nature human behaviour

Article https://doi.org/10.1038/s41562-025-02183-9

# Binary climate data visuals amplify perceived impact of climate change

Received: 26 August 2024

Accepted: 14 March 2025

Published online: 17 April 2025

Check for updates

Grace Liu[1,2], Jake C. Snell[1], Thomas L. Griffiths[1,3,5] & Rachit Dubey[1,4,5]

For much of the global population, climate change appears as a slow, gradual shift in daily weather. This leads many to perceive its impacts as minor and results in apathy (the 'boiling frog' effect). How can we convey the urgency of the crisis when its impacts appear so subtle? Here, through a series of large-scale cognitive experiments ($N = 799$), we find that presenting people with binary climate data (for example, lake freeze history) significantly increases the perceived impact of climate change (Cohen's $d = 0.40$, 95% confidence interval 0.26–0.54) compared with continuous data (for example, mean temperature). Computational modelling and follow-up experiments ($N = 398$) suggest that binary data enhance perceived impact by creating an 'illusion' of sudden shifts. Crucially, our approach does not involve selective data presentation but rather compares different datasets that reflect equivalent trends in climate change over time. These findings, robustly replicated across multiple experiments, provide a cognitive basis for the 'boiling frog' effect and offer a psychologically grounded approach for policymakers and educators to improve climate change communication while maintaining scientific accuracy.

Human-caused climate change is already resulting in substantial social, economic and ecological losses[1]. However, these impacts are not felt uniformly across society. On the one hand, many regions are facing severe climate extremes daily, such as intense flooding, rampant wildfires and widespread droughts[2–5]. On the other hand, a large portion of the global population is currently experiencing only slow and gradual changes due to climate change, such as incrementally rising temperatures or sporadic climate-related disasters[6,7].

The apparent mundanity of these gradual changes is leading to perhaps one of the most troubling outcomes related to climate change: apathy towards the crisis[8–10]. Because most people's climate change judgements are extensively shaped by their personal experiences[11–18], and because most local climates are becoming unstable only at a gradual pace, societies are adjusting to worsening environmental conditions disturbingly fast[6,19–21]. For instance, a recent survey of Floridians found that many people were unable to detect 5-year temperature increases, with their risk perceptions more strongly influenced by personal beliefs and political affiliation than by actual temperature changes[22]. This widespread inability to perceive gradual climate trends is often referred to as the 'boiling frog' effect and is giving a false sense of security to the public and lowering collective motivation to act[9,23].

The slow burn of climate change raises an important question: how can we convey the urgency of the climate crisis when many of its effects seem so subtle and gradual? While the field has made important strides in understanding the causes and consequences of the 'boiling frog' effect, finding ways to break through the indifference remains a considerable challenge.

In this Article, we use a cognitive science lens to explore the psychological processes underlying the 'boiling frog' effect and understand how to counteract it. We conduct a systematic investigation using large-scale cognitive experiments and computational modelling to explore how gradually changing climate data influence perceptions of climate change and identify which data patterns can counteract this effect.

[1]Department of Computer Science, Princeton University, Princeton, NJ, USA. [2]Department of Machine Learning, Carnegie Mellon University, Pittsburgh, PA, USA. [3]Department of Psychology, Princeton University, Princeton, NJ, USA. [4]Department of Communication, University of California, Los Angeles, Los Angeles, CA, USA. [5]These authors jointly supervised this work: Thomas L. Griffiths, Rachit Dubey. e-mail: gliu2@andrew.cmu.edu; rdubey@princeton.edu

https://doi.org/10.1038/s41562-025-02183-9

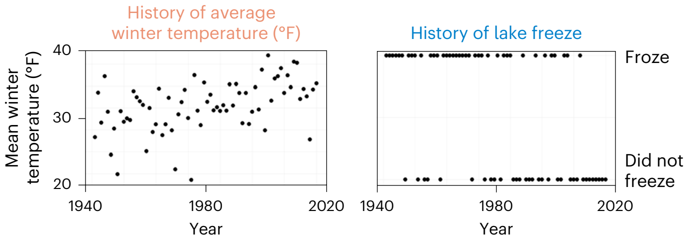


**Fig. 1 | Experiment 1 stimuli.** Examples of graphs presented to participants in experiment 1, showing the continuous condition (left) and the binary condition (right). Both graphs have the same correlation (0.47).

To preview our findings, using a preregistered experiment ($N$ = 799), we show that people perceive climate change as having a greater impact when presented with binary climate data (for example, historical trend of lake freeze) compared with continuous climate data (for example, historical trend of mean winter temperature), even with matched correlation levels. This finding is robust and reproducible, as confirmed by multiple replication studies and experiments with real-world lake freeze and temperature data. A follow-up experiment ($N$ = 398) reveals that binary data enhance perceived impact because they create an 'illusion' of sudden changes, even when the underlying data shift incrementally. To provide a cognitive basis for this illusion, we use computational modelling and show that gradual shifts in binary data are more likely to be perceived as rate changes, while shifts in continuous data are attributed to variance.

Together, these results suggest that binary climate data can amplify the perceived impact of climate change, in part by creating an illusion of sudden shifts, even when changes are gradual. These findings enhance our understanding of the 'boiling frog' effect and offer a way to make the gradual effects of climate change more salient to the public.

## Results

### Climate change is more salient in binary climate data

To investigate how gradual changes can be made more salient, we conducted a large-scale, preregistered experiment ($N$ = 799), examining how binary and continuous climate data influence people's perception of climate change. The preregistration included the data collection protocol, stimuli and data analysis plan (https://osf.io/75mp8).

In the experiment, participants were first introduced to a fictional town called Townsville, known for its chilly winters and ice-skating activities on the local lake during the holiday months. Participants were then randomly assigned to one of two conditions: the 'continuous' condition or the 'binary' condition (see Methods for details). Crucially, the binary and continuous datasets were generated with matched correlation levels, ensuring that any differences in perception could be attributed to the format of presentation rather than selective data manipulation (see Methods for details).

In the continuous condition, participants viewed one of 18 graphs showing Townsville's average winter temperature history from 1939 to 2019. In the binary condition, they viewed one of 18 graphs depicting whether the lake froze completely during the same period. Importantly, the graphs for both conditions were generated in pairs with matched correlations, ranging from 0.1 to 0.7 (Methods). Figure 1 shows an example of a matched correlation pair (correlation 0.47). After viewing the graphs, participants rated, on a scale of 1–10, their perceived impact of climate change on the fictional town, the extent of change in the town's temperature and their perception of change in the frequency of lake freeze.

Figure 2 plots the ratings of the participants in both conditions. We first found that the perceived impact of climate change was significantly higher among participants in the binary condition (mean 7.5, s.d. 2.3) compared with participants in the continuous condition (mean 6.6, s.d. 2.2; $t(764) = 5.52$, $P < 0.001$; Cohen's $d$ ($d$) = 0.40, 95% confidence interval (CI) 0.26–0.54). This result was consistently observed across graphs of all correlation levels (see Supplementary Information for details). In addition, participants in the binary condition (mean 7.3, s.d. 2.1), who viewed the lake freeze graphs, counterintuitively perceived a stronger trend in increasing temperatures than those in the continuous condition, who viewed the temperature graphs (mean 6.6, s.d. 2.2; $t(764) = 4.48$, $P < 0.001$; $d = 0.32$, 95% CI 0.18–0.47). Finally, participants in the binary condition (mean 7.5, s.d. 2.2) perceived the lake freeze frequency to have changed more significantly compared with those in the continuous condition (mean 6.4, s.d. 2.3; $t(764) = 6.86$, $P < 0.001$; $d = 0.50$, 95% CI 0.35–0.64).

**Additional experiments.** To ensure the robustness of these effects, we conducted several follow-up experiments. First, we conducted a replication study ($N$ = 440) and found that the perceived impact of climate change was again amplified in the binary condition compared with the continuous condition (refer to Supplementary Experiment 1 in Supplementary Information). Next, to rule out a potential confounder that participants might be failing to identify the increasing trend in the continuous data, we conducted Supplementary Experiment 2 ($N$ = 301) where the scatterplot of the continuous data also included a trendline. Again, the perception of the impact of climate change was higher in the binary condition (see Supplementary Experiment 2 in Supplementary Information for details). Finally, to address a potential limitation that experiment 1 lacked a neutral control condition to establish a baseline, we conducted Supplementary Experiment 3, where we compared the effects of binary and continuous climate data against a neutral control group that received no climate information. Both binary and continuous data significantly increased perceived climate change impact compared to the control condition, with binary data again having a stronger impact than continuous data (see Supplementary Experiment 3 in Supplementary Information).

