Binary climate data heightens perceived impact of climate change

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ABSTRACT

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 behavioral experiments, we show that presenting people with binary climate data (e.g., lake freeze history) significantly heightens the perceived impact of climate change compared to continuous data (e.g., mean temperature). Computational modeling and follow-up experiments suggest that binary data elevates perceived impact because it creates an "illusion" of sudden shifts. This effect is robustly confirmed through multiple replications and an experiment with real-world freeze and temperature data. These findings provide a cognitive basis for the "boiling frog" effect and offer a novel approach for policymakers and educators to better communicate the urgency of climate change.

Human-caused climate change is already resulting in significant 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 significant 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: growing indifference toward the crisis. Since most people's climate change judgments are significantly shaped by their personal experiences[8–14], and because most local climates are becoming unstable only at a gradual pace, societies are adjusting to worsening environmental conditions disturbingly fast[6,15–17]. For instance, a recent survey of Floridians found that many people were unable to detect five-year temperature increases, with their risk perceptions more strongly influenced by personal beliefs and political affiliation than by actual temperature changes[18]. 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[19,20].

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 significant strides in understanding the causes and consequences of the "boiling frog" effect, finding ways to break through the indifference remains a significant 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 behavioral experiments and computational modeling to explore how gradually changing climate data influences perceptions of climate change and identify which data patterns can counteract this effect.

To preview our findings, using a pre-registered behavioral experiment ($N = 799$), we show that people perceive climate change as having a greater impact when presented with binary climate data (e.g., historical trend of lake freeze) compared to continuous climate data (e.g., historical trend of mean winter temperature), even with matched correlation levels. This finding is robust and reproducible, as confirmed by multiple replication studies. A follow-up experiment ($N = 398$) reveals that binary data enhances perceived impact because it creates an "illusion" of sudden changes, even when the underlying data shifts incrementally. To provide a cognitive basis for this illusion, we employ computational modeling 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. Finally, a follow-up experiment with real-world lake freeze and temperature data ($N = 247$) shows that participants consistently perceive climate change as more severe with lake freeze data than with temperature data.

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 novel approach to making the gradual effects of climate change more salient to the public.

Results

Experiment 1: Climate change is more salient in binary climate data

To investigate how gradual changes can be made more salient, we conducted a large-scale, pre-registered behavioral experiment ($N = 799$), examining how binary and continuous climate data influence people's perception of climate change. The pre-registration included the data collection protocol, stimuli, and the 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).

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. Crucially, the graphs for both conditions were generated in pairs with matched correlations, ranging from 0.1 to 0.7 (see Methods). Figure 1a 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 1b plots the ratings of the participants in both conditions. We first found that the perceived impact of climate change was significantly higher amongst participants in the "binary" condition (mean (M) $= 7.5$, s.d. $= 2.3$) compared to participants in the "continuous" condition (mean (M) $= 6.6$, s.d. $= 2.2$; $t(764) = 5.52, p < 0.0001$). This result was consistently observed across graphs of all correlation levels (see SI for details). Additionally, participants in the "binary" condition($M = 7.3$, s.d. $= 2.1$), who viewed the lake freeze graphs, counter-intuitively perceived a stronger trend in increasing temperatures than those in the "continuous" condition, who viewed the temperature graphs ($M = 6.6$, s.d. $= 2.2$; $t(764) = 4.48, p < 0.0001$). Finally, participants in the "binary" condition ($M = 7.5$, s.d. $= 2.2$) perceived the lake freeze frequency to have changed more significantly compared to those in the "continuous" condition ($M = 6.4$, s.d. $= 2.3$; $t(764) = 6.86, p < 0.0001$).

To ensure the robustness of these effects, we conducted a replication study ($N = 440$) and found that the perceived impact of climate change was again amplified in the "binary" condition compared to the "continuous" condition (refer to SI). To rule out a potential confound that participants might be failing to identify the increasing trend in the continuous data, we conducted a control experiment ($N = 301$) 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 SI for details).

