Rapidly declining remarkability of temperature anomalies may obscure public perception of climate change

Frances C. Moore[a,1], Nick Obradovich[b], Flavio Lehner[c], and Patrick Baylis[d]

[a]Department of Environmental Science and Policy, University of California, Davis, CA 95616; [b]Media Lab, Massachusetts Institute of Technology, Cambridge, MA 02139; [c]Climate and Global Dynamics Laboratory, National Center for Atmospheric Research, Boulder, CO 80305; and [d]Vancouver School of Economics, University of British Columbia, Vancouver, BC, Canada V6T 1Z4

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The changing global climate is producing increasingly unusual weather relative to preindustrial conditions. In an absolute sense, these changing conditions constitute direct evidence of anthropogenic climate change. However, human evaluation of weather as either normal or abnormal will also be influenced by a range of factors including expectations, memory limitations, and cognitive biases. Here we show that experience of weather in recent years—rather than longer historical periods—determines the climatic baseline against which current weather is evaluated, potentially obscuring public recognition of anthropogenic climate change. We employ variation in decadal trends in temperature at weekly and county resolution over the continental United States, combined with discussion of the weather drawn from over 2 billion social media posts. These data indicate that the remarkability of particular temperatures changes rapidly with repeated exposure. Using sentiment analysis tools, we provide evidence for a "boiling frog" effect: The declining noteworthiness of historically extreme temperatures is not accompanied by a decline in the negative sentiment that they induce, indicating that social normalization of extreme conditions rather than adaptation is driving these results. Using climate model projections we show that, despite large increases in absolute temperature, anomalies relative to our empirically estimated shifting baseline are small and not clearly distinguishable from zero throughout the 21st century.

climate change | perception | Twitter | baseline | temperature

Anthropogenic climate change involves the shifting of weather beyond bounds historically experienced by communities and ecosystems. Global average temperatures are now significantly higher than preindustrial levels, an effect that cannot be explained without greenhouse gas emissions, while modeling studies have shown that local temperature anomalies will statistically emerge from the noise of natural variability in the relatively near term (1–4). However, how are temperatures that are extreme in a long-term, historical sense understood and interpreted by people exposed to them? Will increasingly unusual temperatures constitute direct, experiential evidence of a changing climate, or will changing conditions be rapidly normalized so that even large absolute temperature anomalies are not perceived as particularly unusual?

Answers to these questions depend on how the subjective definition of normal temperatures evolves over time as the climate changes: What baseline do people use to evaluate the weather? In a nonstationary climate, the question of what the appropriate climate reference window should be is not obvious. Various baselines, ranging from the preindustrial period to the last 30 y, are used in the scientific literature, reflecting the inherent ambiguity in choosing a stable reference period in a nonstationary series (5, 6). The baseline actually used by nonscientists in evaluating weather as either normal or abnormal is even harder to theoretically specify, since it may be affected by generational turnover, memory limitations, and cognitive biases (7). Possible reference periods such as an individual's lifetime (8), a recent 30-y period (9, 10), or a trailing mean (11) have been hypothesized, but no empirical evidence has yet been presented as to how individuals implicitly define normal conditions or how quickly or slowly that definition changes over time.

This question is not only of theoretical interest. Past work has shown that public policy tends to advance during "windows of opportunity" provided by, among other things, focused public attention (12). Without public perception of a problem, the ability of scientific experts and policy analysts to advance a policy agenda will be limited (13). This potentially poses a challenge for addressing chronic environmental problems such as climate change. If baselines describing "normal" conditions adjust rapidly, the public may not perceive there to be a problem requiring policy intervention, even as environmental conditions steadily deteriorate.

Here we provide evidence that the definition of "normal weather" shifts rapidly over time in a changing climate. We show that the remarkability of particular weekly temperature anomalies, measured as the volume of social media posts about weather they generate, adjusts on approximately a 5-y timescale. We find no evidence, however, that the declining noteworthiness of unusual temperatures is accompanied by reductions in their negative effects on sentiment, implying social normalization of these conditions without adaptation. Using climate model projections we show that, despite large increases in absolute temperature,

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Significance

Climate change exposes people to conditions that are historically unusual but that will become increasingly common over time. What kind of weather do people think of as normal or unusual under these changing conditions? We use the volume of social media posts about weather to measure the remarkability of different temperatures and show that remarkability changes rapidly with repeated exposure to unusual temperatures. The reference point for normal conditions appears to be based on weather experienced between 2 and 8 y ago. This rapidly shifting normal baseline means warming noticed by the general public may not be clearly distinguishable from zero over the 21st century, with potential implications for both the acceptance of global warming and public pressure for mitigation policies.

