Spatial heterogeneity of climate change as an experiential basis for skepticism

Robert K. Kaufmann[a,1], Michael L. Mann[b], Sucharita Gopal[a], Jackie A. Liederman[c], Peter D. Howe[d], Felix Pretis[e,f], Xiaojing Tang[a], and Michelle Gilmore[a]

[a]Department of Earth and Environment, Boston University, Boston, MA 02215; [b]Department of Geography, The George Washington University, Washington, DC 20052; [c]Department of Psychological and Brain Sciences, Boston University, Boston 02215, MA; [d]Environment and Society Department, Utah State University, Logan, UT 84322; [e]Programme for Economic Modelling, INET at the Oxford Martin School, University of Oxford OX1 1NF, Oxford, United Kingdom; and [f]Department of Economics, University of Oxford OX1 3UQ, Oxford, United Kingdom

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We postulate that skepticism about climate change is partially caused by the spatial heterogeneity of climate change, which exposes experiential learners to climate heuristics that differ from the global average. This hypothesis is tested by formalizing an index that measures local changes in climate using station data and comparing this index with survey-based model estimates of county-level opinion about whether global warming is happening. Results indicate that more stations exhibit cooling and warming than predicted by random chance and that spatial variations in these changes can account for spatial variations in the percentage of the population that believes that "global warming is happening." This effect is diminished in areas that have experienced more record low temperatures than record highs since 2005. Together, these results suggest that skepticism about climate change is driven partially by personal experiences; an accurate heuristic for local changes in climate identifies obstacles to communicating ongoing changes in climate to the public and how these communications might be improved.

climate change | climate skepticism | experiential learning | recency weighting | local climate

Despite overwhelming scientific evidence, a significant fraction of the US population does not believe that climate is changing as proxied by a general warming, (1, 2), which we term skepticism. This skepticism is likely caused by many reasons, including two psychological phenomena: climate change is hard to perceive via everyday experience, and climate change is ancillary to everyday concerns (3–6). Under these conditions, experiential learning tends to be more powerful than statistical results (4, 7–10).

Here, we test the hypothesis that skepticism about climate change is partially caused by variations in the direction (warming or cooling) and magnitude of climate change over space (herein spatial heterogeneity), which expose experiential learners to climate heuristics that differ from the global average, by formalizing a simple index that measures local changes in climate and comparing this index with survey-based model estimates of county-level opinion about whether global warming is happening (1). Beyond the predictable impact of demographic factors (11–13), our results indicate that the index for local changes in climate (which may proxy an individual's climate experience) can account for a significant fraction of county-level variations in the percentage of the population that believes that "global warming is happening." These results are tempered by our finding that belief is shaped by more recent experiences. Specifically, belief is diminished by record low temperatures since 2005. Together, these results suggest that skepticism about climate change is driven partially by personal experiences; an accurate heuristic for local changes in climate identifies obstacles to and potential solutions for communicating ongoing changes in climate to the public.

Previous analyses calculate climate heuristics by comparing temperature during a given day (14, 15), week (16), season (3, 17, 18), or year(s) (19, 20) with a long-run average for the corresponding period and classifying this anomaly as either warmer or cooler than average. However, these daily, weekly, seasonal, or annual differences from the mean do not represent a change in climate, which is a change in the long-run weather means. Furthermore, the anomalies are not compared with natural variability, and therefore, they are moot about their probability. As such, these anomalies do not proxy changes in climate, which suggests that poor heuristics could bias previous results regarding the effect of experiential learning on the degree to which the public accepts climate change (3, 14, 18, 20–22).