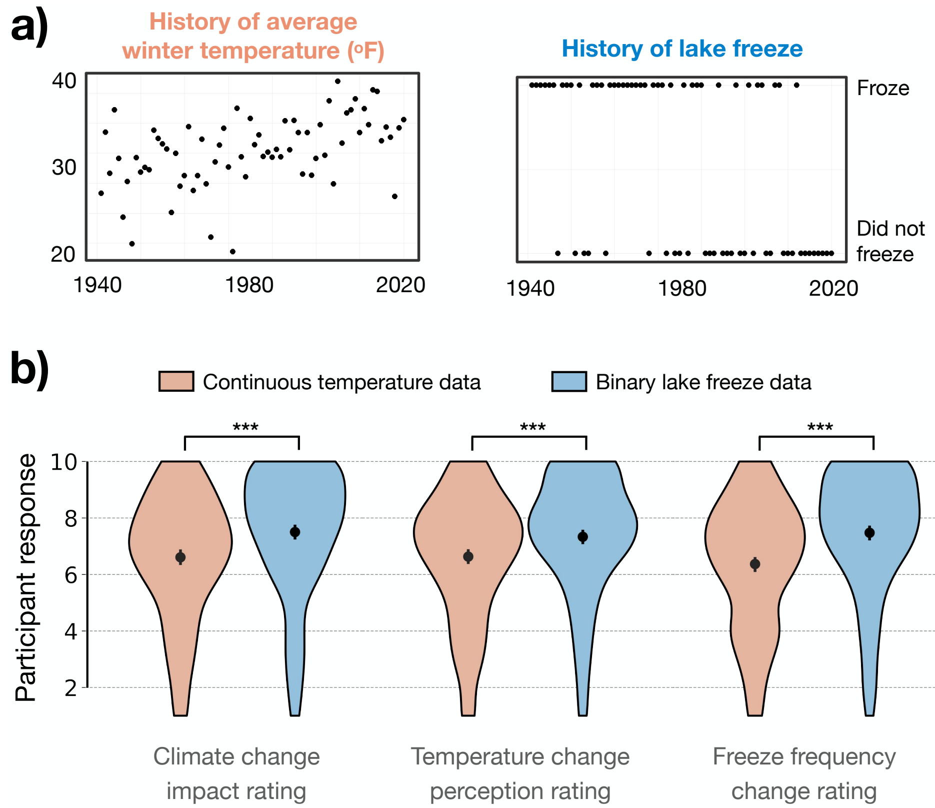

Figure 1. Binary data elevates perceived impact of climate change (a) Examples of graphs presented to participants in Experiment 1, showing the "continuous" condition (left) and the "binary" condition (right). Both graphs have the same correlation (= 0.47). **(b)** Participants in the "binary" condition rated the perceived impact of climate change, temperature change, and freeze frequency change significantly higher than those in the "continuous" condition. The violin plots (colored areas) are kernel density estimations; the means are indicated by black dots, and vertical lines represent standard errors.

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 to continuous data. This effect extends to both concrete changes (i.e., increasing winter temperatures) and less tangible climate change impacts.

Experiment 2: Binary data creates 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[21] and increased emotional valence[22], which we explore further in the 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[23,24]. 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 (see 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 pre-registered behavioral experiment ($N = 398$) to examine how people perceive changepoints in binary and continuous climate data (pre-registration 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