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[1]To whom correspondence should be addressed. Email: fmoore@ucdavis.edu.

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anomalies relative to our empirically estimated shifting baseline are small and not clearly distinguishable from zero throughout the 21st century.

Approach

To investigate our research questions, we employ social media data from Twitter. These data consist of all posts on Twitter between March 2014 and November 2016 geolocated within the continental United States, for a total of 2.18 billion tweets (*SI Appendix*, Fig. S1). Tweets about weather are identified using a "bag-of-words" approach (*Methods*), and the classification was validated manually for 6,000 selectively sampled tweets (*Methods* and *SI Appendix*, Table S1). The sentiment of all tweets that included no weather terms was measured using two classification schemes [Valence Aware Dictionary for sEntiment Reasoning (VADER) and Linguistic Inquiry and Word Count (LIWC)] and a composite sentiment score calculated as the difference between positive and negative sentiment (14, 15). We draw data on daily maximum temperature and total precipitation for the period 1981–2016 from the PRISM Climate Group and aggregate these data to the county or core-based statistical area level from a 0.25° grid (16). We combine the PRISM data with cloud cover and relative humidity data from the NCEP Reanalysis II (17).

We then aggregate our social media and weather data to the weekly level. We employ weekly rather than daily resolution as weeks are a plausible period over which individuals might resolve the seasonal climatology of their area (e.g., "end of March" or "middle of November") (18). For each area–week combination, a 10-y "reference" period is defined as the average of that area's temperature across the years 1981–1990 for each week of the year, a period defined based on the earliest available PRISM data. The effect of gradual changes on perception of temperature anomalies is identified using the spatial and seasonal variation in temperature change since this baseline period. Fig. 1 illustrates one measure of this variation—the difference between reference temperatures and the 2011–2015 mean—for the third week in each calendar month across the United States. It shows substantial variation in exposure to temperature changes, both across space and within the year. This variation is what we use to test whether the response to historically unusual weather conditions changes with repeated exposure to those conditions.

Our principal empirical model regresses the logarithm of the number of weather tweets in each county–week on functions of the reference and more recent temperatures. The model includes controls for precipitation, relative humidity, and cloud cover (to isolate the effect of temperature) as well as differences in Twitter use in counties and over time using the logarithm of the number of Twitter users. County indicator variables (fixed effects) control for all time-invariant difference between counties while state by month of year indicator variables (e.g., December in California) flexibly control for any regional differences in seasonality. Finally, year fixed effects control for common time trends across the United States over the sample period. The residual variation used to identify the causal effect of temperature fluctuations on social media posts about weather is illustrated in *SI Appendix*, Fig. S2. Standard errors (SEs) are clustered at the state level, allowing for spatial and temporal autocorrelation within a state (more details and the regression equation are given in *Methods*).

Results

Using the full sample, we first show that the number of social media posts about weather is affected by temperature and that this effect differs depending on the reference temperature for that county and time of year. People are more likely to comment on weather that is unusual for a particular place and time of year than on the same weather if it is typical (*SI Appendix*, Fig. S3*A*). At the center of the temperature distribution (22 °C), both unusually hot and unusually cold temperatures are equally remarkable. At both hotter and colder ends of the distribution, however, the response is asymmetric so that more extreme temperatures (i.e., colder-than-usual cold temperatures or hotter-than-usual hot temperatures) are most remarkable. More recent temperatures also affect the pattern of comment on the weather. Counties that have experienced temperatures warmer than the reference period in the last 5 y are more likely to comment on cold temperatures and less likely to comment on