To evaluate how the spatial heterogeneity of climate change affects the public's willingness to accept scientific results that the climate is changing, we propose an index that accurately measures local changes in climate based on the number of days per year for which the year of the record high temperature is more recent than the year of the record low temperature. The index (23) is calculated as follows:

$$TMax_i = \sum_{D=1}^{365} (High_{Di} > Low_{Di}) \times 1, \qquad [1]$$

in which $High_{Di}$ is the year of the record high temperature and Low_{Di} is the year of the record low temperature for weather station i on day D. If the year of the record high is more recent, the statement in parentheses is true, and day (D) has a value of one (otherwise, it has a value of zero). For instance, if, for January 1st, the record high occurred at station i in 1998 and the record

Significance

We develop a simple heuristic to measure local changes in climate based on the timing of record high and low temperatures. The metric shows local cooling and warming in the United States and captures two aspects of experiential learning that influence how the public perceives a change in climate: recency weighting and an emphasis on extreme events. We find that skepticism about whether the Earth is warming is greater in areas exhibiting cooling relative to areas that have warmed and that recent cooling can offset historical warming. This experiential basis for skepticism of climate change identifies obstacles to communicating ongoing changes in climate to the public and how these communications might be improved.

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[1]To whom correspondence should be addressed. Email: kaufmann@bu.edu.

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low occurred in 1950, $TMax_i$ would take the value of one, or zero if the record low had occurred after 1998. Daily values of zero or one are summed over the year to calculate $TMax_i$. Because *TMax* can be affected by the minimum sample period (e.g., 30, 40, or 50 years [i.e., 1961 (or earlier) through 2010 or later]) and missing observations (e.g., 5, 10, or 15 observations), these criteria are varied to test how including/excluding weather stations affects our results (*SI Materials and Methods*, *1. Datasets*).

TMax is used as a heuristic for local changes in climate with values that can be interpreted relative to a null hypothesis of no change in climate. Under this null, the probability that a day's temperature will be a record high is equal to the probability that it will be a record low. If local climate is warming, the probability that a day's temperature will be a record high is greater than the probability that the day's temperature will be a record low. Under these conditions, there will be more days on which the record high is more recent than the record low ($TMax > 182$). Deviations from 182 can be evaluated against a binomial distribution; the probability that random chance generates values of *TMax* greater than 201 (207) or less than 163 (157) is less than 5% (1%).

Beyond being an accurate heuristic for local changes in climate, *TMax* captures two aspects of experiential learning that influence how the public perceives a change in climate: recency weighting and an emphasis on extreme events. Record high and low temperatures are rare events that are featured by the local media. This attention is critical because rare events are given more weight in human decision-making (4). The importance of extreme events may be one reason that the public can perceive droughts, floods, and long periods of warmth more accurately than shorter-term temperature anomalies (17, 19). Recognition of record temperatures is reinforced by an emphasis on recent events, which is termed recency weighting (6, 24, 25). Because *TMax* is determined by the most recent records, a high value is consistent with record warmth being more recent than record cold.

Results

Values of *TMax* indicate considerable spatial heterogeneity; local climate in the United States has both cooled and warmed in more locations than expected by chance (Fig. 1). Consistent with a warming climate, the number of stations with values of *TMax* that exceed 201 or 207 is greater than expected by random chance (red in Fig. 1). Nearly 49% of stations have values of *TMax* greater than 207; random chance generates such values for only about 0.5% of the sample. Conversely, there is considerable evidence for local cooling. About 10% of the stations have values of *TMax* below 157 (blue in Fig. 1); again, random chance generates such values for only about 0.5% of the sample. Findings for both warming and cooling are not sensitive to the criteria used to include/exclude weather stations in the calculation of *TMax*.

We test the relation between how the public perceives climate change and the degree to which they believe that global climate is warming (Fig. 2) by regressing the estimated percentage of a county's adult population who agree that global warming is happening (*%Belief*) against county-level values for *TMax* (Fig. S1) and the influence of recent record temperatures (recency weighting) as represented by the most recent record temperature, high (*High*2005) and low (*Low*2005) temperatures since 2005, which is chosen based on the mean residence time of US households (*Materials and Methods*). Regression results indicate that there is a statistically measureable positive relation between county-level values of *TMax* and the percentage of the population that believes that global warming is happening (Table 1).

