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Research Articles

Communicating the Impact of Climate Change on Extreme Weather in India, the United Kingdom, and the United States

Laura Thomas-Walters [1], Matthew H. Goldberg [1], Eric G. Scheuch [1,2], Sanguk Lee [3], Jagadish Thaker [4], Aidan Lyde [1], Seth A. Rosenthal [1], Anthony Leiserowitz [1]

[1] *Yale Program on Climate Change Communication, Yale University, New Haven, CT, USA.* **[2]** *Department of Political Science, Yale University, New Haven, CT, USA.* **[3]** *Division of Media and Communication, Hankuk University of Foreign Studies, Seoul, Republic of Korea.* **[4]** *School of Communication and Arts, University of Queensland, Brisbane, Australia.*

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Corresponding Author: Matthew H. Goldberg, 205 Prospect Street., New Haven, CT 06511, USA. E-mail: matthew.goldberg@yale.edu

Badges for Good Research Practices: Code. Data. Materials. Preregistration.

Abstract

As climate change increasingly affects the likelihood and severity of extreme weather events such as flooding and heat waves around the world, it is more important than ever to encourage both mitigation and adaptation. As an important step, people need to understand the links between climate change and extreme weather. We conducted a preregistered online randomized experiment with over 10,000 participants across India, the UK, and the USA, three countries that are large annual emitters but have different patterns of extreme weather. We tested the impact of different numerical frames (percentage versus times) and types of extreme weather (heat waves versus flooding) on beliefs that climate change made extreme weather in 2023 more likely. All four message treatments had a significant effect, increasing the percentage of participants who believed climate change made extreme weather more likely by 4.5 to 6.1 percentage points. However, there was no main effect of specific event type or numerical framing. We found message treatments also increased worry about climate change in general, although impact on policy support or information-seeking behavior was limited. The findings of this study contribute to the scarce literature on which messages are effective at communicating extreme weather event attribution.

Keywords

extreme event attribution, climate change, extreme weather, environmental communication, numerical framing

Non-Technical Summary

Background

As global temperatures continue to rise, the frequency and severity of extreme weather such as heat waves and flooding will increase. Because of this, effectively communicating the links between extreme weather and climate change is vital.

Why was this study done?

Intensifying climate extremes will necessitate clear and timely information that allows individuals to better prepare for the increased likelihood of extreme weather in their area and recognize the risks and consequences of unaddressed climate change in order to spur individual behavior change and policy support.

What did the researchers do and find?

We conducted an online messaging experiment with over 10,000 adults in India, the UK, and the USA. We measured the impact of information about different types of extreme weather (flooding versus heat waves) on beliefs that climate change made extreme weather in 2023 more likely. We also tested the effectiveness of different numerical frames, namely times versus percentages. We found that just a short, simple phrase that links climate change to extreme weather can significantly impact even distant outcomes like climate change worry and support for government action. However, there was no difference in the impact of numerical framing nor type of extreme weather event. Indeed, there are spillover effects of attribution messages from one type of extreme weather to the other — attributing increased flooding to climate change affects beliefs about heat waves, and vice versa.

What do these findings mean?

Our findings suggest that, rather than focusing resources on testing different wording and frames, it may be more important that people simply hear about the links between climate change and extreme weather. However, we acknowledge that we only vary one framing (the framing of magnitude) and it is possible that other framing variations would produce greater heterogeneity in treatment effects.

Highlights

- Informing people about the impact of climate change on extreme weather events such as heat waves and flooding successfully increased beliefs that climate change made extreme weather in 2023 more likely.
- This is the case regardless of the specific event type or numerical framing.
- There are spillover effects of attribution messages from one type of extreme weather to the other — attributing increased flooding to climate change affects beliefs about heat waves, and vice versa.
- Message treatments can also increase worry about climate change in general, although further impact on more distal outcomes such as policy support or information-seeking behavior is limited.

Extreme weather poses a growing threat to both human communities and natural ecosystems around the world. Climate change is exacerbating the incidence of extreme weather events, making droughts, heat waves, floods, tropical cyclones, and other extreme weather events more likely and severe (IPCC, 2023). As climate change increases the frequency and severity of extreme weather events, the costs of such events are also growing (Newman & Noy, 2023). The impacts of extreme weather include damage to infrastructure, economic losses, food insecurity, and increased human mortality and morbidity (IPCC, 2023). Extreme weather events also threaten natural ecosystems, decreasing biological productivity (Anderegg et al., 2015), increasing vulnerability to other environmental hazards such as pests (Trottier et al., 2017), and reducing ecosystem resilience, or the ability of ecosystems to adapt to longer-term changes in the climate (Turner et al., 2020).

Two prominent examples of climate-change-amplified extreme weather are heat waves and flooding. Heat waves pose a particularly deadly risk to public health by greatly increasing pressure on people's cardiovascular and respiratory systems (Basu & Samet, 2002), leading to increases in morbidity and mortality across the population (Lüthi et al., 2023). Floods meanwhile impose devastating and widespread impacts, including destruction of physical infrastructure and agricultural assets, loss of life, and billions of dollars in damages annually (Bubeck et al., 2017). These events can also aggravate existing chronic mental health issues and be a traumatic experience causing mental health symptoms in their own right (Shukla, 2013). These mental health effects are consistent and vast: with one systematic review finding every case of extreme weather was accompanied by an increase in mental health symptoms, with increases as large as 52% (Rataj et al., 2016). The health impacts of extreme weather occur in both developed and developing countries, with effects documented in all three of our chosen countries, the UK (Cruz et al., 2020), India (Rataj et al., 2016), and the United States (Ahmadiani & Ferreira, 2021).

Extreme Event Attribution

Extreme event attribution (EEA) is the science of determining the extent to which a specific weather event of a severe or unusual nature can be linked to human-caused climate change (Naveau et al., 2020). Advances in EEA now allow for near-real-time analyses to determine how much more likely individual extreme weather events were made by climate change (Swain et al., 2020). Moreover, EEA enables detecting the influence of climate change on daily local weather events and temperature (Gilford et al., 2022; Sippel et al., 2020). For example, the Climate Shift Index (CSI) establishes how much more likely a given air temperature in a specific location has been made by climate change (Climate Central, 2024). EEA can thus support the communication of the links between extreme weather and climate change with scientifically robust messages.