The above findings highlight the core takeaway of this study: people's perception of climate change impact is significantly heightened when viewing binary data compared with continuous data. This effect extends to both concrete changes (that is, increasing winter temperatures) and less tangible climate change impacts.

### The binary climate effect extends to real-world climate data

So far, to study people's perception of climate change in binary and continuous data, we have used simulated data in our experiments. To increase the ecological validity of our findings, we next conducted an experiment with real-world lake freeze and temperature data.

We first gathered time-series data on lake freeze and mean winter temperature for five intermittently freezing lakes that are at high risk

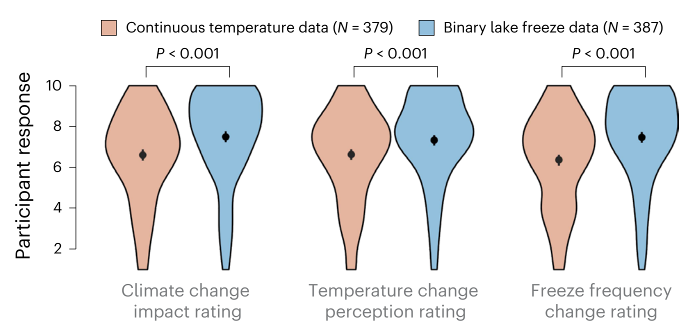


**Fig. 2 | Binary data elevate perceived impact of climate change.** The violin plots display results from experiment 1, showing that participants in the binary condition ($N$ = 387) rated the perceived impact of climate change, temperature change and freeze frequency change significantly higher than those in the continuous condition ($N$ = 379). The coloured areas represent kernel density estimations, the means are indicated by black dots and the vertical lines represent standard errors.

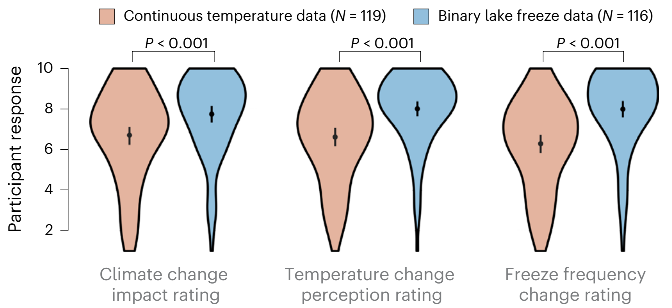


**Fig. 3 | Results of experiment 2 with real-world temperature and freeze data.** The violin plots display participants' ratings of climate change impact, temperature change and freeze frequency change for the two conditions. Means are indicated by black dots, and vertical lines represent standard errors. Participants in the binary condition ($N = 116$) again rated the impact of climate change higher compared to the continuous condition ($N = 119$).

of ice loss. To identify these lakes, we selected the five lakes with the strongest correlations in lake freeze over time from a global database of intermittently freezing lakes[24,25]. We then extracted historical mean winter temperatures for these lakes from the Berkeley Earth gridded temperature database[26], matching each lake's latitude and longitude coordinates with the corresponding temperature grid box (Methods).

Participants ($N = 247$) then took part in an experiment similar to experiment 1. In the binary condition, participants viewed one of the five graphs depicting lake freeze history, whereas, in the continuous condition, they saw one of the five graphs showing winter temperature history. Unlike experiment 1, where participants were informed that the data came from a fictional town, this time, they received contextual information about the actual lake, including its location and recreational activities offered in the lake (for example, ice skating, ice fishing or boating).

As shown in Fig. 3, the perceived impact of climate change was significantly higher among participants in the binary condition (mean 7.8, s.d. 2.0) compared with participants in the continuous condition (mean 6.7, s.d. 2.3; $t(233) = 3.76$, $P < 0.001$; $d = 0.49$, 95% CI 0.23–0.75). Furthermore, there was a significant difference in the perception of change in temperature between participants in the binary condition (mean 8.0, s.d. 1.8) and continuous condition (mean 6.6, s.d. 2.2; $t(233) = 5.36$, $P < 0.001$; $d = 0.70$, 95% CI 0.43–0.96). Similarly, participants in the binary condition (mean 8.0, s.d. 1.9) perceived the lake freeze frequency to have changed more significantly compared with those in the continuous condition (mean 6.3, s.d. 1.7; $t(233) = 6.28$, $P < 0.001$; $d = 0.82$, 95% CI 0.55–1.09). These results extend our findings to real-world lake freeze and temperature data, orienting our findings towards practical climate communication applications. To ensure the robustness of these findings, we also conducted a replication of this experiment (refer to Supplementary Experiment 4 in Supplementary Information). The replication confirmed that the binary condition again amplified perceptions of climate change impact, temperature change and freeze frequency compared with the continuous condition.

## Binary data create an illusion of a changepoint

What might be causing people to perceive a greater climate impact in binary data? Various explanations exist, including reduced mental effort[27] and increased emotional valence[28], which we explore further in 'Discussion'. In addition to these explanations, we propose that binary data may be further heightening perceptions of climate change by creating an illusion of sudden shifts. This perceived abrupt change in binary data can make the impact of climate events seem more pronounced.

Formally, a changepoint is defined as a point in a time series where there is a sudden shift in the parameters of the data distribution, often marked by abrupt changes or jumps[29,30]. In our experiments, both binary and continuous data were generated with a constant rate of change, meaning there were no actual changepoints or sudden shifts (Methods). We hypothesized, however, that people might perceive the binary data as having sudden shifts, which could influence their perception of climate change impact.

To test this, we conducted a preregistered experiment ($N = 398$) to examine how people perceive changepoints in binary and continuous climate data (preregistration link: https://osf.io/2sxer). Similar to experiment 1, participants were introduced to a fictional winter town and randomly assigned to either the continuous or binary condition (see Methods for details). In the continuous condition, participants viewed one of three graphs depicting the town's average winter temperature. In the binary condition, they viewed one of three graphs showing whether the lake froze completely over time. After viewing the graphs, participants first answered a multiple-choice question on whether they observed a changepoint, defined as 'any point that has a pronounced deviation from the typical pattern of temperature/freeze data'. They then used a slider to select the year in which they believed the data had undergone the largest shift. Finally, participants rated their perceived impact of climate change on the town, the extent of temperature change and the frequency of lake freezing on a scale of 1–10.

Figure 4a shows the participants' responses regarding whether they detected a changepoint in the data. Participants in the binary condition (proportion 0.73) were more likely to perceive a changepoint compared with those in the continuous condition (proportion 0.56), as confirmed by a two-sample $z$-test of proportions ($z = -3.47$, $P < 0.001$; odds ratio (OR) 2.10, 95% CI 1.38–3.20). In addition, a higher proportion of participants did not perceive a changepoint in the continuous condition (proportion 0.15) compared with the binary condition (proportion 0.07; $z = 2.53$, $P = 0.011$; OR 2.36, 95% CI 1.19–4.64). The proportion of participants who were unsure about the existence of a changepoint was also higher in the continuous condition (proportion 0.29) than in the binary condition (proportion 0.20; $z = 2.05$, $P = 0.041$; OR 1.62, 95% CI 1.02–2.58).

Participants who viewed the binary data also exhibited greater consensus on the location of the changepoints. Figure 4b shows how frequently each year was identified as a changepoint in the different graphs for the two conditions. The distribution of perceived changepoint years in the binary condition had lower entropy ($H = 3.15$) compared with the continuous condition ($H = 3.56$), indicating that responses in the binary condition were more concentrated around specific years. A follow-up Levene's test for equality of variances confirmed that the two samples had different variances, $F(390) = 31.91$, $P < 0.001$, with the ratio of the empirical variances being 0.489 and the ratio of the empirical s.d. being 0.699. This result suggests that there was greater agreement among participants regarding changepoint locations in the binary condition.

Participants' perception of changepoints also influenced their reported impact of climate change (Fig. 4c). Across both conditions, those who perceived a changepoint reported a higher impact of climate change (mean 7.6, s.d. 1.96) compared with those who did not perceive a changepoint or were unsure (mean 6.7, s.d. 2.1; $t(390) = 4.4$, $P < 0.001$; $d = 0.47$, 95% CI 0.26–0.68). This effect was evident in both conditions. In the continuous condition, perceiving a changepoint was associated with a higher reported impact (mean 7.2, s.d. 2.0) compared with those who did not perceive a changepoint or were unsure (mean 6.5, s.d. 2.1; $t(183) = 2.24$, $P = 0.026$; $d = 0.33$, 95% CI 0.04–0.63). Similarly, in the binary condition, those who perceived a changepoint reported a higher climate impact (mean 7.9, s.d. 1.9) compared with those who did not perceive a changepoint or were unsure (mean 6.9, s.d. 2.1; $t(183) = 2.2$, $P = 0.013$; $d = 0.51$, 95% CI 0.20–0.82).