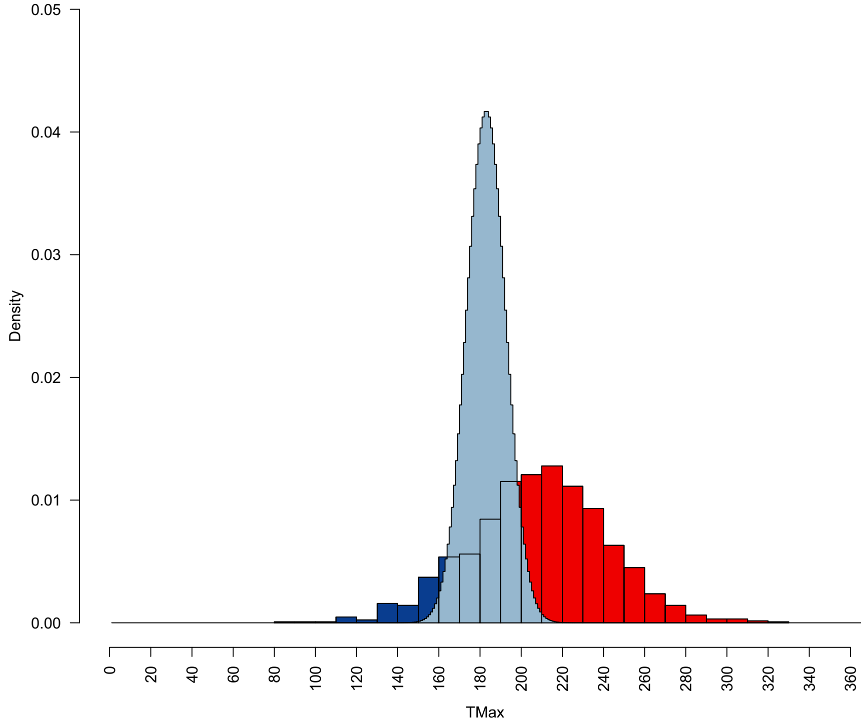

Fig. 1. Distribution of *TMax*. The fraction of observations for a given value of *TMax* expected based on random chance (gray) in a nonchanging climate as given by the binomial distribution is shown together with a histogram of observed *TMax* calculated from stations that have at least 40 y of observations and 10 or fewer missing observations. Areas in red represent the fraction of stations where *TMax* indicates warming beyond that expected by the binomial distribution, whereas areas in blue represent the fraction of stations where *TMax* indicates cooling beyond that expected by the binomial distribution. Note that both the mean and the variance in the observations exceed those of the binomial reference distribution. The number of counties warming is higher than one would expect under a nonchanging climate. The overdispersion (higher variance) is likely the result of spatial heterogeneity in *TMax*—the probability of observing a record high relative to a record low is not constant across different counties because of geographic variation in warming. We use this spatial heterogeneity to explain some of the variation in *%Belief*.

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Table 1. Spatial lag results ($y = \rho\ Wy + x\beta + e$)

Years	Miss	Stations	Spatial autocorrelation ρ	*TMax* (β_1)	*Low2005* (β_2)	*Low2005* (β_3)	*High2005* (β_4)	*High2005* (β_5)	Average *High2005*	Average *Low2005*	Pseudo-R^2
30	5	383	0.670**	0.010**	0.012	−0.003	−0.007	−0.016**	60.6	26.3	0.38
30	10	1,507	0.670**	0.010**	−0.012	−0.007	−0.013*	−0.014**	55.2	27.0	0.38
30	15	2318	0.663**	0.013**	−0.005	−0.011***	−0.012*	−0.012*	48.9	24.4	0.38
40	5	344	0.674**	0.010**	0.017***	−0.003	−0.007	−0.015*	59.0	23.7	0.38
40	10	1,268	0.668**	0.012**	−0.016	−0.009	−0.022**	−0.019**	52.2	23.2	0.38
40	15	2,013	0.658**	0.015**	−0.003	−0.012*	−0.015*	−0.015*	46.15	21.21	0.382
50	5	313	0.668**	0.010**	0.015	−0.005	−0.011	−0.020**	57.24	22.46	0.376
50	10	1,121	0.664**	0.011**	−0.014	−0.007	−0.021**	−0.020**	49.85	21.75	0.378
50	15	1,826	0.661**	0.013**	−0.006	−0.013*	−0.017**	−0.015*	43.93	19.91	0.380

Levels of significance (*5%; **1%; ***10%).