Compared to the advances in attribution science, there has been less research on the communication of EEA, with much of the existing literature focusing on communicating about extreme weather events themselves, rather than how they are attributable to climate change. Communicating the risk posed by extreme weather and its connection to climate change is vital for several reasons. First, the risk of extreme weather to human health and well-being is hard to overstate and communicating that reality is key to increasing individual and societal preparedness for extreme weather, which can help blunt many of its worst impacts (Voskamp & Van de Ven, 2015). Second, given the link between extreme weather experience and climate change attitudes (Marlon et al., 2021), extreme weather events provide important windows of opportunity to shift knowledge and attitudes in a pro-climate direction. Such attitudinal shifts can potentially encourage climate mitigation actions, which in turn, can help lessen the risk of future extreme weather. Crucially, extreme weather attribution offers an opportunity to illustrate that climate change is a current threat, not just a future one (Ettinger et al., 2021). Finally, there is a large gap between public perceptions of the link between climate change and extreme weather and the scientific consensus on the topic (Zanocco et al., 2024). Research on communicating this link can therefore help close that gap.

The Role of Frames

One important question in studying the communication of EEA is whether the type of numerical frame used has an effect. Previous research indicates that the terms used to describe numbers (e.g., absolute vs. relative terminology) can have a substantial impact on how respondents interpret those numbers and adjust their views accordingly (Boyce-Jacino et al., 2022). This may be the result of various cognitive biases such as the numerosity heuristic, whereby people over-infer quantity or probability from numerosity (i.e., they believe something is larger or more likely just because it has more units; Pelham et al., 1994). There is also evidence from neuropsychology that people mentally process small and large numbers differently (Roger et al., 2018). In the context of extreme weather, Thomas-Walters and colleagues (2024) tested the Climate Shift Index as a tool for communicating the link between climate change and the July 2023 heat wave in the United States. They found that numerical framing matters, with framing heat wave attribution in percentage terms (i.e., 400% more likely) slightly more effective than the standard CSI framing, which phrases events in terms of magnitudinal increases (e.g., 5 times more likely). However, they tested impacts in only one country, the US, and looked at messaging around a specific event, both of which leaves unknown the communication potential for messaging about extreme weather generally.

Further, people might respond differently to information about different types of extreme weather events. Some types of extreme weather (e.g., heat waves) are more widely experienced or more easily connected to climate change than others (e.g., flooding; Luber & McGeehin, 2008). They also affect different geographical communities. Reactions to extreme weather information might also be different depending on people's existing risk perceptions and previous exposure to extreme weather events (Demski et al., 2017; Marlon et al., 2021; Valentim, 2021).

Study Context

In this study, we test how reactions to information about extreme weather attribution vary according to both the numerical framing and type of extreme weather event. More specifically, we examine if framing the link as a "percentage" or "times"[1] is more effective, and if the effect differs depending on the specific event emphasized in the message (heat waves vs. flooding). We examine whether previous findings replicate, while also extending the work beyond a single event, beyond a single type of event, and beyond a single country. We use a three-country comparison (India, the UK, and the US) to evaluate how reactions to the link between extreme weather and climate change might differ across countries with different cultural beliefs, political contexts, and experiences with extreme weather. We chose these three countries because, in addition to being three large emitters, either historically (UK), presently (India), or both (US), they also have different patterns of extreme weather events and very different baseline attitudes towards climate change (Leiserowitz et al., 2023).

Each of these three countries are prone to extreme weather events. The United States has experienced an increase in the frequency, severity, and associated costs of extreme weather events over the last several decades. These include heat waves, extreme precipitation, hurricanes, wildfires, drought, and thunderstorms (USGCRP, 2023). The United Kingdom is primarily vulnerable to changes in temperature and precipitation, and climate change is making warmer and wetter climate conditions there more likely (Hanlon et al. 2021; Kendon et al., 2023). In India, extreme heat (Rohini et al., 2016),

1) Note, we use "times" here to mean magnitude or multiplier.

extreme precipitation (Roxy et al., 2017), droughts, flooding, and tropical cyclones have generally increased in frequency and severity (Krishnan et al., 2020).

The people in these three countries also have different baseline beliefs and attitudes towards extreme weather and climate change. In the US, for example, ideology and political partisanship are more important predictors of climate change beliefs than are experiences with extreme weather (Konisky et al., 2016; Lyons et al., 2018; Zanocco et al., 2024). In the UK, the risks associated with heat can be downplayed because, in a country that tends to be cold and wet, heat is often perceived as positive (Taylor et al., 2014). As a result, flooding and wet weather has more tangible impacts and is thus more relevant for enhancing climate change concerns than warm weather (Taylor et al., 2014). While many people in India have observed changes in local weather patterns, most report that they know little to nothing about climate change (Leiserowitz et al., 2024). However, after being given a short definition of global warming, a majority of Indians report that global warming is happening, is caused by human activity, and is causing changes in local weather patterns (Leiserowitz et al., 2024). But there is little research on how we can best communicate the connections between extreme weather and climate change in India.

In summary, few studies have tested how best to communicate the link between extreme weather and climate change; in particular, the effectiveness of different numerical frames. Additionally, almost no studies have examined how effective framing of climate change's effects on extreme weather may vary by country, shaped by important political and social context that defines how climate messages are received. Finally, few studies have made side-by-side comparisons between different types of extreme weather events to see if the type of event in question matters to communication efficacy.

In an online messaging experiment, we test the impact of different numerical frames and types of extreme weather on the belief that climate change made extreme weather in 2023 more likely, as well as several secondary outcomes, such as worry about climate change and support for government action to address climate change. We do this across three countries and also examine individual differences in treatment effects (i.e., do treatments have more impact for people who report having been exposed to/harmed by flooding or heat waves in their local area?). We compare treatments to both a pure control (a message about an unrelated topic) and an active control (which discusses extreme weather events without linking them to climate change). We also explore how treatment effects are moderated by baseline beliefs. We have five preregistered hypotheses:

H1: Every treatment will outperform the controls for all main dependent measures.
H2: The active control will have a small positive effect compared to the pure control.
H3: The "percentage" framing will outperform the "times" framing.
H4: Treatments will have more impact for people who report having been exposed to flooding or heat waves in their local area.
H5: Pre-test differences in beliefs between the 3 countries will explain differences in the effectiveness of the treatments.