These results suggest that, when people perceive climate data as having undergone sudden shifts, they are more likely to perceive greater climate impact. Binary data, in particular, are more likely to

https://doi.org/10.1038/s41562-025-02183-9

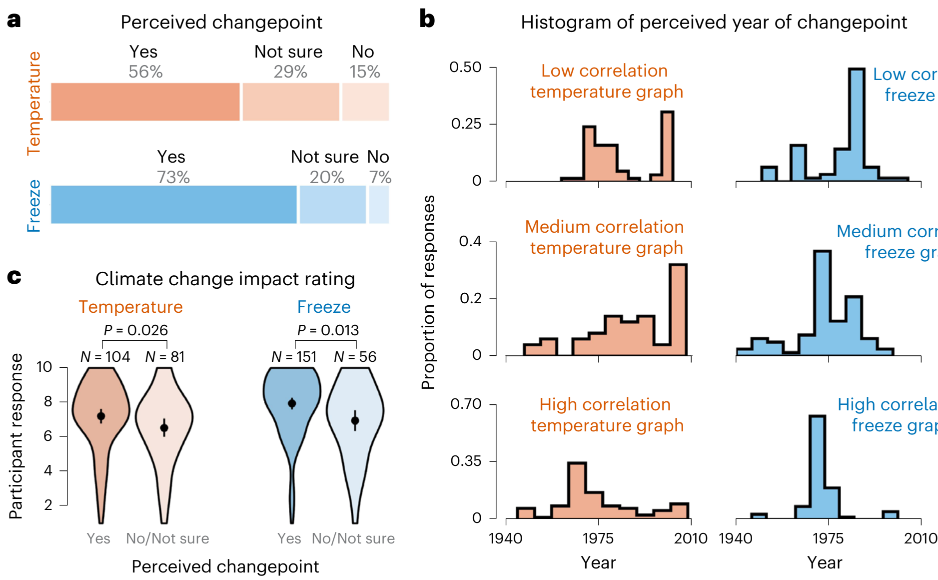


**Fig. 4 | Results of experiment 3. a**, The proportion of participants who responded yes, not sure and no to the question of whether a changepoint exists, shown for the continuous condition (top) and the binary condition (bottom). **b**, Histograms displaying the frequency with which each year was identified as a changepoint across the three different graphs used in the two conditions. Participants had greater consensus regarding the changepoint locations in the binary condition. **c**, Violin plots depicting participants' ratings of climate change impact, separated by whether they identified a changepoint (yes) versus those who did not or were unsure (no + unsure), across both continuous and binary conditions. Means are marked by black dots, and vertical lines represent standard errors. The number of participants in each group is shown at the top of the plots.

create the impression of abrupt changes, even when the underlying data shift gradually. This tendency to perceive sudden shifts in binary data helps to explain why people may perceive a greater impact of climate change compared with continuous data.

**Additional experiment.** In addition to the experiment described above, we conducted a follow-up study ($N = 200$) to investigate whether emotional valence contributes to the heightened perception of climate change impact in binary data (see Supplementary Experiment 5 for details). We varied the emotional valence of binary graphs by using high-valence ('froze' versus 'did not freeze') versus low-emotional ('above 29 °F' versus 'below 29 °F') labels for the same binary data. We found that valence partially explains our results when trends were unclear. However, when trends were more evident, participants exposed to both high- and low-valence graphs perceived climate change impacts similarly. This suggests that, in cases of clear trends, the illusion of changepoints may play a more prominent role in driving the amplified perception of climate change.

## Simulating changepoint detection in binary and continuous data

Why do people perceive sudden shifts in gradual binary data? Here, we develop a Bayesian model of changepoint detection and show that this optimal model is also prone to exhibiting this illusion. This is because gradual shifts in binary data are often attributed to changes in the underlying data distribution, while similar shifts in continuous data are attributed to the distribution's variance. This suggests that the changepoint illusion is perhaps an inherent property of gradual binary data.

**An optimal Bayesian model of changepoint detection.** Consider the task of identifying where a pattern changes in a sequence of events. In binary data (for example, coin flips), a shift might involve changing the probability of heads versus tails. In continuous data (for example, temperature readings), it could mean a change in the average temperature. Using Bayesian modelling, we estimate these shifts by calculating the probability of a changepoint at each position.

Formally, let $\mathbf{X}$ be a series of observations of length $N$. The decision-maker's objective is to identify changepoints, where the statistical properties of the data alter. A changepoint $\delta$ at position $i$ indicates that the data before $i$ follow a distribution with parameters $\theta_1$, and the data after follow a different distribution with parameters $\theta_2$ (ref. 31).

Given the observed data $\mathbf{X}$, the probability of a changepoint at $i$ that is, $P(\delta = i|\mathbf{X})$, can be computed using Bayes' rule

$$P(\delta = i|\mathbf{X}) \propto P(\mathbf{X}|\delta = i)P(\delta = i), \tag{1}$$

where $P(\mathbf{X}|\delta = i)$ is the likelihood of the data given a changepoint at index $i$, and $P(\delta = i)$ is the prior probability of a changepoint at index $i$ before observing the data. Equation (1) allows the decision-maker to update their belief about the presence of a changepoint by considering both the evidence from the data and any prior assumptions about where changepoints might occur.

In the simplest case, the decision-maker a priori assumes that each point in time is equally likely to be a changepoint and uses a uniform prior for $P(\delta = i)$. The likelihood $P(\mathbf{X}|\delta = i)$ depends on assumptions about the data's underlying distribution.

For binary data, we assume a Bernoulli distribution, modelling outcomes with two possible values, such as success or failure. We further assume that each observation is independent and identically distributed (i.i.d.) within segments. If there is a changepoint at $i$, then $\{x_1, \ldots, x_i\}$ are sampled from a Bernoulli distribution with parameter $\theta_1$, and $\{x_{i+1}, \ldots, x_N\}$ are sampled from a Bernoulli distribution with parameter $\theta_2$. Using equation (1), the probability for a changepoint at $i$ in the binary setting can be calculated as

$$P(\delta = i|\mathbf{X}) \propto P(\delta = i) \prod_{t=1}^{i} P(x_t|\theta_1) \prod_{t=i+1}^{N} P(x_t|\theta_2), \tag{2}$$

where $\prod_{t=1}^{i} P(x_t|\theta_1)$ is the likelihood of the data $\{x_1, \ldots, x_i\}$ being generated from a Bernoulli distribution with parameter $\theta_1$ and $\prod_{t=i+1}^{N} P(x_t|\theta_2)$ is the likelihood of the data $\{x_{i+1}, \ldots, x_N\}$ being generated from a different Bernoulli distribution with parameter $\theta_2$.

https://doi.org/10.1038/s41562-025-02183-9

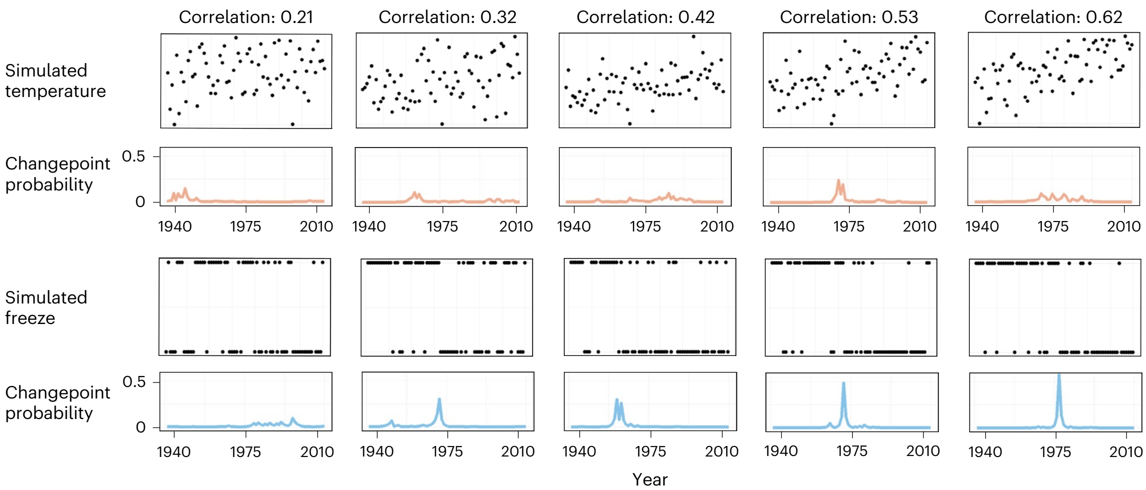


**Fig. 5 | Simulation results.** An illustration of how gradual changes are perceived as sudden changes in binary data. Top: the changepoint probability output of the Bayesian model for various correlation levels in temperature data. In most graphs, there is a somewhat uniform distribution of changepoint probabilities, with no specific concentration at any point. Bottom panel: binary data result in more pronounced peaks in the changepoint probability distribution, particularly as correlation increases. Note that these are example illustrations and do not represent all graphs used in the simulation experiment.