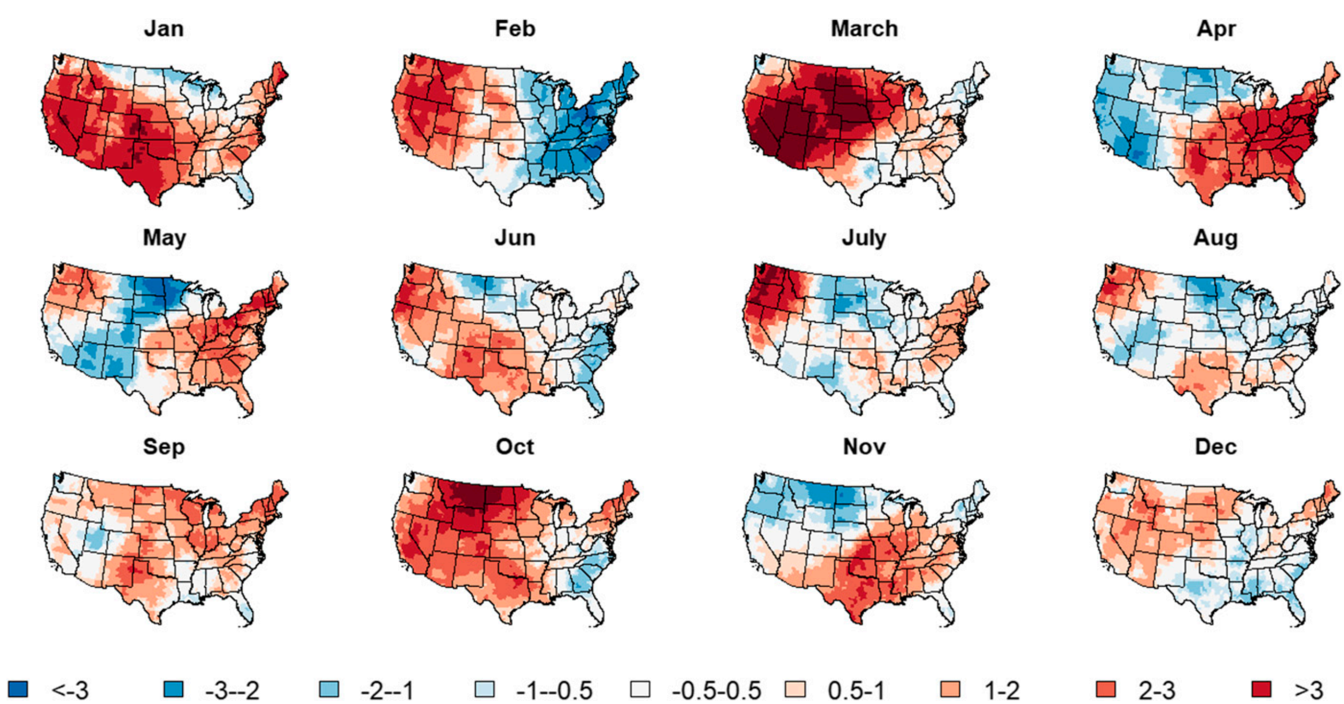

Fig. 1. Spatial and seasonal variation in the change in average temperatures between the reference period (1981–1990) and the 2011–2015 mean (in degrees Celsius). Values shown are averaged for the third week in each month.

warm temperatures than counties without recent warming, consistent with an adjustment of expectations in response to recent conditions (*SI Appendix*, Fig. S3*B*). The converse is also true: Counties experiencing recent cooling are less likely to comment on cool weather and more likely to comment on warm weather. *SI Appendix*, Table S2 summarizes these regressions and shows that models that allow a county's response to temperature to differ depending on its history of temperature in recent and earlier time periods are preferred to those that do not allow this heterogeneity.

We use a finite distributed lag model to more precisely estimate the influence of past exposure to temperature anomalies on the remarkability of current temperatures. For each county–week in our sample we use its 15-y history of temperature anomalies, defined relative to the 1981–1990 reference period, to estimate how behavior adjusts in response to repeated exposure to altered temperatures. The model allows for nonlinear effects of temperature anomalies that change smoothly over time (for additional details see *Methods*). Given the asymmetry in the response to temperature anomalies noted above, we split our sample and estimate responses separately for the hottest and coldest quarter of baseline temperatures (greater than 28.3 °C and less than 13.6 °C, respectively). Since humidity is known to be important in driving adverse physiological effects of hot temperatures, we further restrict the hot sample to county–weeks with relative humidity greater than 80% [corresponding to a heat index of 32 °C or greater (19)].

Fig. 2 *A* and *C* show the effect of contemporaneous temperature anomalies in the cold and hot parts of the sample, respectively. In both cases, more extreme temperatures (i.e., cold anomalies at cold temperatures and hot anomalies at hot temperatures) are more remarkable than reference temperatures. These extreme temperatures have been shown to be socially consequential along several dimensions, including mortality risk, emotional state and mental health, and economic productivity (20–23). It is therefore perhaps unsurprising that they should generate more comment than more typical and less consequential temperatures.