Method

The materials, data, analysis code, and preregistration needed to reproduce this experiment and corresponding analyses are available on our Open Science Framework (OSF) page (see Thomas-Walters et al., 2025). All analyses were preregistered unless stated otherwise. Our research protocol was exempt from review by the Yale University Institutional Review Board. All subjects gave informed consent.

Sample

Data were collected from April 15, 2024 to June 2, 2024. Adults living in the US, UK, and India were recruited from the Dynata panel. For our US and UK samples, we used quotas for age, gender, and political affiliation in order to ensure a representative sample, using benchmarks from recent nationally-representative samples in the US (Leiserowitz et al., 2023) and the British Office for National Statistics, respectively. For our India sample, given that there are no substantial political differences in climate beliefs and attitudes, we used quotas for age, gender, and education to match benchmarks from a nationally-representative sample in India (Leiserowitz et al., 2024). See Section 1 in the Supplementary Information, Thomas-Walters et al. (2026) (hereafter SI) for tables displaying sample characteristics for each country, a comparison against our target benchmarks, and rates of exclusion. Participants in India could choose whether to take the survey in English or Hindi. We translated the survey into Hindi by paying for a professional translation service from the participant recruitment service we used. The translation was then checked by one of the co-authors who is a native Hindi speaker.

Our target sample size was 9,000 (500 respondents per condition per country). This enabled us to detect effect sizes much smaller than the smallest effect size of interest, d = 0.15. Power analysis showed that 700 respondents per condition would be needed to detect d = 0.15, (based on the pwr package in R at 80% power and an alpha level of 0.05). However, that is a conservative estimate of power requirements because it does not account for the additional power gained by controlling for a pre-treatment measure of the outcomes (Gerber & Green, 2012).

Fourteen thousand one hundred and seventy-three (14,173) people completed the survey but 2,604 were removed for failing an attention check. In addition, 626 participants were removed for dropping out of the study before being assigned to a treatment, and 130 participants were excluded due to missing data in at least one of the outcomes or moderators. This resulted in a sample size of 10,813.

Materials and Procedure

The survey began with pre-treatment measures of climate change beliefs and risk perceptions, an attention check, and moderator variables, followed by random assignment to one of the experimental conditions. Next came post-treatment outcomes, and demographic questions. Each section is described in more detail below. See Thomas-Walters et al. (2025) for the full survey. Participants were randomly assigned to one of six conditions (two controls and four treatments):

1. Pure control.
2. Active control.
3. Heat waves as percentage.
4. Floods as percentage.
5. Heat waves as times.
6. Floods as times.

Random assignment was conducted using Qualtrics and successfully generated equivalent groups across all of our key demographic variables within all countries in our study (see OSF files at Thomas-Walters et al., 2025).

Treatment and Control Conditions

Treatments and control consisted of a short text (see full materials at Thomas-Walters et al. (2025). The pure control discussed cheetahs and their speed. The active control was a short paragraph about extreme weather, with no mention of climate change. The treatments all started with the same first paragraph and then added a sentence at the end about how extreme weather (either heat waves or floods) in 2023 was affected by climate change (Table 1). For numerical framing we used equivalent multiplier (times) and percentage framings, either “3 times more likely” or “200% more likely” (N.B: increasing something by 100% is the same as doubling it, so “200% more likely” and “3 times more likely” are equivalent).

Outcomes

The main outcome measured the extent to which participants think climate change made extreme weather generally more likely in 2023 (1 = *Not at all more likely*, 5 = *Extremely more likely*). As secondary outcomes, we measured the extent to which participants think climate change made, a) heat waves, and b) flooding more likely, the extent to which participants think climate change made these events worse, worry about climate change, and support for government action to address climate change (a three item index; Spearman-Brown coefficient = 0.75–0.79). These outcomes were measured both pre- and post-treatment. We also had a binary "information seeking" outcome. Participants were told they could find out more about the influence of climate change on extreme weather in their region, by visiting the World Weather Attribution website. We tracked whether participants clicked a link to visit this website.

Table 1

List of Conditions and Their Text

Condition	Text
Pure control	Cheetahs are one of the world's most-recognizable cats, known for their speed. They can run at up to 71 miles per hour. Cheetahs have many adaptations that enhance their ability to sprint. Their legs are proportionally longer than those of other big cats; an elongated spine increases stride length at high speeds; they have special paw pads for extra traction; and a long tail helps them balance.
Active control	Extreme weather events, such as heat waves and flooding, pose major challenges to communities worldwide. Heat waves are prolonged periods of extreme high temperatures, often accompanied by intense sunlight. Heat waves increase the risk of heat-related illnesses, put stress on vulnerable populations, and strain the healthcare system and electric grid. Flooding poses a different but equally serious threat, submerging rural and urban areas in rising waters. Torrential rains, swollen rivers, or storm surges increase the potential for destructive floods, causing infrastructure damage, displacement of communities, and loss of life. Extreme weather kills hundreds of thousands of people every year.
Heat Waves %	[Active control] + Scientists say climate change made heat waves at least 200% more likely in 2023.
Heat Waves Times	[Active control] + Scientists say climate change made heat waves at least 3 times more likely in 2023.
Floods %	[Active control] + Scientists say climate change made floods at least 200% more likely in 2023.
Floods Times	[Active control] + Scientists say climate change made floods at least 3 times more likely in 2023.

Moderators

For subgroup analyses we measured whether participants reported having experienced a heat wave or flood in their local area in the last two years, their exposure to extreme weather events like heat waves or flooding in the media in the last year, their level of worry about climate change, and for US participants, their political affiliation. We used political affiliation as a moderator for US participants as there is substantial *a priori* evidence that political partisanship is an important predictor of climate change beliefs in the US (Goldberg et al., 2021; Hamilton et al., 2015; McCright & Dunlap, 2011).

Demographics

Finally, we collected socio-demographic data on age, gender, education, income, race, and political affiliation. Some of these questions varied according to the country of the participants. In the US, for example, political affiliation was measured based on two questions. First, whether participants thought of themselves as Republican, Democrat, Independent, other, or no party/not interested in politics. Then, if a respondent chose Independent or other, they were asked if they thought of themselves as closer to the Republican Party, Democratic Party, or neither. Respondents that chose the Republican or Democratic party were categorized as members of that party, whereas respondents who chose “neither” were categorized as Independents. For the UK and India, participants were asked about their voting intention in the upcoming 2024 general elections in each country.