For continuous data, we assume a normal distribution, which is suitable for modelling continuously varying data such as temperature readings. If a changepoint is present at $i$, the data before the changepoint are modelled by a normal distribution with mean $\mu_1$ and variance $\sigma^2$, and the data after $i$ follow a normal distribution with a different mean $\mu_2$ and the same variance $\sigma^2$. The probability for a changepoint is calculated as

$$\begin{aligned} P(\delta = i|\mathbf{X}) \propto P(\delta = i) \prod_{t=1}^{i} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x_t-\mu_1)^2}{2\sigma^2}\right) \\ \prod_{t=i+1}^{N} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x_t-\mu_2)^2}{2\sigma^2}\right) \end{aligned} \quad . \qquad (3)$$

Equations (2) and (3) enable us to calculate the probability of a changepoint at any point $i$ for both binary and continuous settings (refer to Supplementary Information for detailed derivations and final equations).

**Explaining the illusion of changepoints in binary data.** To simulate changepoint detection in binary and continuous data, we first generated 30 pairs of gradually changing time-series data (both binary and continuous) across various matched correlation levels, ranging from 0.1 to 0.7. We then computed the changepoint probability for the different points in the data (using equations (2) and (3)).

Similar to the results of experiment 2, we found that the entropy of the changepoint probability distributions for the binary time series (mean entropy 2.9, s.d. 0.8) was lower compared with the entropy of the changepoint probability distributions for the continuous time series (mean entropy 3.3, s.d. 0.5; $t(58) = -2.79$, $P = 0.009$; $d = 0.51$, 95% CI 0.11–0.91). That is, similar to the human participants, the Bayesian model is also more likely to detect changepoints in binary data, as indicated by higher probabilities and sharper peaks at specific points, alongside generally lower entropy. As an illustration, Fig. 5 plots the changepoint probability output of the Bayesian model for different binary and continuous graphs across various correlation levels. The changepoint probability distribution exhibits more pronounced peaks in binary data, and the model is more likely to detect changepoints in binary data, particularly as correlation increases.

One key reason why the probability of changepoints is lower in continuous data is that gradual shifts are often absorbed by the variance of the normal distribution. To further investigate this, we conducted an additional simulation where we fitted the continuous data using a normal distribution with a variance significantly smaller than the true variance of the data (we used $\sigma^2 = 1$, which is 2.6 times lower than the true variance). Here, the model became more sensitive to subtle changes and resulted in a more peaked posterior distribution of changepoint locations (refer to Supplementary Information for details). This suggests that the apparent changepoints in binary data may be an inherent feature of binary patterns, whereas continuous data, with their implicit variance, naturally smooth out gradual changes.

## Discussion

For a long time, many scientists, including the authors of this study, held onto the hope that, when the impacts of climate change became undeniable, people and governments would finally act decisively[7]. Perhaps a devastating hurricane, heat wave or flood—or even a cascade of disasters—would make the severity of the problem impossible to ignore, spurring large-scale action. Yet, our response continues to resemble the fate of the proverbial boiling frog, failing to notice the creeping danger until it is too late[9]. The most unsettling possibility is that we might continue sleepwalking into disaster; the atmosphere will keep growing unstable, but not dramatically or fast enough to command sustained attention, allowing climate change to be treated as a gradual background noise.

Here, through multiple cognitive studies, we demonstrate that presenting climate data in binary terms can make the impacts of climate change more salient compared with continuous data. Gradual shifts in binary data often create the perception of sudden changes, amplifying the perceived impact. Importantly, our approach does not involve selective data presentation but rather compares datasets with matched correlation levels in different formats (binary versus continuous), ensuring accuracy in climate change communication. While our study shows how progress can be made in enhancing the salience of climate change—an essential first step towards more meaningful engagement and response—future work should investigate how this work can be extended to drive concrete action. In the remainder of the Article, we discuss applications to real-world climate communication, consider alternative explanations for the heightened salience of binary data, and outline limitations and future directions.

### Practical implications for climate communication

There are immediate practical applications to these findings, particularly in the design and visualization of climate data. An extensive body of research has studied the cognitive processes underlying effective visualizations[32–35] and highlighted the importance of effective climate data visuals[36–41]. Our study contributes to this literature by emphasizing the value of binary climate graphs and suggesting key directions for improving climate communication.

For instance, policymakers and journalists could use binary visuals to simplify complex climate data and make it more relatable for the public. Rather than showing gradual temperature increases, reports could highlight clear shifts, such as the loss of white Christmases, the inability to ice-skate in winters, or summer outdoor activities disrupted by wildfire pollution. These representations could make the data more accessible and evoke stronger emotional responses, encouraging action. This approach could also help communities understand how their local climate is changing. For example, in areas where rainfall patterns are changing and/or where droughts are becoming more frequent, binary data could highlight the worsening of drought conditions by illustrating the shift from occasional to recurring severe droughts. This could help communities recognize how once-rare events are becoming increasingly common. However, it is important that such visuals are used responsibly, ensuring that they accurately represent the underlying data and do not mislead the public. We suggest that binary visuals should be presented alongside continuous data when possible, allowing audiences to understand both the gradual trends and the more salient shifts.

Our findings also provide an explanation for the popularity of the 'climate stripes' visual[42]. By using colour gradients to distinguish between above-average and below-average temperatures, the stripes simplify a gradual trend into a clear, binary-like shift. This binary structure enhances the perception of climate change, which may explain their widespread resonance in public discourse. Future tools, such as interactive dashboards, could allow users to toggle between binary and continuous visuals, leading to a greater sense of urgency.

### Relevance to changepoint detection and biases

Beyond its practical implications, our work also makes important theoretical contributions, particularly in understanding how people reason about change. Detecting and responding to changes is crucial for decision-making, and psychologists have extensively studied how people identify changes in data patterns and when they tend to underreact or overreact[30,43–48]. These studies typically involve detecting changes in non-stationary environments, where data suddenly shift from one distribution to another. By contrast, our study examined data that gradually shifted over time without sudden changes. In doing so, we uncovered a bias about how people perceive sudden shifts in gradual binary data more readily than in continuous data. This phenomenon is somewhat analogous to the 'hot hand' fallacy, where people tend to see patterns in random sequences[49]. However, unlike the 'hot hand' studies, which explore perceptions of randomness[50,51], our study used clear, gradually increasing patterns and still found that people perceived abrupt changes in binary data. By focusing on how people interpret slowly changing data and identifying key biases in these patterns, our study enhances the understanding of change detection and response, complementing prior research focused on more abrupt or dramatic changes.

### Alternative explanations for the perceived binary data effect

While our study primarily focused on how perceptions of changepoints might amplify the perceived impacts of climate change in binary data, it is important to recognize that there are several other factors that could be contributing to this heightened perception. One reason may be that binary data graphs could be reducing cognitive load and are computationally easier to parse owing to fewer value comparisons[27,52–55]. Another possibility is that lake freeze graphs might elicit stronger emotional responses than temperature graphs (for example, people might relate more to the consequences of decreased freeze, such as fewer opportunities for ice skating). This is consistent with research showing that emotional valence affects climate judgements[28,56–58] as well as perceptions of changes and tipping points[59,60] (see also Supplementary Experiment 5).