Fig. 2 *B* and *D*, however, show that the remarkability of these temperatures decays rapidly with repeated exposure. In the cold sample, cold anomalies experienced between 2 and 8 y ago reduce the remarkability of contemporaneous temperatures (*SI Appendix*, Fig. S4*A*). This means that cold anomalies in a county that has experienced these anomalies for more than 5 y in a row are no longer remarkable (Fig. 2*B*). This effect is driven by a precisely estimated effect of lagged temperature anomalies between 2 and 8 y ago operating in the opposite direction of the contemporaneous effect (*SI Appendix*, Fig. S4*A*). An equal and opposite response is observed for warm anomalies at cold temperatures (*SI Appendix*, Fig. S4*B*). The decline in remarkability of hot temperatures with repeated exposure occurs even more rapidly (Fig. 2*D*), although the lagged effects for this smaller sample are less precisely estimated (*SI Appendix*, Fig. S4*C*).

SI Appendix gives information on the robustness of these results to alternate specifications. Results at both hot and cold temperatures are robust to alternate specifications of the temperature response and lag structure (*SI Appendix*, Fig. S5). Not limiting the hot sample to locations with high humidity, however, results in a smaller contemporaneous effect and large error bars, particularly for the lag coefficients (*SI Appendix*, Fig. S6). This may be due to the importance of humidity in driving physiological discomfort at hot temperatures, or because subsetting the sample removes hot states in the southwest such as Texas and Arizona with high penetration of air conditioners.

Two mechanisms could be driving the rapid decline we observe in the noteworthiness of unusual temperatures with repeated exposure. One possibility is that people are able to quickly adapt so as to lower the psychological or physiological