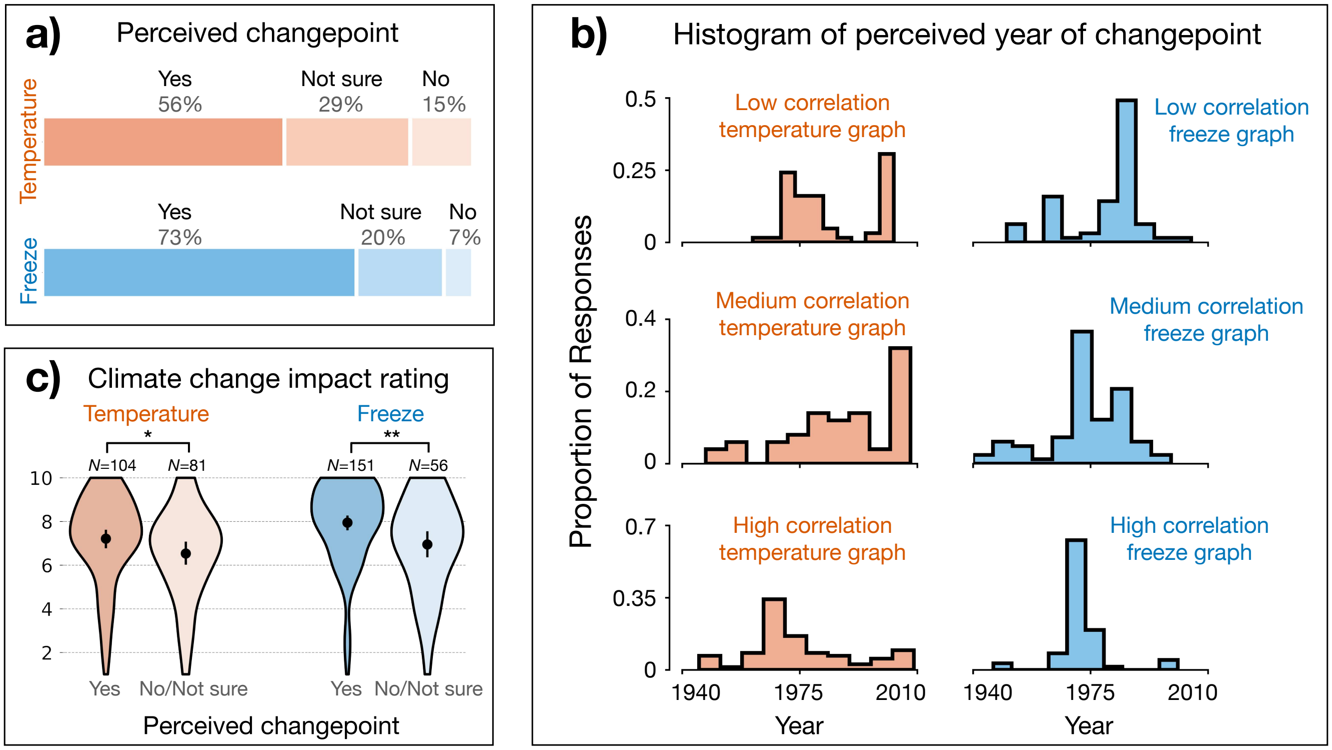

Figure 2. Results of Experiment 2. (a) Proportion of participants who responded Yes, Not Sure, and No to the question of whether a changepoint exists, shown for the "continuous" condition (top) and the "binary" condition (bottom). **(b)** Histograms displaying the frequency with which each year was identified 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.

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 most significant 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 2a 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 to those in the 'continuous' condition (proportion = 0.56), as confirmed by a two-sample Z-test of proportions ($z = -3.47, p < 0.0001$). Additionally, a higher proportion of participants did not perceive a changepoint in the "continuous" condition (proportion = 0.15) compared to the "binary" condition (proportion = 0.07, $z = 2.53, p = 0.011$). 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, $z = 2.05, p = 0.041$).

Participants who viewed the binary data also exhibited greater consensus on the location of the changepoints. Figure 2b 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 to 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, $F(390) = 31.91, p < 0.0001$, with the ratio of the empirical variances being 0.489. 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 (Figure 2c). Across both conditions, those who perceived a changepoint reported a higher impact of climate change ($M = 7.65$, $s.d. = 1.96$) compared to those who did not perceive a changepoint or were unsure ($M = 6.7$, $s.d. = 2.1$; $t(390) = 4.4$, $p < 0.0001$). This effect was evident in both conditions: In the "continuous" condition, perceiving a changepoint was associated with a higher reported impact ($M = 7.21$, $s.d. = 2.0$) compared to those who did not perceive a changepoint or were unsure ($M = 6.53$, $s.d. = 2.1$; $t(183) = 2.24$, $p = 0.026$). Similarly, in the "binary" condition, those who perceived a changepoint reported a higher climate impact ($M = 7.95$, $s.d. = 1.9$) compared to those who did not perceive a changepoint or were unsure ($M = 6.95$, $s.d. = 2.1$; $t(183) = 2.2$, $p = 0.013$).