Another possible explanation for our findings is grounded in construal level theory, which suggests that psychologically distant events (for example, abstract temperature trends) are processed at a higher construal level, while more proximal events (for example, a freezing lake) evoke lower-level, concrete thinking[61]. Binary data, by highlighting specific, tangible changepoints (for example, 'froze' versus 'did not freeze'), may serve as a construal level manipulation, bringing the impacts of climate change closer to participants' experiences. Thus, binary climate data can help to ground abstract impacts of climate change in concrete and relatable terms. This finding contributes to the existing literature on construal level theory and climate change[62,63] and also suggests a potential low-cost intervention to counteract climate apathy.

Another explanation is that perceiving changepoints in binary data may signal a tipping point, leading people to believe that notable changes have occurred[59,60,64]. Recent research shows that people have a 'binary bias', where they tend to categorize continuous data into binary terms, which then biases their decision-making[65,66]. Our study contributes to this literature by documenting a specific bias within the context of binary data perception. Relatedly, binary data may influence how people infer future trends, particularly regarding perceptions of irreversibility or tipping points. People often project social and historical trends forward to anticipate future outcomes[67]. By creating an illusion of a changepoint, binary data may evoke a stronger sense of irreversible change, influencing how people perceive the urgency and impacts of climate change.

### Limitations and future work

While our study focused on how different formats of climate data affect perceptions of climate change impacts, it is also crucial to examine how people respond to these changes over time. An important barrier to climate action is that people tend to rapidly adapt and habituate to worsening environmental conditions[68,69]. This tendency to adjust to new normals, whether positive or negative, is a pervasive aspect of human behaviour[70,71]. Future research should explore how sensitivity to persistent environmental changes evolves and whether binary data patterns could help to mitigate such adaptation. For instance, would people be less likely to become accustomed to a lake that has abruptly stopped freezing or a town that has suddenly become much hotter?

While binary data can enhance salience, they also risk oversimplifying complex climate issues, potentially leading to misinterpretation or distortion of the facts. Future research should explore ways to present binary data that convey critical information without losing complexity. For example, combining binary visuals with continuous data or providing additional context could help people better understand the nuances of climate change. In addition, while binary data may initially heighten perception, it is unclear whether this effect persists over time. Future studies should investigate whether repeated exposure leads to reduced sensitivity and how to mitigate this effect.

Another limitation of our study is that participants observed the data in a single sitting and processed it retrospectively. In real-world settings, people experience climate change not only retrospectively (for example, via graphs or media communications) but also through their direct, lived experiences, encountering data incrementally over time rather than all at once. Future research should investigate climate change perception when data are presented sequentially, as this approach could more accurately reflect how individuals encounter and process climate information in their daily lives.

## Conclusion

Combatting climate change apathy is a vital step towards slowing the progression of warming. We posit that building an understanding of how people reason about change is key to overcoming this apathy. Given that climate impacts are often nonlinear and threshold-bound[72,73], we need more strategic communication. Rather than warning the frog that the water is warming gradually, we should define a clear threshold for unacceptable conditions. It is a straightforward binary variable.

## Methods

All experiments were approved by Princeton's institutional review board (IRB 10859). For all experiments, informed consent was obtained from all participants before the experiments began. Each participant could participate in only one experiment (including pilots). Note that we did not collect any demographic information (for example, gender or age) about the participants for the experiments. For all experiments, participants were randomly assigned to the different conditions and they were blind to which conditions they were assigned to. Experiment 1 was preregistered on 29 May 2024, and it included the data collection protocol, stimuli and data analysis plan (https://osf.io/75mp8). Experiment 3 was preregistered on 3 July 2024 and also included the data collection protocol, stimuli and data analysis plan (https://osf.io/2sxer). All the statistical tests reported in this Article are two-tailed tests.

### Generation of binary and continuous climate data

For our experiments, we generated paired time series with 80 data points each across a correlation range of 0.1–0.7. Each pair included a binary and a continuous time series with matched correlations.

To generate the binary data with the desired correlation, we used an iterative algorithm that adjusted the slope and intercept of a linear model until the correlation fell within the specified range. The slope was determined through a linear search, and the *y* intercept was set so that the probability of freezing was 0.5 at the midpoint of the time series, ensuring a smooth, gradual change in probability over time (refer to Supplementary Information for the algorithm's pseudo-code).

For each binary time series, we generated the corresponding continuous data by applying a linear transformation to exactly match the correlation level (refer to Supplementary Information for details). The transformed continuous data were then adjusted to match the mean and variance of winter temperatures from the Berkeley Earth dataset[26] for 31 intermittently freezing lakes[24]. All experiment stimuli and the code to generate them are publicly available via GitHub at https://github.com/graliuce/climate_change_detection/tree/main/experiment_stimuli.

### Experiment 1

For the experiment, we first generated 18 paired time series across the correlation range of 0.1–0.7 for a total of 36 time series. Using the difference in means (0.93) and s.d. (2.26) of responses to the climate question from a pilot experiment, we calculate a sample size of 743 to have a power level of 90%. We then recruited 799 USA-based participants from the online research platform Prolific and paid them US$0.40 for participation (our study took approximately 2 min to complete).

Following the preregistered exclusion criteria, we removed participants who did not pass a simple attention check question or those who viewed the graphs for less than 2 s. This led to the exclusion of 33 participants, leaving a final sample of 766 participants ($N = 379$ in the continuous condition and $N = 387$ in the binary condition). Code for reproducing the results of all experiments is available via GitHub at https://github.com/graliuce/climate_change_detection/tree/main.

Participants were randomly assigned to either the continuous or binary condition. In the continuous condition, they viewed one of 18 continuous graphs, randomly sampled, with the *y* axis labelled as mean winter temperature and the *x* axis representing years (1939–2019). In the binary condition, participants saw one of 18 binary graphs, randomly sampled, with the *y* axis indicating whether the lake froze and the *x* axis showing years (1939–2019). After viewing the graphs, participants in both conditions were asked to provide, on a scale of 1–10, their subjective rating in response to the following questions:

(1) In your view, how much do you think Townsville has been affected by climate change? (where 1 indicates 'not affected at all' and 10 indicates 'extremely affected').
(2) In your view, how much do you think the temperature of Townsville has changed in the last 50 years? (where 1 indicates 'remained the same' and 10 indicates 'changed a lot').
(3) In your view, how much do you think the frequency at which the lake freezes has changed in Townsville in the last 50 years? (where 1 indicates 'remained the same' and 10 indicates 'changed a lot').

Question 1 measured perceptions of the overall impact of climate change, while questions 2 and 3 evaluated perceptions of changes in temperature and lake freezing frequency.

### Experiment 2

Using the difference in means (0.66) and s.d. (1.8) of participant responses to the climate question from a pilot experiment, we calculated a sample size of 234 for a power level of 80%. We recruited 247 USA-based participants from the online research platform Prolific, paying US$0.40 for participation (the study took approximately 2 min to complete). We removed participants who failed a simple attention check or viewed the graphs for less than 2 s, resulting in the exclusion of 12 participants. This left a final sample of 235 participants ($N = 119$ in the continuous condition and $N = 116$ in the binary condition).

This experiment aimed to replicate experiment 1 using real-world lake freeze and temperature data. We first obtained publicly available ice-on and ice-off records for 31 intermittently freezing lakes across the Northern Hemisphere[24], including freeze records for Lake Vattern from the NSIDC Global Lake and River Ice Phenology Database[25]. We then filtered the data to include only lakes with more than five no-freeze years in the twentieth century, leaving 20 lakes. From these, for our experiment, we selected the five lakes with the highest correlations in freeze trends over time. Historical mean winter temperatures (December, January and February) for these lakes were extracted from the Berkeley Earth gridded temperature database[26], matched to the lakes' latitude and longitude coordinates.

Participants took part in an experiment similar to experiment 1 but were given additional information about the lake relevant to the stimulus, including details about the location and recreational activities offered in the lake.

### Experiment 3

For the experiment, we generated three pairs of time series, totalling six time series. Each pair covered a distinct correlation range: one with low correlation (0.1–0.3), one with medium correlation (0.3–0.5) and one with high correlation (0.5–0.7). Using the difference in proportion (0.145) of participants who failed to detect a changepoint from a pilot experiment, we calculated a sample size of 240 for a power level of 90%. We then recruited 398 USA-based participants from the online research platform Prolific, paying US$0.40 for participation (the study took approximately 2 min to complete). Following our preregistered exclusion criteria, we removed participants who failed a simple attention check or viewed the graphs for less than 2 s, resulting in the exclusion of eight participants. This left a final sample of 392 participants ($N = 185$ in the continuous condition and $N = 207$ in the binary condition).