Estimation results suggest that spatial variations in *TMax* (comparing observed patterns of *TMax* relative to all counties experiencing *TMax* at its sample mean) lead *%Belief* to vary ±4% points (Fig. S2) across counties (positive if increased and negative if decreased). This effect suggests that the public's willingness to believe that global warming is happening depends in part on the degree to which they personally experience a warmer or cooler climate. These results are robust to the differential criteria used to include/exclude weather stations in the calculation of *TMax* and the estimation method (*SI Materials and Methods*, *4. Econometric Specification* and *SI Materials and Methods*, *5. Spatial Regression*).

The effect of *TMax* on *%Belief* is strongly mediated by one component of recency weighting: record low temperatures after 2005. For counties that experience high warming over the entire

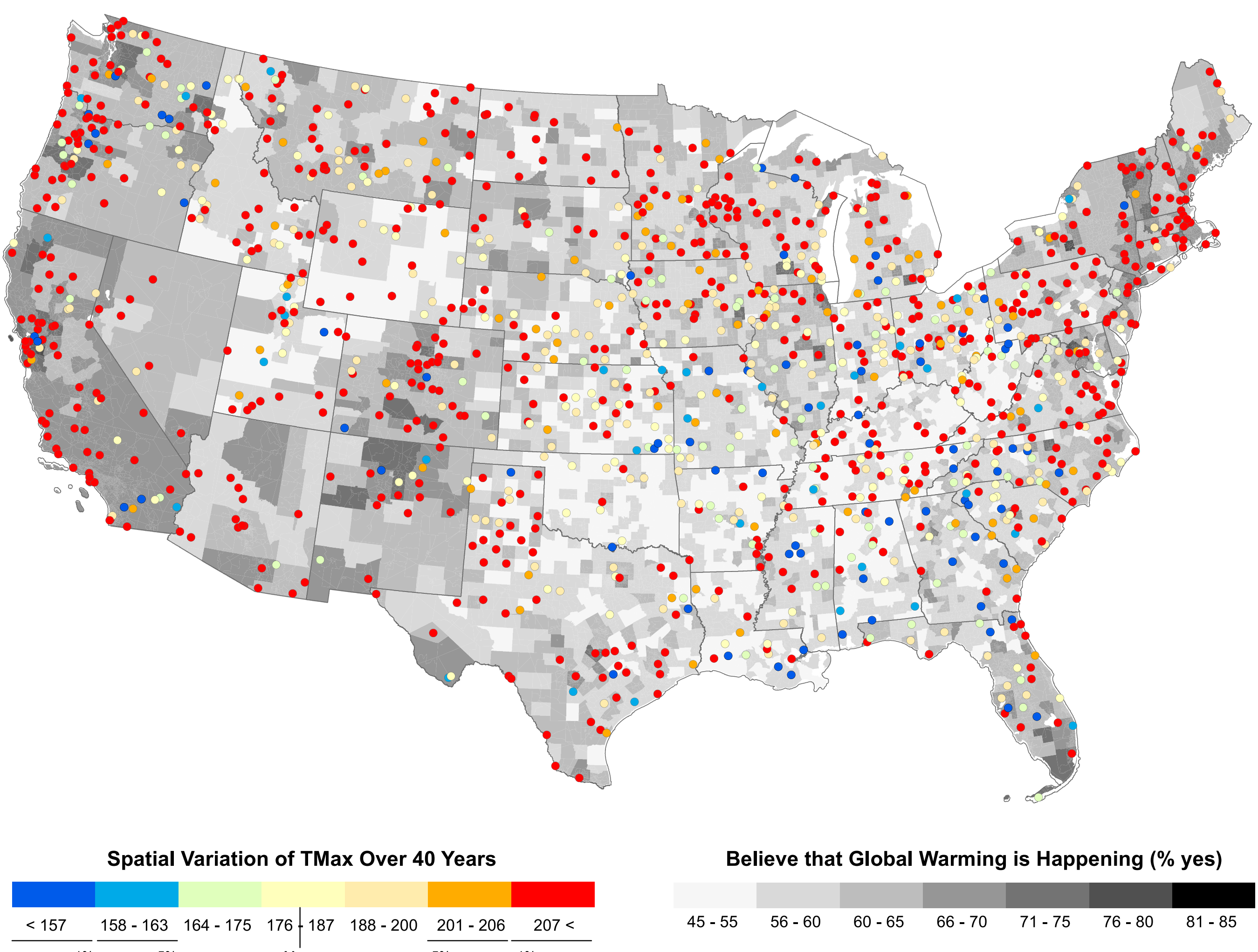

Fig. 2. Belief in climate change and heuristics for local changes in climate. The fraction of a county's population that answered yes to the question "do you think that global warming is happening?" (1) is indicated by shading. Station values of $TMax_i$ are indicated by colored circles. Red and blue circles identify stations with values that are higher and lower, respectively, than expected by random chance as indicated by a binomial distribution.

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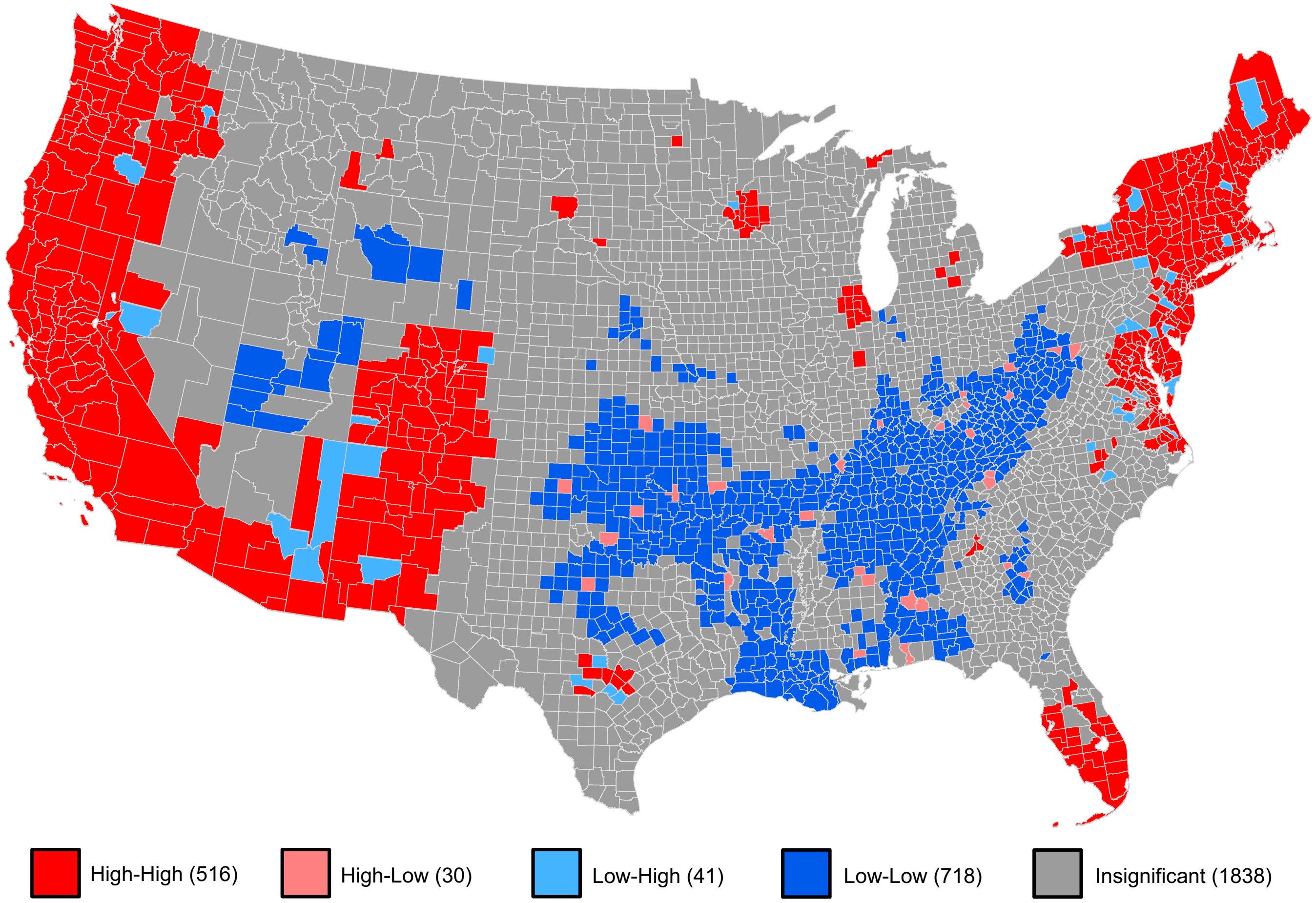