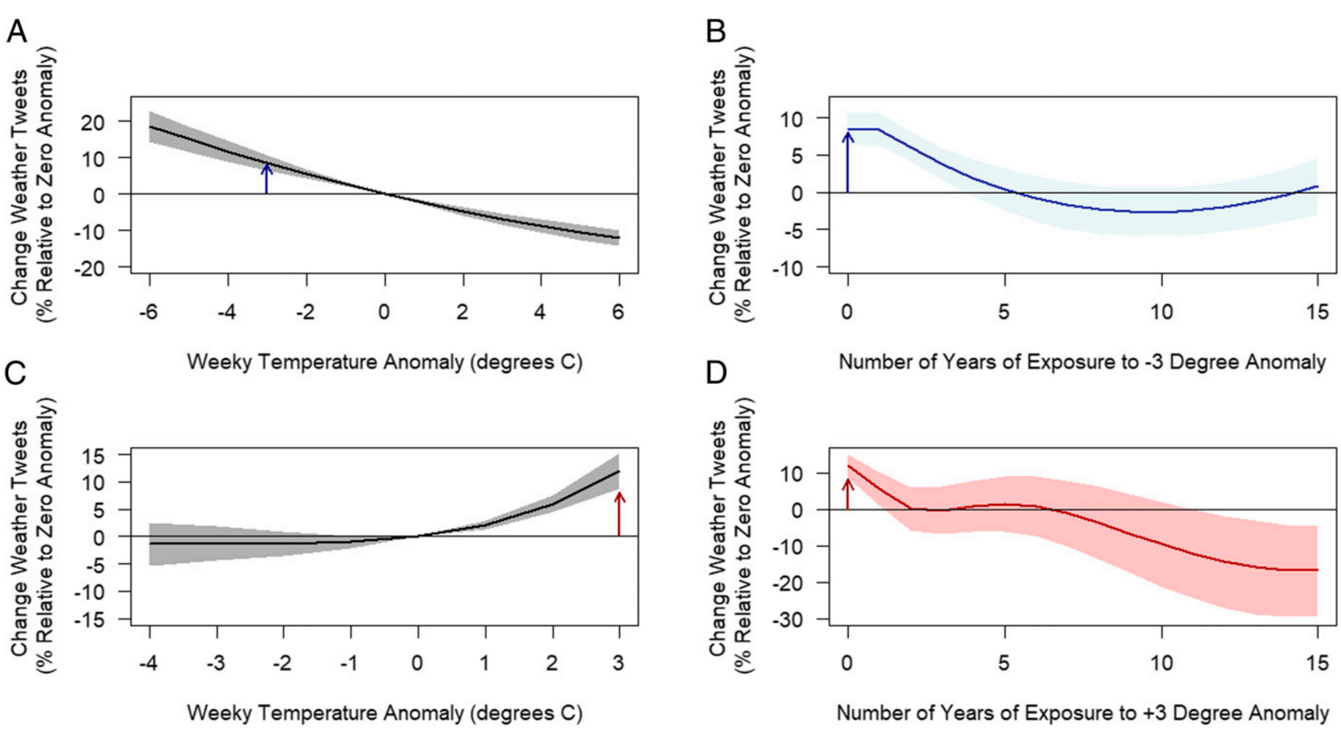

Fig. 2. Effect of current and past temperature anomalies on social media posts about weather. (*A*) Contemporaneous effect of temperature anomalies for the cold sample (lowest quartile mean weekly maximum temperature). (*B*) Effect of a −3 °C temperature anomaly in the cold sample (20th percentile of the distribution) as a function of number of years of exposure to that temperature. (*C*) Contemporaneous effect of temperature anomalies for the hot and humid sample (highest quartile mean weekly maximum temperature and relative humidity >80%). (*D*) Effect of a +3 °C temperature anomaly (95th percentile of the distribution) in the hot and humid sample as a function of number of years exposure to that temperature. Shaded areas show the 95% confidence interval. Arrows are for visual reference and show the same effect plotted across two graphs: the instantaneous effect of a −3 °C temperature anomaly in the cold sample (blue arrow) or a +3 °C anomaly in the hot sample (red arrow).

negative effects of extreme temperatures: Temperature anomalies become unremarkable because they are less consequential. This would be a positive interpretation of the results shown in Fig. 2 since it implies that private, individual adaptation is highly effective and occurs quickly. An alternative possibility is that declining remarkability is due to altered expectations but not adaptation: Temperature anomalies become unremarkable because they are less surprising, but no less consequential. This would mean that the adverse effects of extreme temperatures are rapidly normalized in that they quickly become socially unremarkable. Moreover, since changing expectations should drive people to adapt to new conditions, if declining remarkability is not accompanied by reduced impact it would suggest adaptation options available to individuals are limited.

To distinguish between these two divergent interpretations, we look for evidence of adjustment in the sentiment associated with extreme temperatures under repeated exposure. Previous work has shown that average sentiment expressed in all social media posts is more negative at both very high and very low temperatures, implying these conditions negatively affect people's mood, well-being, and emotional state (21). We use this as our measure of the consequences of extreme temperatures because it can be measured for the same population and at the same geographic scale and spatial and temporal resolution as our remarkability measure, allowing for direct comparisons between the two.

Fig. 3 shows the change in sentiment associated with temperature anomalies. The more remarkable temperatures identified in Fig. 2 are associated with negative sentiment. Cold anomalies at cold temperatures and hot anomalies at hot temperatures with high humidity both result in more negative expressed sentiment (Fig. 3 *A* and *C*). However, we find no evidence of adaptation to these adverse effects on the 15-y timescale examined here. Temperature anomalies continue to have negative effects on sentiment even after 5–10 y of continuous exposure, long after those anomalies have become unremarkable (Fig. 3 *B* and *D*). Thus, our data suggest the rapid decline in remarkability is a result of changing expectations of weather with little adaptation to the adverse effects of weather extremes.

Based on the empirical results shown in Fig. 2, we derive a learning model that describes how baselines of normal weather adjust in response to experienced temperatures. Lagged periods during which the instantaneous effect of temperature anomalies are reversed are a "learning period" that defines the baseline against which instantaneous temperatures are evaluated. We use the estimated lagged coefficients to define this period and the weighting of years within it (*Methods* and *SI Appendix*, Fig. S4). We use results from the cold rather than the hot and humid sample to define the learning process because they are more precisely estimated and indicate a longer time for the updating process, meaning our findings on the rate of adjustment will err conservatively. The pattern shown in Fig. 2 is consistent with baselines being determined based on weather between 2 and 8 y ago (*SI Appendix*, Fig. S7). Weather experienced between 2 and 4 y ago is particularly important, providing empirical support for the hypothesized "recency bias" (24, 25).

We apply this learning model to climate model projections for the 21st century under RCP 8.5. Fig. 4 shows the annual, population-weighted temperature anomalies over the continental United States, for 40 realizations of internal variability (26). Anomalies are defined relative to both a fixed 30-y baseline (1981–2010) and to a shifting baseline defined using our empirically estimated learning model. While persistent warming over the 21st century results in very large temperature anomalies defined relative to a fixed historical baseline, the empirically derived, rapidly shifting baseline results in much smaller temperature anomalies, only slightly above zero. Moreover, given internal climate variability, anomalies relative to the shifting baseline are not clearly distinguishable from zero: Across the 40 realizations, these temperature anomalies are less than zero (i.e., cooler than expected) in 26% of years on average.