Data Analysis

We used linear regressions with the full dataset to test the impact of each treatment message on each outcome. We compared each message relative to the pure control. These regressions are our primary analyses, controlling for the pre-treatment measure of the corresponding dependent variable, to enhance measurement precision and statistical power (Gerber & Green, 2012). We included a country-level control in each regression. All effect sizes are reported in standard deviation units (by standardizing the DV to have a mean of 0 and a *SD* of 1), except for the binary information-seeking variable. We repeated this analysis with an unadjusted regression as a secondary sensitivity analysis (see Section 2 in the SI; Thomas-Walters et al., 2026). We also repeated the main analysis with ordinal logistic regressions (see Section 3 in the SI; Thomas-Walters et al., 2026). Finally, we also compared the treatments to the active control rather than the pure control (see Section 4 in the SI; Thomas-Walters et al., 2026). The pattern of results across all these sensitivity analyses was similar to what we have reported here.

To investigate the effects of message framing overall, we generated two dummy variables: a) numeric information framing, and b) extreme weather event type framing. For the dummy variable with numeric information framing, Floods % and Heat Waves % were grouped to represent Percentage framing, whereas Floods Times and Heat Waves Times were grouped to represent Times framing. For the dummy variable with extreme weather event type framing, Floods % and Floods Times were grouped to represent the Floods framing, and Heat Waves % and Heat Waves Times were grouped to indicate the Heat Waves framing. Then, we used linear regressions to examine the impacts of framing on each outcome, while controlling for the pre-treatment measure of the corresponding dependent variable.

To assess individual differences in treatment effects, depending on factors such as personal experience with extreme weather events and media exposure, we applied the same regression model as described above with the addition of an interaction term between the treatment effects and each of the moderator variables.

Deviations From the Pre-Registration

This exploratory analysis grew out of an earlier analysis based on the Global Warming's Six Americas segmentation (Leiserowitz et al., 2021). One component of the Six Americas relevant to our treatment is individual worry about climate change. Upon reviewing our preregistered analysis of the Six Americas, we saw it relevant to test the particular sub-variable most relevant to our treatment.

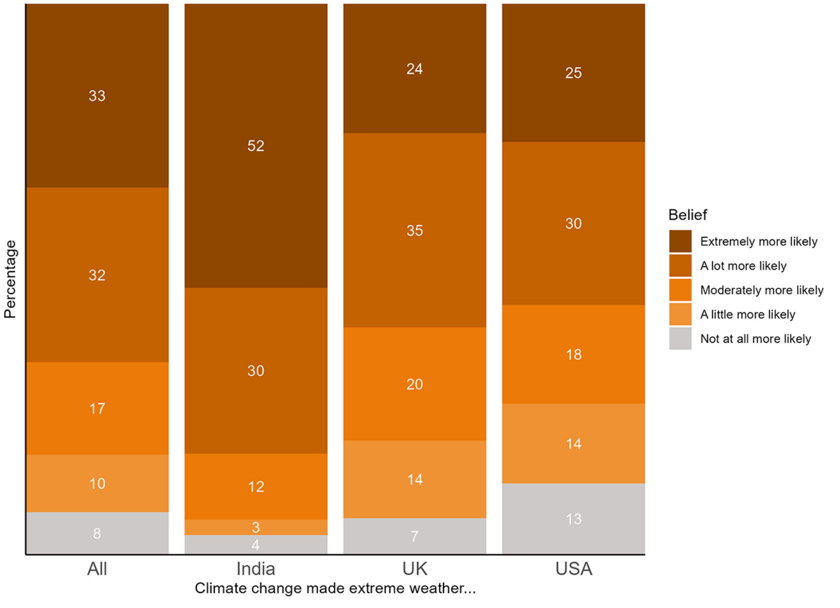
Results

Baseline Beliefs

Prior to the intervention, the majority of respondents already believed that climate change made extreme weather in 2023 "a lot" or "extremely" more likely (65%; Figure 1). This was similar for both floods (67%) and heat waves (65%). However, there was variation by country, with 82% of Indian respondents, but only 59% of Britons and 55% of Americans, believing that climate change made extreme weather in 2023 "a lot" or "extremely" more likely.

Figure 1

Baseline Beliefs About the Impact of Climate Change on Extreme Weather



Note. UK = United Kingdom; USA = United States of America. Percentages may not sum to 100 due to rounding to the nearest whole number.

People who reported having experienced an extreme weather event in their local area in the last two years were more likely than those who did not to say climate change made extreme weather in 2023 “a lot” or “extremely” more likely (81% versus 46%). The same pattern held for people who reported hearing about extreme weather events in the media on at least a weekly basis (78%) versus those who did not (48%). Further, the level of reported exposure to media coverage of extreme weather events varied greatly by country, with far more Indian respondents (74%) hearing about extreme weather on a weekly or daily basis compared to UK (44%) or US respondents (49%; SI Section 3, Thomas-Walters et al., 2026).

Main Outcome

Effects on Belief That Climate Change Made Extreme Weather More Likely

Our main outcome variable was the belief that climate change made extreme weather in 2023 more likely (Figure 2). In line with Hypotheses 1 and 2, every treatment, including the active control, successfully increased this belief compared to the pure control across the whole sample. Treatment effects ranged from $d = 0.06$ (95% CI [0.03, 0.10], $p < 0.001$)

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for the active control to $d = 0.14$ (95% CI [0.10, 0.18], $p < 0.001$) for both the Heat Waves % and Flood % treatments. To give a more intuitive sense of these effect sizes, we calculated the percentage point difference in the belief that climate change made extreme weather "a lot" or "extremely" more likely using unstandardized data. The treatments increased the percentage of participants who believed climate change made extreme weather more likely by 4.5 percentage points (Flood Times) to 6.1 percentage points (Flood %).