Fig. 3. Local Moran's *I* bivariate clusters of county anomalies for observed values of %*Belief* (%*Belief* – US average of %*Belief*) and the corresponding anomalies for the predicted values of %*Belief* (predicted %*Belief* – US average of predicted %*Belief*) from Eq. **2**. Areas with above-average %*Belief* and above-average predicted values of %*Belief* (red), above-average %*Belief* and below-average predicted values of %*Belief* (pink), below-average %*Belief* and above-average predicted values of %*Belief* (light blue), below-average %*Belief* and below-average predicted values of %*Belief* (blue), and statistically insignificant local clustering (gray) are shown.

sample period ($TMax > 201$), increases in the number of record low temperatures since 2005 reduce the percentage of the population that believes that global warming is happening by up to 4% (*SI Materials and Methods*, *7. The Experiential Effect of Climate Change*). Conversely, record high temperatures since 2005 in counties that cool over the sample period ($TMax < 182$) have little effect on %*Belief*.

The total estimated effect of right-hand side variables, including *TMax* and recency weighting, is between −5 and +3% points for different counties (Figs. S3–S7) and comparable with the spatial variation in %*Belief*, which has an SD of 4.9% points, with one-half of all counties falling within 3% points of the mean (and median) of 59% (Figs. S2 and S8). As such, perceptions of local changes in climate can account for a significant portion of the county-level differences in %*Belief* (*SI Materials and Methods*, *6. Interpreting the Regression Coefficients*) and suggest that personal experience is an important determinant of the public's willingness to accept the scientifically established fact that Earth is warming (Figs. 2 and 3 and Fig. S9).

Discussion

The importance of experiential learning creates several challenges to a public consensus needed to implement meaningful climate change policy. Local cooling, as indicated by low values for *TMax* and high values for *Low*2005, identifies 718 counties where personal heuristics support experiential learning that is consistent with high levels of climate skepticism (Fig. 3). Here, contradictions between personal experiences with local changes in climate and the scientific evidence for climate change seem settled in favor of personal experience. Changing this weighting in favor of scientific evidence will be difficult given the importance of personal experience.

Adding to this difficulty, our result suggests that the public tends to ignore local conditions when they are inconsistent with their beliefs (18). A recent spate of record high temperatures does little to reduce climate skepticism among residents who live in counties that have a relatively large number of record low temperatures over the sample period. Conversely, climate skepticism in counties with high values for *TMax* rises in response to a relatively small number of record low temperatures since 2005 (*Low*2005 is about one-half *High*2005) (Table 1). Asymmetric effects suggest biases that distort logic by allowing skeptics to maximize the importance of the record cold temperatures, because its inconsistency with global warming reinforces their nonbelief (26). This asymmetry may be partially responsible for the relatively small number of counties ($n = 514$) where experiential learning is consistent with high levels of acceptance of climate change (Fig. 3).