These results suggest that when people perceive climate data as having undergone sudden shifts, then they are more likely to perceive greater climate impact. Binary data, in particular, is more likely to create the impression of abrupt changes, even when the underlying data shifts gradually. This tendency to perceive sudden shifts in binary data helps explain why people may perceive a greater impact of climate change compared to continuous data.

Simulation 1: 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 (e.g., coin flips), a shift might involve changing the probability of heads versus tails. In continuous data (e.g., temperature readings), it could mean a change in the average temperature. Using Bayesian modeling, 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 δ at position i indicates that the data before i follows a distribution with parameters θ_1, and the data after follows a different distribution with parameters θ_2[25].

Given the observed data $\mathbf{X}$, the probability of a changepoint at i i.e., $P(\delta = i|\mathbf{X})$, 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, modeling 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 $\{x_1, \dots, x_i\}$ are sampled from a Bernoulli distribution with parameter θ_1, and

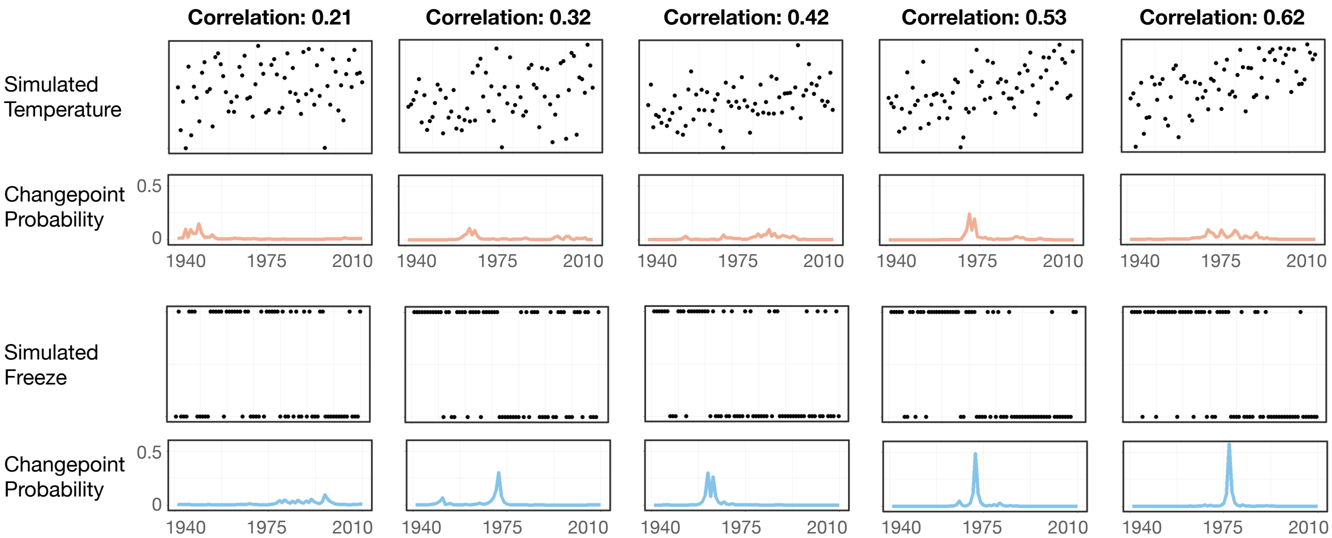

Figure 3. Simulation results. An illustration of how gradual changes are perceived as sudden changes in binary data. The top panel shows the changepoint probability output of the Bayesian model for various correlation levels in temperature data. In most graphs, there is a somewhat uniform distribution of changepoint probabilities, with no specific concentration at any point. In contrast, the bottom panel shows that binary data results 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.

$\{x_{i+1},\ldots,x_N\}$ are sampled from a Bernoulli distribution with parameter θ_2. Using Equation 1, the probability for a changepoint at i in the binary setting can be calculated as follows:

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

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 θ_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 θ_2.