As Figure 2 shows, there is heterogeneity across countries, with treatments being more effective in the UK and the US than in India. Every treatment increased this belief compared to the Pure Control in the UK, with the Heat Waves % treatment being the most effective ($d = 0.19$, 95% CI [0.13, 0.25], $p < 0.001$). In the US all but the Active Control were significant, with the Flood % treatment being the most effective ($d = 0.18$, 95% CI [0.12, 0.24], $p < 0.001$). However, in India only the Heat Waves % treatment had a statistically significant impact ($d = 0.11$, 95% CI [0.03, 0.2], $p = 0.01$).

We also tested the impact of event type (flooding vs. heat waves) and numerical framing (percentage vs. times) overall. Figure 3 shows the average impact of each binary variable. Contrary to Hypothesis 3, there is no significant difference between the Heat Waves and Floods conditions or the percentage and times conditions, either in the whole sample or in any individual country.

Secondary Outcomes

Effects on Belief That Climate Change Made Extreme Weather Worse

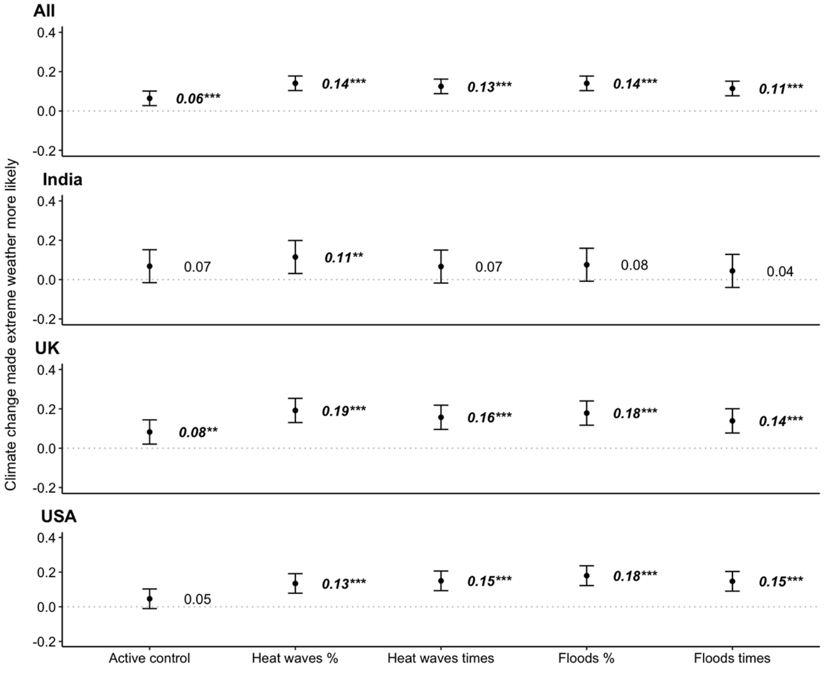
Every treatment increased the strength of belief that climate change made extreme weather in 2023 worse (see SI Section 6 for results by country; Thomas-Walters et al., 2026). The Floods % treatment had the largest impact ($d = 0.16$, 95% CI [0.12, 0.20], $p < 0.001$).

Effects on Belief That Climate Change Made Flooding More Likely or Worse

Every treatment (including the heat wave-specific treatments) increased the strength of belief that climate change made flooding in 2023 more likely (see SI Section 7 for results by country; Thomas-Walters et al., 2026). The Floods % treatment had the largest impact ($d = 0.16$, 95% CI [0.12, 0.19], $p < 0.001$). Similarly, every treatment increased the strength of agreement that climate change made flooding in 2023 worse, even the heat wave-specific treatments. The Floods % treatment again had the largest impact ($d = 0.19$, 95% CI [0.15, 0.23], $p < 0.001$).

Figure 2

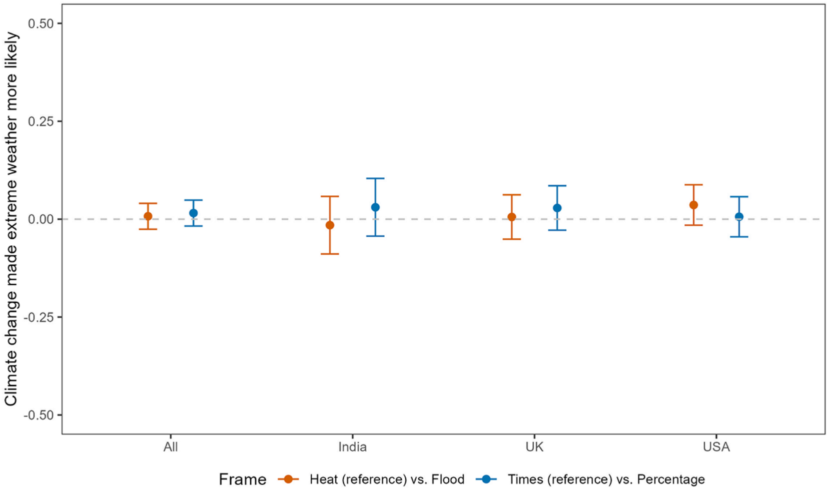
Effect of Messages on the Belief That Climate Change Made the Extreme Weather in 2023 More Likely, Compared to the Pure Control Condition



Note. Error bars represent 95% confidence intervals (CI). Effect size estimates are standardized mean differences, controlling for pre-treatment measurement of the dependent variable. UK = United Kingdom; USA = United States of America. Times = 3X more likely; % = 200% more likely.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Figure 3

Effect of Numerical Framing and Extreme Weather Event Type on the Belief That Climate Change Made the Extreme Weather In 2023 More Likely, Compared to the Pure Control Condition



Note. Error bars represent 95% confidence intervals (CI). Effect size estimates are standardized mean differences, controlling for pre-treatment measurement of the dependent variable. UK = United Kingdom; USA = United States of America. Times = 3X more likely; Percentage = 200% more likely.

Effects on Belief That Climate Change Made Heat Waves More Likely OR Worse

Every treatment (including the flooding-specific treatments) increased the strength of belief that climate change made heat waves in 2023 more likely (see SI Section 8 for results by country; Thomas-Walters et al., 2026). The Heat Waves % treatment had the largest impact (d = 0.17, 95% CI [0.13, 0.21], $p < 0.001$). Similarly, every treatment increased the strength of agreement that climate change made heat waves in 2023 worse. The Flood % treatment had the largest impact (d = 0.18, 95% CI [0.13, 0.22], $p < 0.001$).