Despite these obstacles, our results suggest a way to supplement the information used to communicate ongoing changes in climate. In addition to monthly temperature anomalies, agencies may want to report the number of new record high and low

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temperatures. To enhance public understanding, these records could be framed as a wager against the hypothesis that global temperature is warming, in which a dollar is won for each record low and a dollar is lost for each record high. Defining the wager against a warming climate is consistent with the null hypothesis of scientific inquiry (no change in climate) and biases in human perception; loss aversion holds that people perceive a dollar lost as more valuable than a dollar gained (27).

Materials and Methods

We obtain data on the 24-h daily high and low temperatures for 18,713 stations located in the United States (28). Each station is classified according to the number of years for which data are available and the number of observations that are missing. For each station that satisfies a set of selection criteria, we calculate the value of *TMax* using Eq. **1**. We also record the number of most recent record high (*High*2005) and low (*Low*2005) temperatures between 2005 and the last observation, which is 2010 or later (*SI Materials and Methods*, *2. A Local Measure of Climate Change*). To be included, stations must have a minimum sample of 30, 40, or 50 y and be missing at most 5, 10, or 15 observations (*SI Materials and Methods*, *1. Datasets*).

Values for *TMax*, *High*2005, and *Low*2005 are assigned to counties based on spatial proximity. All or any portions of a county are assigned to its nearest weather station based on Thiessen polygons created for each station, which assign an area closest to each station relative to all other stations (excluding water bodies) (Fig. S1). Spatially assigned values of *TMax*, *High*2005, and *Low*2005 are aggregated to counties ($_c$) in two ways: (*i*) as a county-wide mean and (*ii*) as a population-weighted mean (29). Population weights are defined as the percentage of voting age population living in any portion of the county (that has been assigned to the nearest weather station).

Each dataset is used to estimate the following regression:

$$\begin{aligned}\%Belief_c = {} & \alpha + \beta_1 TMax_c + \beta_2 High2005_c \times (TMax_c \le 163) + \beta_3 High2005_c \\ & \times (163 < TMax_c \le 182) + \beta_4 Low2005_c \times (182 > TMax_c \le 201) \\ & + \beta_5 Low2005_c \times (TMax_c > 201) + \mu_c,\end{aligned} \quad [2]$$

in which %*Belief* is the fraction of a county's population that answers yes to the question "do you think that global warming is happening?" (1), α and β values are regression coefficients, and μ is the regression error that is estimated using ordinary least squares (OLS) and a spatial simultaneous lag model. We expect β_1, β_2, and β_3 to be positive (record warmth increases belief), whereas β_4 and β_5 should be negative (record cold reduces belief).

Because %*Belief* is a proportion observed on the interval (0,1), we also estimate Eq. **2** by applying a logit transformation to $\%Belief_i$ as a check for robustness (Table S1). To account for spatial autocorrelation, Eq. **2** is estimated as a spatial simultaneous lag model of the form (*SI Materials and Methods*, *5. Spatial Regression*):

$$y_c = \rho W y_j + X_c' \beta + \varepsilon_c, \quad [3]$$

in which W is a K nearest neighbor row standardized weights matrix ($K = 5$), Wy_j is the spatial lagged values of c neighbors j, ρ is a spatial autoregressive slope coefficient, β is a vector of regression coefficient for all independent variables for observation c (X_c), and ε_c is an $N \times 1$ vector of white noise error. Residuals from all OLS estimates show signs of significant spatial autocorrelation ($P < 0.01$) using the lm.morantest from R's spdep package (30–32). The use of a spatial lag is validated ($P < 0.01$) for all datasets through robust versions of the Lagrange Multiplier test for spatially dependent linear models (28).

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