For continuous data, we assume a Normal distribution, which is suitable for modeling continuously varying data like temperature readings. If a changepoint is present at i, the data before the changepoint is modeled by a Normal distribution with mean μ_1 and variance σ^2, and the data after i follows a Normal distribution with a different mean μ_2 and the same variance σ^2. The probability for a changepoint is calculated as follows:

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

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 the SI 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 to the entropy of the changepoint probability distributions for the continuous time series (mean Entropy = 3.3, s.d. = 0.5; $t(58) = -2.79, p = 0.01$).

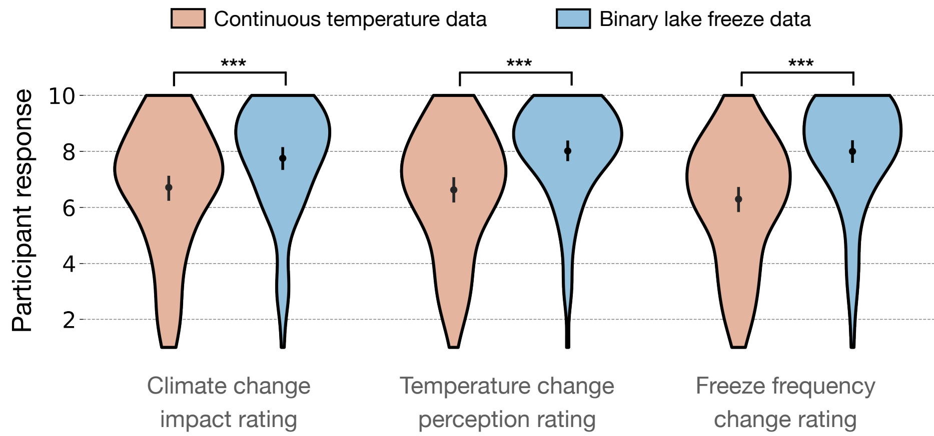

Figure 4. Results of Experiment 3 with real-world temperature and freeze data. Violin plots display participants' ratings of climate change impact, temperature change, and freeze frequency change for the two conditions. Means are indicated by black dots, and vertical lines represent standard errors. Participants in the "binary" condition again rated the impact of climate change higher compared to the "continuous" condition.

That is, similar to the human participants, the Bayesian model is also more likely to detect changepoints in binary data, as evidenced by higher probabilities and sharper peaks at specific points, alongside generally lower entropy. As an illustration, Figure 3 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 SI for details). This suggests that the apparent changepoints in binary data may be an inherent feature of binary patterns, whereas continuous data, with its implicit variance, naturally smoothes out gradual changes.

Experiment 3: 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 a replication of Experiment 1 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 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[26,27]. We then extracted historical mean winter temperatures for these lakes from the Berkeley Earth gridded temperature database[28], matching each lake's latitude and longitude coordinates with the corresponding temperature grid box (see 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, 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).

As shown in Figure 4, the perceived impact of climate change was significantly higher amongst participants in the "binary" condition (mean (M) = 7.76, s.d. = 2.0) compared to participants in the "continuous" condition ($M = 6.71$, s.d. = 2.3; $t(233) = 3.76, p < 0.0001$). Further, there was a significant difference in the perception of change in temperature between participants in the "binary" condition($M = 8.0$, s.d. = 1.8) and "continuous" condition ($M = 6.6$, s.d. = 2.2; $t(233) = 5.36, p < 0.0001$). Similarly, participants in the "binary" condition ($M = 8.0$, s.d. = 1.9) perceived the lake freeze frequency to have changed more significantly compared to those in the "continuous" condition ($M = 6.3$, s.d. = 1.7; $t(233) = 6.28, p < 0.0001$). These results extend our findings to real-world lake freeze and temperature data, orienting our findings toward practical climate communication applications. We also refer the readers to the SI for a replication of this experiment.

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's too late[19]. 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 behavioral studies, we demonstrate that presenting climate data in binary terms can make the impacts of climate change more salient compared to continuous data. Gradual shifts in binary data often create the perception of sudden changes, amplifying the perceived impact. While our study shows how progress can be made in enhancing the salience of climate change–an essential first step toward more meaningful engagement and response–future work should investigate how this work can be extended to drive concrete action.