Effects on Worry About Climate Change

Three of the treatments increased worry about climate change (see SI Section 9 for results by country; Thomas-Walters et al., 2026). These were Heat Waves %, Heat Waves Times, and Floods Times. The Heat Waves % (d = 0.06, 95% CI [0.02, 0.09], p = 0.004) and Floods Times (d = 0.06, 95% CI [0.02, 0.10], p = 0.002) treatments had the largest impact.

Effects on Support for Government Action to Address Climate Change

Only the Heat Waves % and Heat Waves Times treatments increased support for government action to address climate change (see SI Section 10 for results by country; Thomas-Walters et al., 2026). Both had an effect of d = 0.03 (95% CI [0.01, 0.06], p = 0.02).

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However, this was mostly driven by the UK sample — no treatments were significant in the US or India.

Effects on Information Seeking

Only 3.2% of the whole sample clicked on the link to find out more about extreme weather in their area (specifically, 5.6% in India, 1.6% in UK, and 2.3% in US). No treatments had a significant effect on this behavior (SI Section 11; Thomas-Walters et al., 2026).

Subgroup Effects

For all subgroup analyses we report effects on the main outcome only (belief that climate change made extreme weather in 2023 more likely). Effects on the other outcomes can be found in SI Section 12–14 (see Thomas-Walters et al., 2026).

Personal Experience of Extreme Weather

We examined whether treatment effects differed depending on personal experience with extreme weather, Hypothesis 5 (SI Section 12; Thomas-Walters et al., 2026). For our main outcome, the Floods % treatment was more effective for people who reported having *not* experienced extreme weather events in the past two years versus for people who reported having experienced them (d = 0.18, 95% CI [0.13, 0.24] and d = 0.10, 95% CI [0.05, 0.15], respectively). For other treatments, the treatment effects did not significantly differ according to reported personal experience.

Media Exposure to Extreme Weather

Next, we investigated how the frequency of hearing about extreme weather in the media moderates the impact of the treatments (SI Section 13; Thomas-Walters et al., 2026). For the main outcome there was an interaction effect for two treatments, Heat Waves % and Heat Waves Times. Heat Waves % was more effective for people with a low versus mean or high level of media exposure (d = 0.19, 95% CI [0.14, 0.24], d = 0.14, 95% CI [0.10, 0.18], and d = 0.09, 95% CI [0.04, 0.14], respectively). Similarly, the Heat Waves Times was more effective for people with a low versus mean or high level of media exposure (d = 0.17, 95% CI 0.12, 0.22], d = 0.13, 95% CI 0.09, 0.16], and d = 0.08, 95% CI [0.03, 0.13] respectively).

Baseline Beliefs

Finally, we looked at whether baseline beliefs moderate the impact of the treatments (SI Section 14; Thomas-Walters et al., 2026). In line with Hypothesis 4 there was an interaction effect for every treatment for the main outcome. Participants who had lower levels of belief that climate change made extreme weather more likely at baseline moved more in response to the treatments, compared to those with mean or higher baseline beliefs. For example, the Heat Waves Times was more effective for people with lower baseline beliefs versus people with the mean or higher baseline beliefs (d = 0.20, 95% CI [0.14, 0.25], d = 0.13, 95% CI [0.09, 0.16], and d = 0.06, 95% CI [0.003, 0.11], respectively).

Discussion

Informing people about the impact of climate change on extreme weather events such as heat waves and flooding successfully increases beliefs that climate change made extreme weather in 2023 more likely. This is the case regardless of the specific event type or numerical framing. Message treatments can also increase worry about climate change, although subsequent impact on policy support or information-seeking behavior is limited. The findings of this study contribute to the scarce literature on which messages are effective at communicating extreme weather event attribution.

Given the generally positive effect of the active control message, our results suggest that just talking about extreme weather can prime beliefs about the links between climate change and extreme weather. However, specifically attributing floods and heat waves to climate change is best. We even find a spillover effect of attribution messages from one type of extreme weather to the other — attributing increased flooding to climate change affects beliefs about heat waves, and vice versa. As every framing we tested worked overall and we observed no backfire effects, we recommend communicating the links between climate change and extreme weather to all audiences. Just a short, simple phrase that links climate change to extreme weather at the end of a paragraph can significantly impact even distal outcomes like worry and support for government action.

We did observe some differences depending on the country of the respondents. Broadly speaking, all of the treatments increased beliefs that climate change made extreme weather in 2023 more likely in the UK and the US, and although message effects varied, the differences between specific messages were rarely statistically significant. However in India, many messages did not increase these beliefs. We suspect this is partially due to a ceiling effect (SI Section 14; Thomas-Walters et al., 2026). In other words, beliefs were already very high at baseline, such that there was not much room to increase them. This might in part be because Indian participants reported greater exposure to both extreme weather itself and media reporting of extreme weather. Rather than focusing on basic beliefs, it may be better to engage the Indian public with a focus on their policy support or individual behaviors (although neither moved in response to the specific treatments tested here). Unfortunately, there is not much literature comparing climate change and extreme weather messaging effects across these three countries. There are several large, multi-country studies of climate change messaging generally (e.g., Ballew et al., 2025; Vlasceanu et al., 2024), which similarly tend to find high pre-intervention beliefs in climate change can lead to ceiling effects. In addition to differences in pre-treatment beliefs, we also acknowledge demographic differences, especially educational attainment, might play a role, as might differential exposure to different types of extreme weather events. While both of these factors might play a role in ceiling effects, they are worth considering in their own right.

We found that people who reported having heard about extreme weather in the media more frequently also had stronger pre-existing beliefs about its links to climate change. Since many individuals get their weather information filtered through media outlets (Bloodhart et al., 2015), how journalists frame extreme weather can play a large role in public perception. Previous research in the United States has found that media outlets have historically framed the link between extreme weather and climate change as uncertain or a source of scientific disagreement, while in India, despite frequent coverage of extreme weather, the media often fails to mention the link to climate change at all (Painter et al., 2024). Even when scientifically accurate, communicating the uncertainty of event attribution can pose a major challenge to message effectiveness while discussing the link between extreme weather and climate exchange (Ettinger et al., 2021; Gustafson & Rice, 2020). The lack of clear communication around the growing evidence linking extreme weather events to climate change may limit the effectiveness of such coverage in affecting climate change beliefs and behaviors. News coverage ought to instead ensure that communications about extreme weather and climate change are clear and concise.