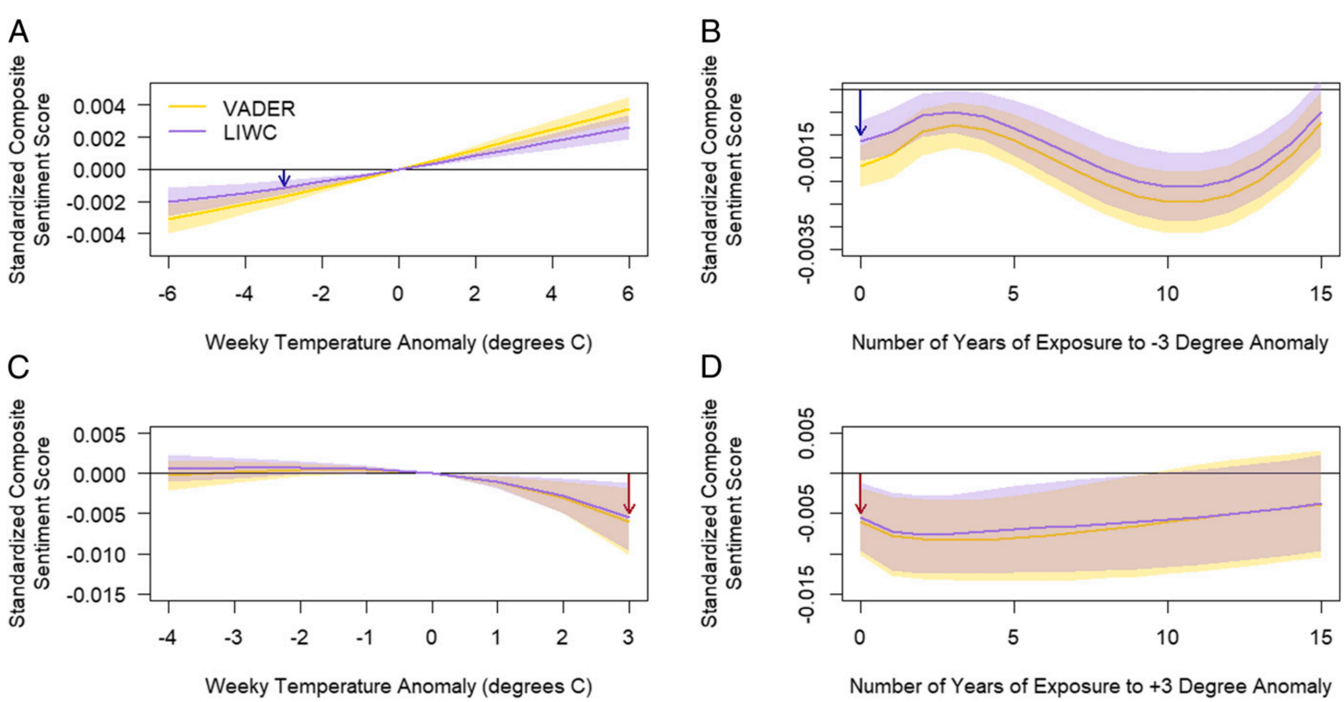

Fig. 3. Effect of current and past temperature anomalies on sentiment expressed in social media posts using two sentiment measures. (*A*) Contemporaneous effect of temperature anomalies for the cold sample. (*B*) Effect of a −3 °C temperature anomaly in the cold sample as a function of number of years of exposure to that temperature. (*C*) Contemporaneous effect of temperature anomalies for the hot and humid sample. (*D*) Effect of a +3 °C temperature anomaly in the hot and humid sample as a function of number of years exposure to that temperature. Shaded areas show the 95% confidence interval. Arrows are for visual reference and show the same effect of plotted across two graphs: the instantaneous effect of a −3 °C temperature anomaly in the cold sample (blue arrow) or a +3 °C anomaly in the hot sample (red arrow).