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[29–32] and highlighted the importance of effective climate data visuals[33–38]. Our study contributes to this literature by emphasizing the value of binary climate graphs and suggesting key research directions for improving climate communication.

Beyond its practical implications, our work also makes significant 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[24,39–43]. These studies typically involve detecting changes in non-stationary environments–where data suddenly shifts from one distribution to another. In contrast, our study examined data that gradually shifted over time without sudden changes. In doing so, we uncovered a novel bias: 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[44]. However, unlike the "hot hand" studies, which explore perceptions of randomness[45,46], 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.

While our study primarily focused on how perceptions of changepoints might amplify the perceived impacts of climate change in binary data, it's 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 require less mental effort and are computationally easier to parse due to fewer value comparisons[21,47–50]. Another possibility is that lake freeze graphs might elicit stronger emotional responses than temperature graphs (e.g., 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 judgments[22,51–53] as well as perceptions of changes and tipping points[54,55]. To investigate this further, we conducted an additional experiment ($N = 200$; see SI for details) where we varied the emotional valence of binary graphs by using high valence ("Froze" vs. "Did not Freeze") versus low emotional labels ("Above 29° F" versus "Below 29° F") 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.

One reason why perceiving changepoints in binary data might enhance the perception of climate change is that these changepoints can signal a tipping point, leading people to believe that significant changes have occurred[54–56]. Additionally, 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[57,58]. Our study contributes to this literature by documenting a specific bias within the context of binary data perception.

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. A significant barrier to climate action is that people tend to rapidly adapt and habituate to worsening environmental conditions[59,60]. This tendency to adjust to new "normals," whether positive or negative, is a pervasive aspect of human behavior[61,62]. Future research should explore how sensitivity to persistent environmental changes evolves and whether binary data patterns could help 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?

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 (e.g., 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 is presented sequentially, as this approach could more accurately reflect how individuals encounter and process climate information in their daily lives.

Combating climate change apathy is a vital step towards slowing the progression of warming. We posit that building a comprehensive understanding of how people reason about change is key to overcoming this apathy. Given that climate impacts are often non-linear and threshold-bound[63,64], 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's a straightforward binary variable.

Methods

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 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).

For each binary time series, we generated the corresponding continuous data by applying a linear transformation to exactly match the correlation level (refer to SI for details). The transformed continuous data was then adjusted to match the mean and variance of winter temperatures from the Berkeley Earth dataset[28] for 31 intermittently freezing lakes[26]. All experiment stimuli and the code to generate them are publicly available here: `https://github.c` om/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. We then recruited 799 US-based participants from the online research platform Prolific and paid them US\$0.40 for participation (our study took approximately 2 minutes to complete). All experiments were approved by Princeton's Institutional Review Board. For this and the following experiments, informed consent was obtained from all participants before the experiments began.

Following the pre-registered exclusion criteria, we removed participants who did not pass a simple attention check question or those who viewed the graphs for less than two seconds. 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 here: 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 labeled 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

For the experiment, we generated 3 pairs of time series, totaling 6 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). We then recruited 398 US-based participants from the online research platform Prolific, paying US\$0.40 for participation (the study took approximately 2 minutes to complete). Following our pre-registered exclusion criteria, we removed participants who failed a simple attention check or viewed the graphs for less than two seconds, resulting in the exclusion of 8 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 5 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.

Experiment 3

We recruited 247 US-based participants from the online research platform Prolific, paying US$0.40 for participation (the study took approximately 2 minutes to complete). We removed participants who failed a simple attention check or viewed the graphs for less than two seconds, resulting in the exclusion of 12 participants. This left a final sample of 235 participants ($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[26], including freeze records for Lake Vattern from the NSIDC Global Lake and River Ice Phenology Database[27]. We then filtered the data to include only lakes with more than five no-freeze years in the 20th 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, February) for these lakes were extracted from the Berkeley Earth gridded temperature database[28], matched to the lakes' latitude and longitude coordinates.

Participants took part in a similar experiment 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.

Data Availability

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

Code Availability

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

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