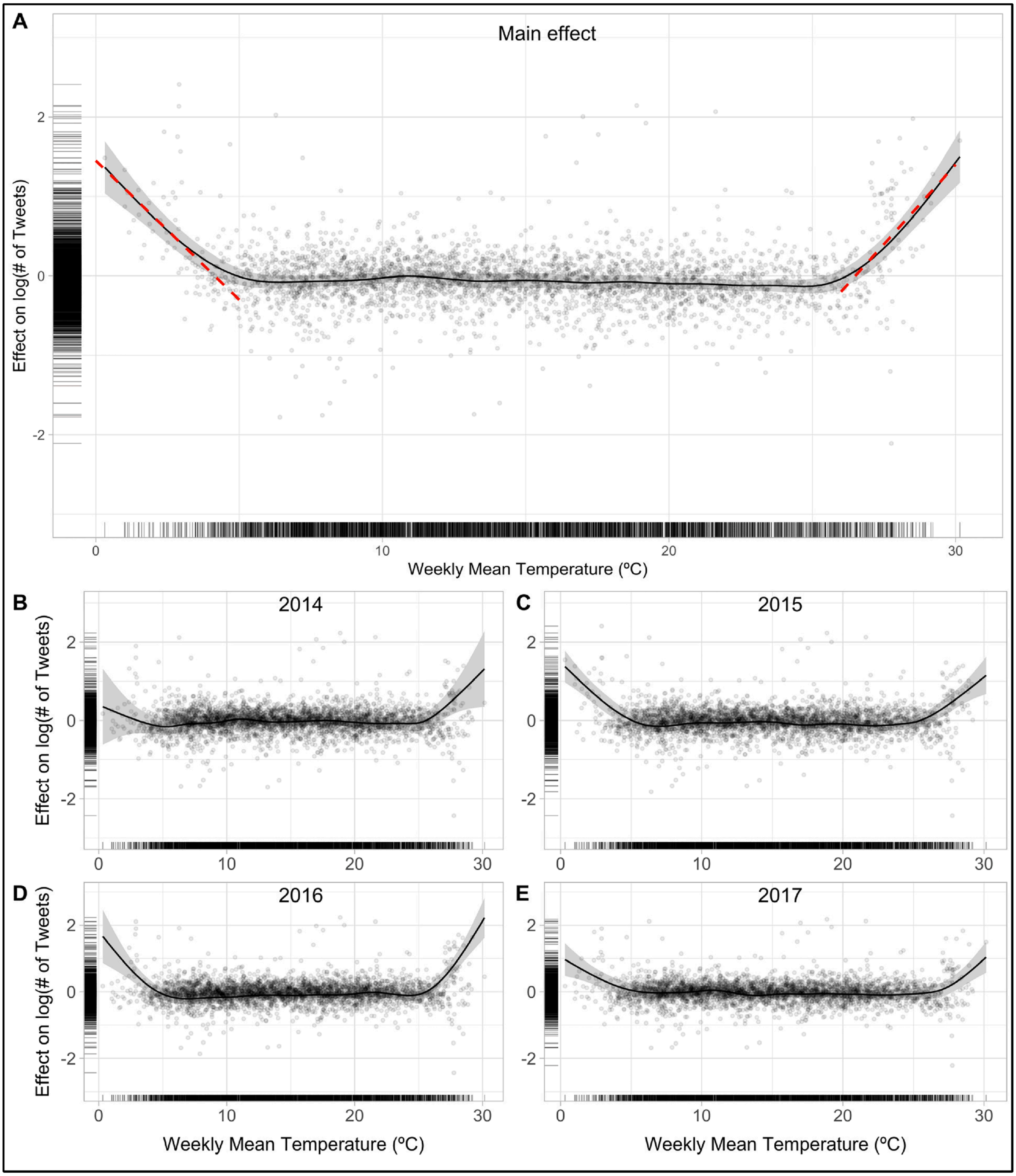

Fig. 4. Main effect (A) and annual effects (B for 2014, C for 2015, D for 2016 and E for 2017) of weekly mean temperature on logarithmized number of climate change-related tweets, as part of a GAM model with a Gaussian distribution and an identity link function. The other covariates are a smooth effect of time, a linear term for year, and a random smooth of region. The solid line is the GAM smoother, the gray polygon shows the 95% CI, points are raw data, the dotted segments in panel A are a linear approximation of the slope at the higher and lower end. A sensitivity analysis based on an alternative model showed that these results are robust (see Appendix B).