Participants then took part in an experiment similar to experiment 1, with two additional questions. First, after viewing the binary or continuous graph, participants were asked whether they observed a changepoint, choosing from 'yes,' 'no' or 'not sure'. A changepoint was defined as 'a point showing a pronounced deviation from the typical pattern of temperature or freeze data'. Second, after answering this question, participants were then asked to use a slider to indicate the year where they noticed the most pronounced shift from the typical pattern.

### Simulation 1

For the simulation, we generated 30 pairs of time-series data across the correlation range (0.1–0.7), with five pairs per interval of 0.1 correlation increase, for a total of 60 time series. We then used our model to compute the changepoint probability for each point in every time series and evaluated changepoint detection performance between continuous and binary data.

### Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

## Data availability

Anonymized participant data for all our experiments are available via GitHub at https://github.com/graliuce/climate_change_detection/.

## Code availability

The code to run the analyses and reproduce the figures is available via GitHub at https://github.com/graliuce/climate_change_detection/.

## References


1. Lee, H. et al. *IPCC, 2023: Climate Change 2023: Synthesis Report, Summary for Policymakers. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (eds Core Writing Team, Lee, H. & Romero, J.) (IPCC, 2023).
2. Mirza, M. M. Q. Climate change, flooding in South Asia and implications. *Reg. Environ. Change* **11**, 95–107 (2011).
3. Jones, M. W. et al. *Climate Change Increases the Risk of Wildfires: January 2020* (ScienceBrief, 2020).
4. Lane, M. E., Kirshen, P. H. & Vogel, R. M. Indicators of impacts of global climate change on us water resources. *J. Water Resour. Plan. Manag.* **125**, 194–204 (1999).
5. Hatfield, J. L. et al. Indicators of climate change in agricultural systems. *Clim. Change* **163**, 1719–1732 (2020).
6. Egan, P. J. & Mullin, M. Recent improvement and projected worsening of weather in the united states. *Nature* **532**, 357–360 (2016).
7. Hansen, J., Sato, M., Glascoe, J. & Ruedy, R. A common-sense climate index: is climate changing noticeably? *Proc. Natl Acad. Sci. USA* **95**, 4113–4120 (1998).
8. Jackson, J. & Jacquet, J. in *Ecosystem Approaches to Fisheries* (eds Christensen, V. & Maclean, J.) 128–141 (2011).
9. Moore, F. C., Obradovich, N., Lehner, F. & Baylis, P. Rapidly declining remarkability of temperature anomalies may obscure public perception of climate change. *Proc. Natl Acad. Sci. USA* **116**, 4905–4910 (2019).
10. Roberts, D. The scariest thing about global warming (and COVID-19): 'shifting baselines syndrome' means we could quickly get used to climate chaos. *Vox* https://www.allsides.com/news/2020-07-08-0454/scariest-thing-about-global-warming-and-covid-19 (5 December 2020).
11. Li, Y., Johnson, E. J. & Zaval, L. Local warming: daily temperature change influences belief in global warming. *Psychol. Sci.* **22**, 454–459 (2011).
12. Egan, P. J. & Mullin, M. Turning personal experience into political attitudes: the effect of local weather on Americans' perceptions about global warming. *J. Polit.* **74**, 796–809 (2012).
13. Zaval, L., Keenan, E. A., Johnson, E. J. & Weber, E. U. How warm days increase belief in global warming. *Nat. Clim. Change* **4**, 143–147 (2014).
14. Broomell, S. B., Winkles, J.-F. & Kane, P. B. The perception of daily temperatures as evidence of global warming. *Weather Clim. Soc.* **9**, 563–574 (2017).
15. Howe, P. D., Marlon, J. R., Mildenberger, M. & Shield, B. S. How will climate change shape climate opinion? *Environ. Res. Lett.* **14**, 113001 (2019).
16. Hazlett, C. & Mildenberger, M. Wildfire exposure increases pro-environment voting within democratic but not republican areas. *Am. Polit. Sci. Rev.* **114**, 1359–1365 (2020).
17. Luo, Y. & Zhao, J. Attentional and perceptual biases of climate change. *Curr. Opin. Behav. Sci.* **42**, 22–26 (2021).
18. Marlon, J. R. et al. Hot dry days increase perceived experience with global warming. *Glob. Environ. Change* **68**, 102247 (2021).
19. Rocklöv, J. Misconceptions of global catastrophe. *Nature* **532**, 317–318 (2016).
20. Howe, P. D. Extreme weather experience and climate change opinion. *Curr. Opin. Behav. Sci.* **42**, 127–131 (2021).
21. Wappenhans, T., Valentim, A., Klüver, H. & Stoetzer, L. F. Extreme weather events do not increase political parties' environmental attention. *Nat. Clim. Change* https://doi.org/10.1038/s41558-024-02024-z (2024).
22. Marlon, J. R. et al. Detecting local environmental change: the role of experience in shaping risk judgments about global warming. *J. Risk Res.* **22**, 936–950 (2019).
23. Sharpe, S. Telling the boiling frog what he needs to know: why climate change risks should be plotted as probability over time. *Geosci. Commun.* **2**, 95–100 (2019).
24. Sharma, S., Blagrave, K., Filazzola, A., Imrit, M. & Hendricks Franssen, H.-J. Patterns of ice cover for 31 lakes in the northern hemisphere. *figshare* https://doi.org/10.6084/m9.figshare.13043078.v1 (2020).
25. Benson, B., Magnuson, J. & Sharma, S. Global lake and river ice phenology database, version 1. *National Snow and Ice Data Center* https://doi.org/10.7265/N5W66HP8 (2000).
26. Rohde, R. A. & Hausfather, Z. The Berkeley earth land/ocean temperature record. *Earth Syst. Sci. Data* **12**, 3469–3479 (2020).
27. Ajani, K. et al. Declutter and focus: empirically evaluating design guidelines for effective data communication. *IEEE Trans. Vis. Comput. Graph.* **28**, 3351–3364 (2021).
28. Feldman, L. & Hart, P. S. Is there any hope? How climate change news imagery and text influence audience emotions and support for climate mitigation policies. *Risk Anal.* **38**, 585–602 (2018).
29. Reeves, J., Chen, J., Wang, X. L., Lund, R. & Lu, Q. Q. A review and comparison of changepoint detection techniques for climate data. *J. Appl. Meteorol. Climatol.* **46**, 900–915 (2007).
30. Brown, S. D. & Steyvers, M. Detecting and predicting changes. *Cogn. Psychol.* **58**, 49–67 (2009).
31. Adams, R. P. & MacKay, D. J. Bayesian online changepoint detection. Preprint at https://arxiv.org/abs/0710.3742v1 (2007).
32. Cleveland, W. S. & McGill, R. Graphical perception: theory, experimentation, and application to the development of graphical methods. *J. Am. Stat. Assoc.* **79**, 531–554 (1984).
33. Shah, P. & Carpenter, P. A. Conceptual limitations in comprehending line graphs. *J. Exp. Psychol. Gen.* **124**, 43–61 (1995).
34. Carpenter, P. A. & Shah, P. A model of the perceptual and conceptual processes in graph comprehension. *J. Exp. Psychol. Appl.* **4**, 75–100 (1998).
35. Hegarty, M. The cognitive science of visual-spatial displays: implications for design. *Top. Cogn. Sci.* **3**, 446–474 (2011).
36. McMahon, R., Stauffacher, M. & Knutti, R. The unseen uncertainties in climate change: reviewing comprehension of an IPCC scenario graph. *Clim. Change* **133**, 141–154 (2015).
37. Harold, J., Lorenzoni, I., Shipley, T. F. & Coventry, K. R. Cognitive and psychological science insights to improve climate change data visualization. *Nat. Clim. Change* **6**, 1080–1089 (2016).