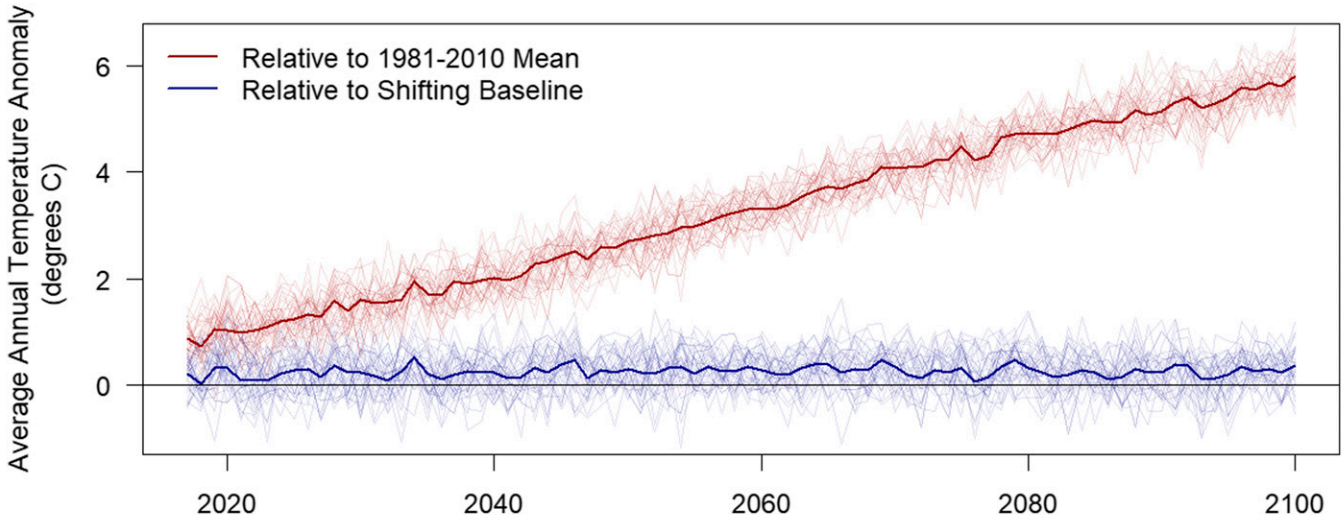

Fig. 4. Effect of shifting baselines on the remarkability of temperature anomalies. Population-weighted annual average temperature anomalies over the continental United States under RCP 8.5 with 40 realizations of internal variability (26). Anomalies are defined relative to a fixed 30-y period (1981–2010) and relative to a shifting baseline defined using our estimated learning process. Population weighting uses population density fixed at 2015 values (37).

Discussion

Here we show that the remarkability of temperature depends not just on its absolute value but that it is affected by past experience and resultant expectations. More specifically, the subjective baseline against which temperature is evaluated appears to be dominated by recent experience. Temperatures initially considered remarkable rapidly become unremarkable with repeated exposure over a roughly 5-y timescale. Since expectation adjustment is rapid relative to the pace of anthropogenic climate change, this shifting subjective baseline has large implications for the notability of temperature anomalies as climate change progresses. Further, we find no evidence for effective adaptation over similar timescales, at least as measured using the negative effects of extreme temperatures on expressed sentiment.

Collectively, these data provide empirical evidence of the "boiling frog" effect with respect to the human experience of climate change. This apocryphal metaphor describes a phenomenon whereby the negative effects of a gradually changing environment become normalized so that corrective measures are never adopted, even when those affected would have chosen to avoid these impacts *ex-ante*. Although casually discussed in regard to climate change, the potential for normalization of steadily worsening environmental conditions has been noted in other fields, particularly with respect to biodiversity decline and ecosystem health (27, 28). Here we provide evidence for this social normalization occurring in a large population and show that it can happen at rapid timescales, much faster than generational turnover.

The question of how the rapidly declining remarkability of temperature extremes relates to stated belief in anthropogenic climate change or support for mitigation policies is not straightforward. Many studies have identified a link between local temperature anomalies and stated belief in global warming (10, 18, 29–31), with evidence that this is driven by individuals substituting their personal experience for more relevant data on global temperatures (32). Our results imply that this effect alone will not necessarily lead to widespread belief in anthropogenic climate change with increasing warming, as the notability of local temperature anomalies will adjust over time. As an initial investigation of the role remarkability might play in determining policy-relevant variables, we conduct a simple regression of the variation in county-level belief in climate change (*SI Appendix*, Fig. S8) on local temperature anomalies, calculated either using the shifting baseline or a fixed reference baseline (*SI Appendix*, Fig. S9 and *Supplementary Methods*). We find a relationship between belief in climate change and temperature anomalies calculated relative to the shifting baseline even when controlling for warming since the reference period and for state-level variation (model 4, *SI Appendix*, Table S3). These initial results suggest a role for relatively recent experience of weather in shaping climate change beliefs, similar to findings by other authors (24). Further work is needed to more fully establish the connection between our metric of remarkability, stated belief in climate change, and support for climate change policy.