Similar to previous research (Thomas-Walters et al., 2024), we found that treatments were sometimes more effective for people with less exposure to extreme weather, either via personal experience or hearing about it in the media. We found significant interactions between our treatment and three moderators: previous exposure to media about extreme weather, previous exposure to extreme weather, and baseline beliefs about climate change's contributions to extreme weather. Treatments were more effective among those who self-reported not experiencing extreme weather, who had consumed less media about extreme weather, and those who had lower baseline beliefs. Plausibly, these last two populations might partially overlap. We hypothesize that this is due to a sensitization effect, whereby messages work better on people who have not already been "pre-treated" (Druckman & Leeper, 2012).

We saw less movement on more distal outcomes like worry about climate change or support for government action. Most of the treatment effects for worry about climate change seemed to be driven by the US participants. Similarly, both heat wave treatments increased support for government action, but this was entirely driven by the UK participants. However, none of our treatments were written to specifically affect action-oriented outcomes. They were focused on beliefs about the links between climate change and extreme weather and were clearly effective in that regard. Future research should test more tailored messaging about mitigation and adaptation behaviors.

Limitations and Recommendations for Future Research

Although we tested both numerical frames and specific types of extreme weather events, there is still much more research needed to explore the effects of different message framings in this area. For example, research could test messages about the increasing negative impacts of extreme weather events on future generations, or local hazard risks. Indeed, it would be wise to also investigate the psychological models already held by the public regarding extreme weather event attribution (e.g., see McClure et al., 2022).

We also acknowledge that the method of administering this survey (distributing over the internet) means that, while we set quotas for key representative benchmarks, our samples are non-representative in ways that may not show up in traditional quotas. Specifically, we had no way of reaching the portion of each target population without internet access. This is a particular concern in India. Future research should explore alternative survey administration methods that can reach populations without internet access, particularly in regions of India where this limitation is most significant.

Despite the large samples used here, which are representative on key demographics (SI Section 1; Thomas-Walters et al., 2026), they still only represent three countries. More research is needed to identify effective messages in other regions, ones that disproportionately contribute to climate change and/or will suffer the impacts. As part of this, it would be useful to include behavioral outcomes that measure the impact of these messages on pro-environmental actions.

All messages were effective, yet the effect sizes presented here may actually be a conservative estimate of the impact of messaging around climate change and extreme weather for two reasons. First, including a pretest measure of the outcomes could have biased the results towards the null by asking participants to pre-commit their beliefs, since there is some evidence that this matters for beliefs about environmental measures (Poluektova et al., 2024). Second, we chose a relatively neutral way of communicating the scientific evidence, and the messages could have been worded more strongly. For example, changing “Scientists say....” to “Scientific evidence shows....”.

Finally, as the science of EEA currently tends to link specific events to climate change, so too have previous studies in this area (e.g., Thomas-Walters et al., 2024). Here however the treatment messages explained the impact of climate change on extreme weather generally. Although specific extreme weather events provide good intervention points to message about climate change, the broader impacts of extreme weather generally may be more influential than a single heat wave or flood on attitudes and behaviors. Improving the scientific evidence base of EEA generally may be helpful to practitioners.

Conclusion

Informing people about the impact of climate change on extreme weather events such as heat waves and flooding successfully increases beliefs that climate change made extreme weather in 2023 more likely. This is the case regardless of the specific event type or numerical framing. Message treatments can also increase worry about climate change, although further impact on more distal outcomes such as policy support or information-seeking behavior is limited. Our findings suggest that, rather than focusing resources on testing different wording and frames, it may be more important that people simply hear about the links between climate change and extreme weather. However, we acknowledge that we only vary one framing (the framing of magnitude) and it is possible that other framing variations would produce greater heterogeneity in treatment effects.

Openness and Transparency Statements

The present article has been checked by its handling editor(s) for compliance with the journal's open science and transparency policies. The completed *Transparency Checklist* is publicly available at: https://doi.org/10.23668/psycharchives.21875

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Data Availability. The code, data and supplementary materials are available at Thomas-Walters et al. (2025). Additional supplementary information is available at Thomas-Walters et al. (2026).

Supplementary Materials. The following table provides an overview of the accessibility of supplementary materials (if any) for this paper.

Type of supplementary material	Availability/Access
Data	
CSI global data	Thomas-Walters et al. (2025).
Code	
Code and output	Thomas-Walters et al. (2025).
Material	
Survey and materials	Thomas-Walters et al. (2025).
Supplementary tables and charts	Thomas-Walters et al. (2026).
Study/Analysis preregistration	
Preregistration	Thomas-Walters et al. (2025).
Other	
Read Me file - Global CSI.	Thomas-Walters et al. (2025).
Global CSI Codebook.	Thomas-Walters et al. (2025).

Badges for Good Research Practices.

Open data: YES.

Open code: YES.

Open materials: YES.

Preregistration: YES.

Diversity statement: NO.

Note: YES = the present article meets the criteria for awarding the badge. NO = the present article does not meet the criteria for awarding the badge *or* the criteria are not applicable.

References

Ahmadiani, M., & Ferreira, S. (2021). Well-being effects of extreme weather events in the United States. *Resource and Energy Economics, 64*, Article 101213. https://doi.org/10.1016/j.reseneeco.2020.101213

Anderegg, W. R., Hicke, J. A., Fisher, R. A., Allen, C. D., Aukema, J., Bentz, B., Hood, S., Lichstein, J. W., Macalady, A. K., McDowell, N., Pan, Y., Raffa, K., Sala, A., Shaw, J. D., Stephenson, N. L., Tague, C., & Zeppel, M. (2015). Tree mortality from drought, insects, and their interactions in a changing climate. *New Phytologist, 208*(3), 674–683. https://doi.org/10.1111/nph.13477

Ballew, M. T., Thomas-Walters, L., Goldberg, M. H., Verner, M., Lu, J., Marshall, J., Rosenthal, S. A., & Leiserowitz, A. (2025). Climate change messages can promote support for climate action globally. *Global Environmental Change, 90*, Article 102951. https://doi.org/10.1016/j.gloenvcha.2024.102951