38. Newell, R., Dale, A. & Winters, C. A picture is worth a thousand data points: exploring visualizations as tools for connecting the public to climate change research. *Cogent Soc. Sci.* **2**, 1201885 (2016).
39. Wardekker, A. & Lorenz, S. The visual framing of climate change impacts and adaptation in the IPCC assessment reports. *Clim. Change* **156**, 273–292 (2019).
40. Harold, J., Lorenzoni, I., Shipley, T. F. & Coventry, K. R. Communication of IPCC visuals: IPCC authors' views and assessments of visual complexity. *Clim. Change* **158**, 255–270 (2020).
41. Li, N. & Molder, A. L. Can scientists use simple infographics to convince? Effects of the 'flatten the curve' charts on perceptions of and behavioral intentions toward social distancing measures during the covid-19 pandemic. *Public Underst. Sci.* **30**, 898–912 (2021).
42. Hawkins, E. Warming stripes for 1850–2018 using the WMO annual global temperature dataset. *Climate Lab Book* https://www.climate-lab-book.ac.uk/2018/2018-visualisation-update/ (2018).
43. Chinnis, J. O. Jr & Peterson, C. R. Nonstationary processes and conservative inference. *J. Exp. Psychol.* **84**, 248–251 (1970).
44. Theios, J., Brelsford, J. W. & Ryan, P. Detection of change in nonstationary binary sequences. *Percept. Psychophys.* **9**, 489–492 (1971).
45. Barry, D. M. & Pitz, G. F. Detection of change in nonstationary, random sequences. *Organ. Behav. Hum. Perform.* **24**, 111–125 (1979).
46. Massey, C. & Wu, G. Detecting regime shifts: the causes of under- and overreaction. *Manag. Sci.* **51**, 932–947 (2005).
47. Kremer, M., Moritz, B. & Siemsen, E. Demand forecasting behavior: system neglect and change detection. *Manag. Sci.* **57**, 1827–1843 (2011).
48. Levari, D. E. et al. Prevalence-induced concept change in human judgment. *Science* **360**, 1465–1467 (2018).
49. Gilovich, T., Vallone, R. & Tversky, A. The hot hand in basketball: on the misperception of random sequences. *Cogn. Psychol.* **17**, 295–314 (1985).
50. Zhao, J., Hahn, U. & Osherson, D. Perception and identification of random events. *J. Exp. Psychol. Hum. Percept. Perform.* **40**, 1358–1371 (2014).
51. Yu, R. Q., Osherson, D. & Zhao, J. Alternation blindness in the representation of binary sequences. *J. Exp. Psychol. Hum. Percept. Perform.* **44**, 493–502 (2018).
52. Lee, M. D. & Vickers, D. *Psychological Approaches to Data Visualisation* DSTO Research Report DSTO–RR–0135 (DSTO, 1998).
53. Lee, M. D., Butavicius, M. A. & Reilly, R. E. Visualizations of binary data: a comparative evaluation. *Int. J. Hum. Comput. Stud.* **59**, 569–602 (2003).
54. Shah, P., Freedman, E. G. & Vekiri, I. in *The Cambridge Handbook of Visuospatial Thinking* 426–476 (2005).
55. Franconeri, S. L., Padilla, L. M., Shah, P., Zacks, J. M. & Hullman, J. The science of visual data communication: what works. *Psychol. Sci. Public Interest* **22**, 110–161 (2021).
56. Leviston, Z., Price, J. & Bishop, B. Imagining climate change: the role of implicit associations and affective psychological distancing in climate change responses. *Eur. J. Soc. Psychol.* **44**, 441–454 (2014).
57. Wong-Parodi, G. & Feygina, I. Engaging people on climate change: the role of emotional responses. *Environ. Commun.* **15**, 571–593 (2021).
58. Dubey, R., Hardy, M. D., Griffiths, T. L. & Bhui, R. AI-generated visuals of car-free US cities help improve support for sustainable policies. *Nat. Sustain.* **7**, 399–403 (2024).
59. O'Brien, E. & Klein, N. The tipping point of perceived change: asymmetric thresholds in diagnosing improvement versus decline. *J. Pers. Soc. Psychol.* **112**, 161–185 (2017).
60. O'Brien, E. When small signs of change add up: the psychology of tipping points. *Curr. Dir. Psychol. Sci.* **29**, 55–62 (2020).
61. Trope, Y. & Liberman, N. Construal-level theory of psychological distance. *Psychol. Rev.* **117**, 440–463 (2010).
62. Spence, A., Poortinga, W. & Pidgeon, N. The psychological distance of climate change. *Risk Anal. Int. J.* **32**, 957–972 (2012).
63. Brügger, A., Morton, T. A. & Dessai, S. 'Proximising' climate change reconsidered: a construal level theory perspective. *J. Environ. Psychol.* **46**, 125–142 (2016).
64. Lamberson, P. et al. Tipping points. *Q. J. Polit. Sci.* **7**, 175–208 (2012).
65. Fisher, M. & Keil, F. C. The binary bias: a systematic distortion in the integration of information. *Psychol. Sci.* **29**, 1846–1858 (2018).
66. Fisher, M., Newman, G. E. & Dhar, R. Seeing stars: how the binary bias distorts the interpretation of customer ratings. *J. Consum. Res.* **45**, 471–489 (2018).
67. Sparkman, G. & Walton, G. M. Dynamic norms promote sustainable behavior, even if it is counternormative. *Psychol. Sci.* **28**, 1663–1674 (2017).
68. Pauly, D. et al. Anecdotes and the shifting baseline syndrome of fisheries. *Trends Ecol. Evol.* **10**, 430 (1995).
69. Papworth, S. K., Rist, J., Coad, L. & Milner-Gulland, E. J. Evidence for shifting baseline syndrome in conservation. *Conserv. Lett.* **2**, 93–100 (2009).
70. Frederick, S. & Loewenstein, G. in *Well-Being: The Foundations of Hedonic Psychology* (eds Kahneman, D. et al.) 302–329 (Russell Sage Foundation, 1999).
71. Dubey, R., Griffiths, T. L. & Dayan, P. The pursuit of happiness: a reinforcement learning perspective on habituation and comparisons. *PLoS Comput. Biol.* **18**, e1010316 (2022).
72. Burkett, V. R. et al. Nonlinear dynamics in ecosystem response to climatic change: case studies and policy implications. *Ecol. Complex.* **2**, 357–394 (2005).
73. Schlenker, W. & Roberts, M. J. Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proc. Natl Acad. Sci. USA* **106**, 15594–15598 (2009).


## Acknowledgements

We thank D. Yu, G. Vecchi, M. Ross, R. Bhui, S. Dikker, W. J. Ma and Z. Dulberg for comments and discussions. This work was supported by funds from the NOMIS foundation to T.L.G. The funders had no role in the study design, data collection and analysis, decision to publish or preparation of the manuscript.

## Author contributions

All authors developed the study concept. G.L. developed the software, conducted the experiments and analysed the data with contributions from R.D. G.L. and J.C.S. conducted the model simulations. R.D. and T.L.G. supervised the study design and model development. All authors discussed and interpreted the results. G.L. and R.D. drafted the paper, and J.C.S. and T.L.G. provided critical revisions. All authors approved the final version of the paper for submission.

## Competing interests

The authors declare no competing interests.

## Additional information

**Supplementary information** The online version contains supplementary material available at https://doi.org/10.1038/s41562-025-02183-9.

**Correspondence and requests for materials** should be addressed to Grace Liu or Rachit Dubey.

https://doi.org/10.1038/s41562-025-02183-9

**Peer review information** *Nature Human Behaviour* thanks Nathan Geiger, Joel Ginn and Johannes Reichl for their contribution to the peer review of this work. Peer reviewer reports are available.

**Reprints and permissions information** is available at www.nature.com/reprints.

# nature portfolio

Corresponding author(s): Rachit Dubey, Grace Liu

Last updated by author(s): Mar 3, 2025

# Reporting Summary

Nature Portfolio wishes to improve the reproducibility of the work that we publish. This form provides structure for consistency and transparency in reporting. For further information on Nature Portfolio policies, see our Editorial Policies and the Editorial Policy Checklist.

## Statistics

For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

| n/a | Confirmed | |
|---|---|---|
| ☐ | ☒ | The exact sample size (*n*) for each experimental group/condition, given as a discrete number and unit of measurement |
| ☐ | ☒ | A statement on whether measurements were taken from distinct samples or whether the same sample was measured repeatedly |
| ☐ | ☒ | The statistical test(s) used AND whether they are one- or two-sided<br>*Only common tests should be described solely by name; describe more complex techniques in the Methods section.* |
| ☐ | ☒ | A description of all covariates tested |
| ☐ | ☒ | A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons |
| ☐ | ☒ | A full description of the statistical parameters including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals) |
| ☐ | ☒ | For null hypothesis testing, the test statistic (e.g. $F$, $t$, $r$) with confidence intervals, effect sizes, degrees of freedom and $P$ value noted<br>*Give P values as exact values whenever suitable.* |
| ☒ | ☐ | For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings |
| ☒ | ☐ | For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes |
| ☐ | ☒ | Estimates of effect sizes (e.g. Cohen's $d$, Pearson's $r$), indicating how they were calculated |

*Our web collection on statistics for biologists contains articles on many of the points above.*

## Software and code

Policy information about availability of computer code

| | |
|---|---|
| Data collection | We collected our data using the online platform Prolific. Our experiment was coded using HTML5 and Javascript ES2023. Data analysis and model simulations were performed using Python 3.13.2. All code and data is available in this public repository: https://github.com/graliuce/climate_change_detection/tree/main |
| Data analysis | We collected our data using the online platform Prolific. Our experiment was coded using HTML5 and Javascript ES2023. Data analysis and Data analysis and model simulations were performed using custom code written in Python 3.13.2. All code and data is available in this public repository: https://github.com/graliuce/climate_change_detection/tree/main |

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Portfolio guidelines for submitting code & software for further information.