One question is the role played by the media in driving the effects we estimate. If news coverage responds to, rather than shapes, public ideas of notable events, then their role is epiphenomenal. If news coverage drives public perceptions of newsworthiness, however, then some of the rapid decline in remarkability we estimate might be driven by editorial judgments. Inspection of a sample of tweets suggests the media organizations make up less than 5% of our dataset, meaning they alone cannot fully explain the effect we estimate. However, if news coverage influences the likelihood of individuals' commenting on the weather, then their effect will be larger. Irrespective of the mechanism, however, the declining noteworthiness of changing temperatures implies short-lived public attention and therefore that the "windows of opportunity" to advance climate policy on government agendas may be severely limited (12).

Finally, we note that our results pertain only to ambient average temperatures. It may well be that more acute extreme events such as storms, droughts, wildfires, or floods may be both more consequential and more salient and therefore less prone to normalization (33). Previous work has found that other variables such as changes in phenology or snowfall might be more strongly attributed to climate change in the public consciousness (34). In addition, a high-emissions scenario will produce absolute temperatures that exceed the range of our data. It is possible that physiological or biological thresholds at these temperatures could result in nonlinear responses not accounted for here.

The preindustrial period is often used as a standard reference point in both climate science and policy (35), and unmitigated greenhouse gas emissions over the 21st century will result in large warming relative to this baseline. Understanding how these historically unusual temperatures are evaluated by people affected, and in particular whether these temperature anomalies provide direct sensory evidence for the existence of climate change, requires knowing how weather is socially determined to be "normal" or "unusual." Here we present evidence that the definition of normal adjusts rapidly in response to changed conditions, despite the negative consequences of those changes persisting. This results in temperatures that are largely unremarkable over the 21st century, even in a high-emissions scenario. When coupled with results from the existing literature, our finding suggests it may be unlikely that rising temperatures alone will be sufficient to produce widespread support for mitigation policies.

Methods

Data Sources and Processing. Twitter data are the set of geolocated tweets between March 2014 and the end of November 2016 with device locations within the continental United States. The total sample is 2.18 billion tweets, coming from 12.8 million unique users. Tweets discussing weather were identified using a simple bag-of-words approach. If the tweet contained one of a list of words (given in *SI Appendix*, *Supplementary Methods*) it was classified as a "weather tweet." This classification was validated manually for 6,000 tweets (*SI Appendix*, *Supplementary Methods*). Results of this classification are given in *SI Appendix*, Table S1. Additional information on the weather, Twitter data, and sentiment analysis is given in *SI Appendix*.

Regression Analysis. All regressions include fixed effects for state by month of year, year, and county, therefore controlling for all region-specific seasonal variation, all common changes across years, and time-invariant differences between counties. Residuals are clustered at the state level. Controls for precipitation, cloud cover, and relative humidity are included to isolate the effect of temperature. The finite dynamic lag model (Figs. 2 and 3) allows the nonlinear effect of temperature anomalies to vary flexibly over time by fitting an interaction surface between the anomaly and the lag. Sentiment analysis is conducted at the core-based statistical area level with a slightly different set of weather controls (discussion in *SI Appendix*). Regression equations and more detailed methodology are given in *SI Appendix*.

Applying the Learning Model. We define a "learning period" as the years during which experience of past temperature anomalies reverses the effect of the current anomaly (i.e., during which there is evidence for diminishing surprise resulting from adjustment of expectations). The learning model is defined as the weighted sum of temperature anomalies experienced during the learning period, with weights given by the relative magnitude of the estimated lagged coefficients. In other words, the subjectively defined, moving baseline is given by

$$\tilde{B}_{cwy} = \sum_{k=2}^{8} w_k T_{c,w,y-k}$$

$$w_k = \frac{\hat{\beta}_k}{\sum_{j=2}^{8} \hat{\beta}_J},$$

where $\hat{\beta}_k$ is the estimated effect of the temperature anomaly k years ago (*SI Appendix*, Fig. S4A). Weights are calculated for the −3° temperature anomaly (~50% of the cold sample has temperature anomalies smaller than 3° in magnitude). Since $\tilde{B}_{cwy}$ is a nonlinear function of regression coefficients, SEs are calculated from the estimated variance–covariance matrix using the delta method (36).

Temperature anomalies are calculated for the 21st century based on 40 simulations from 1980 to 2100 with the Community Earth System Model under RCP 8.5 (26). Population-weighted averages are taken over the continental United States (2015 distribution) (37). Rolling perceptual baselines are calculated for the period 2010–2100 based on the estimated learning model and then temperature anomalies are calculated on an annual basis relative both to the 1980–2010 average and to the rolling perceptual baseline.

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