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CRediT authorship contribution statement

C. Mumenthaler: Conceptualization, Methodology, Investigation, Formal analysis, Data curation, Visualization, Writing - original draft. **O. Renaud:** Formal analysis, Writing - original draft. **R. Gava:** Conceptualization, Methodology, Writing - review & editing. **T. Brosch:** Conceptualization, Methodology, Funding acquisition, Writing - original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A:. Alternate Model 5 and 5b used to estimate the relation between the number of tweets referring to climate change and weekly temperature volatility using a tweedie distribution with a log link function.

Table A1.

Table A1
Alternate Model 5 and 5b used to estimate the relation between the number of tweets referring to climate change and weekly temperature volatility using a tweedie distribution with a log link function.

Alternate Model 5				
Parametric coefficients	*Estimate*	*Std. Error*	*t-value*	*p-value*
Intercept	4.112	0.557	7.379	< 0.0001
year2015	−0.139	0.460	−0.301	0.7632
year2016	−0.161	0.647	−0.249	0.8035
year2017	−0.547	0.787	−0.695	0.4871
Smooth terms	*edf*	*Ref.df*	*F-value*	*p-value*
s(time)	183.617	199.394	23.829	< 0.0001
s(voltemp)	9.419	11.520	3.060	0.0006
s(voltemp) : year2014	3.234	4.027	1.446	0.2139
s(voltemp) : year2015	3.483	4.348	1.986	0.0655
s(voltemp) : year2016	3.614	4.467	15.200	< 0.0001
s(voltemp) : year2017	3.989	4.933	20.224	< 0.0001
s(time, region)	106.769	133	391.010	< 0.0001
Alternate Model 5b				
Parametric coefficients	*Estimate*	*Std. Error*	*t-value*	*p-value*
Intercept	4.104	0.558	7.361	< 0.0001
year2015	−0.140	0.460	−0.305	0.7608
year2016	−0.145	0.648	−0.224	0.8226
year2017	−0.537	0.788	−0.682	0.4953
Smooth terms	*edf*	*Ref.df*	*F-value*	*p-value*
s(time)	183.616	199.392	23.846	< 0.0001
s(voltemp) : year2014	5.371	6.741	0.363	0.8762
s(voltemp) : year2015	5.877	7.380	0.411	0.8969
s(voltemp) : year2016	6.093	7.563	19.556	< 0.0001
s(voltemp) : year2017	7.151	8.812	20.418	< 0.0001
s(time, region)	106.924	133	390.286	< 0.0001

The table shows the estimated parametric and non-parametric components, with their corresponding standard errors, *t*-values, effective degrees of freedom, *F*-statistic and *P*-values.

Appendix B:. Alternate Model 5 and 5b used to estimate the relation between the number of tweets referring to climate change and weekly mean temperature using a tweedie distribution with a log link function.

Table B1.

Table B1
Alternate Model 5 and 5b used to estimate the relation between the number of tweets referring to climate change and weekly mean temperature using a tweedie distribution with a log link function.

Alternate Model 5				
Parametric coefficients	*Estimate*	*Std. Error*	*t-value*	*p-value*
Intercept	3.908	0.524	7.457	< 0.0001
year2015	0.007	0.438	0.016	0.9873
year2016	0.005	0.610	0.008	0.9936
year2017	−0.109	0.739	−0.147	0.8828
Smooth terms	*edf*	*Ref.df*	*F-value*	*p-value*
s(time)	179.494	197.474	19.041	< 0.0001
s(meantemp)	12.887	15.154	9.117	< 0.0001
s(meantemp) : year2014	3.621	4.540	0.623	0.6468
s(meantemp) : year2015	4.022	5.030	0.102	0.9900
s(meantemp) : year2016	3.887	4.862	1.439	0.1888
s(meantemp) : year2017	4.289	5.365	1.301	0.2467
s(time, region)	102.171	133	359.658	< 0.0001
Alternate Model 5b				
Parametric coefficients	*Estimate*	*Std. Error*	*t-value*	*p-value*
Intercept	3.866	0.525	7.365	< 0.0001
year2015	0.037	0.439	0.084	0.9332
year2016	0.096	0.611	0.157	0.8751
year2017	−0.064	0.740	−0.087	0.9307
Smooth terms	*edf*	*Ref.df*	*F-value*	*p-value*
s(time)	179.671	197.550	19.179	< 0.0001
s(meantemp) : year2014	9.725	11.817	2.379	0.0053
s(meantemp) : year2015	10.966	13.233	9.339	< 0.0001
s(meantemp) : year2016	10.513	12.771	10.663	< 0.0001
s(meantemp) : year2017	12.053	14.431	4.650	< 0.0001
s(time, region)	102.413	133	361.882	< 0.0001

The table shows the estimated parametric and non-parametric components, with their corresponding standard errors, *t*-values, effective degrees of freedom, *F*-statistics and *P*-values.

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