## Data

Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A description of any restrictions on data availability
- For clinical datasets or third party data, please ensure that the statement adheres to our policy

Anonymized participant data for all our experiments is available here: https://github.com/graliuce/climate_change_detection/tree/main

## Research involving human participants, their data, or biological material

Policy information about studies with human participants or human data. See also policy information about sex, gender (identity/presentation), and sexual orientation and race, ethnicity and racism.

| | |
|---|---|
| Reporting on sex and gender | This information was not collected as our central hypothesis and research questions are not dependent on these factors. |
| Reporting on race, ethnicity, or other socially relevant groupings | This information was not collected as our central hypothesis and research questions are not dependent on these factors. |
| Population characteristics | See above |
| Recruitment | For all studies, we collected data using the online research platform Prolific. All participants were blind to the study purposes and they were recruited in a randomized manner using Prolific. The researchers were blind to which conditions the participants were assigned during the study. We note that caution should be exercised when generalizing our results beyond participants that don't use the Prolific platform.<br><br>All participants took part in our study using Computer (through an online interface). No researcher was present with the participants when they took our study -- participants took part in the study online through their personal computer. |
| Ethics oversight | All experiments were approved by the Princeton's IRB board. Informed consent was obtained from the participants prior to their participation, the text of which was approved by the Princeton's IRB board. |

Note that full information on the approval of the study protocol must also be provided in the manuscript.

# Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☒ Behavioural & social sciences ☐ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

# Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

| | |
|---|---|
| Study description | All studies reported in the paper are Quantitative.<br><br>In Experiment 1, participants were first introduced to a fictional town called Townsville, known for its chilly winters and ice-skating activities on the local lake during the holiday months. Participants were then randomly assigned to one of two conditions: the “continuous” condition or the “binary” condition (see Methods). Crucially, the binary and continuous datasets were generated with matched correlation levels, ensuring that any differences in perception could be attributed to the format of presentation rather than selective data manipulation. In the “continuous” condition, participants viewed one of 18 graphs showing Townsville’s average winter temperature history from 1939 to 2019. In the “binary” condition, they viewed one of 18 graphs depicting whether the lake froze completely during the same period. Importantly, the graphs for both conditions were generated in pairs with matched correlations, ranging from 0.1 to 0.7. After viewing the graphs, participants rated, on a scale of 1 – 10, their perceived impact of climate change on the fictional town, the extent of change in the town’s temperature, and their perception of change in the frequency of lake freeze.<br><br>In Experiment 2, to increase the ecological validity of our findings, we conducted an experiment with real-world lake freeze and temperature data. Participants took part in an experiment similar to Experiment 1. In the “binary” condition, participants viewed one of the five graphs depicting lake freeze history, while in the “continuous” condition, they saw one of the five graphs showing winter temperature history. Unlike Experiment 1, where participants were informed that the data came from a fictional town, this time, they received contextual information about the actual lake, including its location and recreational activities offered in the lake (e.g., ice skating, ice fishing, or boating). |

| | |
|---|---|
| | In Experiment 3, participants were introduced to a fictional winter town and randomly assigned to either the “continuous” or “binary” condition (see Methods for details). In the “continuous” condition, participants viewed one of three graphs depicting the town’s average winter temperature. In the “binary” condition, they viewed one of three graphs showing whether the lake froze completely over time. After viewing the graphs, participants first answered a multiple-choice question on whether they observed a changepoint, defined as “any point which has a pronounced deviation from the typical pattern of temperature/freeze data.” They then used a slider to select the year in which they believed the data had undergone the largest shift. Finally, participants rated their perceived impact of climate change on the town, the extent of temperature change, and the frequency of lake freezing on a scale of 1 – 10. |
| Research sample | For our experiments, we generated paired time series with 80 data points each across a correlation range of 0.1 to 0.7. Each pair included a binary and a continuous time series with matched correlations. To generate the binary data with the desired correlation, we employed an iterative algorithm that adjusted the slope and intercept of a linear model until the correlation fell within the specified range. The slope was determined through a linear search, and the y-intercept was set so that the probability of freezing was 0.5 at the midpoint of the time series, ensuring a smooth, gradual change in probability over time (refer to the SI for the algorithm’s pseudo-code).<br>For each binary time series, we generated the corresponding continuous data by applying a linear transformation to exactly match the correlation level. The transformed continuous data was then adjusted to match the mean and variance of winter temperatures from the Berkeley Earth dataset for 31 intermittently freezing lakes.<br><br>In Experiment 1, we recruited 799 US-based participants from the online research platform Prolific and paid them \$0.40 for participation (our study took approximately 2 minutes to complete).<br><br>In Experiment 2, we recruited 247 US-based participants from the online research platform Prolific and paid them \$0.40 for participation (our study took approximately 2 minutes to complete).<br><br>In Experiment 3, we recruited 398 US-based participants from the online research platform Prolific and paid them \$0.40 for participation (our study took approximately 2 minutes to complete).<br><br>We didn't collect any demographic information from the subjects (note that our sample wasn't a representative sample). We choose to use this sample for our experiments because our aim was to test the general effects of continuous data and binary data on perception of climate change (independent of characteristics such as gender, age, etc). |
| Sampling strategy | In Experiment 1, 2, and 3, participants were randomly assigned to one of the two conditions -- the continuous or the binary condition. The sample size for all studies was chosen based on a power analysis based on the results of prior pilot studies. Importantly, we chose the sample size prior to collecting the data (which is noted in the pre-registrations as well). |
| Data collection | For all studies, we collected data using the online research platform Prolific. All participants were blind to the study purposes and which condition they were assigned to. The researchers were also blind to which conditions the participants were assigned during the study.<br><br>All participants took part in our study using Computer (through an online interface). No researcher was present with the participants when they took our study -- participants took part in the study online through their personal computer. |
| Timing | Experiment 1 data was collected over 3 days from June 1-3, 2024.<br>Experiment 2 data was collected over 2 days from Aug 10-12, 2024<br>Experiment 3 data was collected over 2 days from Jul 5-7, 2024 |
| Data exclusions | In Experiment 1, participants who failed a simple attention check or spent less than 2 seconds viewing the graphs were excluded, following pre-registered exclusion criteria. This resulted in the exclusion of 33 participants, leaving a final sample of 766 participants (N = 379 in the continuous condition and N = 387 in the binary condition).<br><br>In Experiment 2, the exclusion criteria were applied again, resulting in the exclusion of 12 participants. The final sample included 235 participants (N = 119 in the continuous condition and N = 116 in the binary condition).<br><br>In Experiment 3, the same exclusion guidelines were followed, leading to the exclusion of 8 participants. The final sample consisted of 392 participants (N = 185 in the continuous condition and N = 207 in the binary condition). |
| Non-participation | This data was not collected as the recruitment was done via the online platform Prolific (participants could freely decide to drop the study anonymously). |
| Randomization | In all experiments i.e., Experiments 1,2, and 3, participants were randomly assigned to one of two conditions -- the continuous or the binary condition. |

# Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

## Materials & experimental systems

| n/a | Involved in the study |
|---|---|
| ☒ | ☐ Antibodies |
| ☒ | ☐ Eukaryotic cell lines |
| ☒ | ☐ Palaeontology and archaeology |
| ☒ | ☐ Animals and other organisms |
| ☒ | ☐ Clinical data |
| ☒ | ☐ Dual use research of concern |
| ☒ | ☐ Plants |

## Methods

| n/a | Involved in the study |
|---|---|
| ☒ | ☐ ChIP-seq |
| ☒ | ☐ Flow cytometry |
| ☒ | ☐ MRI-based neuroimaging |

## Plants

| | |
|---|---|
| Seed stocks | N/A |
| Novel plant genotypes | N/A |
| Authentication | N/A |