Basu, R., & Samet, J. M. (2002). Relation between elevated ambient temperature and mortality: A review of the epidemiologic evidence. *Epidemiologic Reviews, 24*(2), 190–202. https://doi.org/10.1093/epirev/mxf007

Bloodhart, B., Maibach, E., Myers, T., & Zhao, X. (2015). Local climate experts: The influence of local TV weather information on climate change perceptions. *PLoS One, 10*(11), Article e0141526. https://doi.org/10.1371/journal.pone.0141526

Boyce-Jacino, C., Peters, E., Galvani, A. P., & Chapman, G. B. (2022). Large numbers cause magnitude neglect: The case of government expenditures. *Proceedings of the National Academy of Sciences of the United States of America, 119*(28), Article e2203037119. https://doi.org/10.1073/pnas.2203037119

Bubeck, P., Otto, A., & Weichselgartner, J. (2017). Societal impacts of flood hazards. *Oxford research encyclopedia of natural hazard science*. https://doi.org/10.1093/acrefore/9780199389407.013.281

Cruz, J., White, P. C., Bell, A., & Coventry, P. A. (2020). Effect of extreme weather events on mental health: A narrative synthesis and meta-analysis for the UK. *International Journal of Environmental Research and Public Health, 17*(22), Article 8581. https://doi.org/10.3390/ijerph17228581

PsychOpen GOLD

Climate Central. (2024). *Climate Shift Index.* https://www.climatecentral.org/tools/climate-shift-index

Demski, C., Capstick, S., Pidgeon, N., Sposato, R. G., & Spence, A. (2017). Experience of extreme weather affects climate change mitigation and adaptation responses. *Climatic Change, 140*(2), 149–164. https://doi.org/10.1007/s10584-016-1837-4

Druckman, J. N., & Leeper, T. J. (2012). Learning more from political communication experiments: Pretreatment and its effects. *American Journal of Political Science, 56*(4), 875–896. https://doi.org/10.1111/j.1540-5907.2012.00582.x

Ettinger, J., Walton, P., Painter, J., Osaka, S., & Otto, F. E. L. (2021). "What's up with the weather?" Public engagement with extreme event attribution in the United Kingdom. *Weather, Climate, and Society, 13*(2), 341–352. https://doi.org/10.1175/WCAS-D-20-0155.1

Gerber, A. S., & Green, D. P. (2012). *Field experiments: Design, analysis, and interpretation.* W. W. Norton.

Gilford, D. M., Pershing, A., Strauss, B. H., Haustein, K., & Otto, F. E. L. (2022). A multi-method framework for global real-time climate attribution. *Advances in Statistical Climatology, Meteorology and Oceanography, 8*(1), 135–154. https://doi.org/10.5194/ascmo-8-135-2022

Goldberg, M., Gustafson, A., Ballew, M., Rosenthal, S., & Leiserowitz, A. (2021). Identifying the most important predictors of support for climate policy in the United States. *Behavioural Public Policy, 5*(4), 480–502. https://doi.org/10.1017/bpp.2020.39

Gustafson, A., & Rice, R. E. (2020). A review of the effects of uncertainty in public science communication. *Public Understanding of Science, 29*(6), 614–633. https://doi.org/10.1177/0963662520942122

Hamilton, L. C., Hartter, J., Lemcke-Stampone, M., Moore, D. W., & Safford, T. G. (2015). Tracking public beliefs about anthropogenic climate change. *PLoS One, 10*(9), Article e0138208. https://doi.org/10.1371/journal.pone.0138208

Hanlon, H. M., Bernie, D., Carigi, G., & Lowe, J. A. (2021). Future changes to high impact weather in the UK. *Climatic Change, 166*(3–4), Article 50. https://doi.org/10.1007/s10584-021-03100-5

IPCC. (2023). *Climate Change 2023: Synthesis report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 35–115). Intergovernmental Panel on Climate Change. https://doi.org/10.59327/IPCC/AR6-9789291691647

Kendon, M., McCarthy, M., Jevrejeva, S., Matthews, A., Williams, J., Sparks, T., & West, F. (2023). State of the UK climate 2022. *International Journal of Climatology, 43*(S1), 1–83. https://doi.org/10.1002/joc.8167

Konisky, D. M., Hughes, L., & Kaylor, C. H. (2016). Extreme weather events and climate change concern. *Climatic Change, 134*(4), 533–547. https://doi.org/10.1007/s10584-015-1555-3

Krishnan, R., Sanjay, J., Gnanaseelan, C., Mujumdar, M., Kulkarni, A., & Chakraborty, S. (Eds.). (2020). *Assessment of climate change over the Indian region: A report of the Ministry of Earth Sciences (MoES), Government of India.* Springer. https://doi.org/10.1007/978-981-15-4327-2

Leiserowitz, A., Maibach, E., Rosenthal, S., Kotcher, J., Lee, S., Verner, M., Ballew, M., Carman, J., Myers, T., Goldberg, M., Badullovich, N., & Marlon, J. (2023). *Climate change in the American mind: Beliefs & attitudes, Spring 2023.* Yale Program on Climate Change Communication.

Leiserowitz, A., Roser-Renouf, C., Marlon, J., & Maibach, E. (2021). Global Warming's Six Americas: A review and recommendations for climate change communication. *Current Opinion in Behavioral Sciences, 42*, 97–103. https://doi.org/10.1016/j.cobeha.2021.04.007

Leiserowitz, A., Thaker, J., Verner, M., Goddard, E., Carman, J., Rosenthal, S., Modala, N., Talwar, M., Deshmukh, Y., Shukla, G., Marlon, J., Ballew, M., & Goldberg, M. (2024). *Climate change in the Indian mind, 2023.* Yale Program on Climate Change Communication. https://climatecommunication.yale.edu/publications/climate-change-in-the-indian-mind-2023

Luber, G., & McGeehin, M. (2008). Climate change and extreme heat events. *American Journal of Preventive Medicine, 35*(5), 429–435. https://doi.org/10.1016/j.amepre.2008.08.021

Lüthi, S., Fairless, C., Fischer, E. M., Scovronick, N., Armstrong, B., de Sousa Zanotti Stagliorio Coelho, M., Guo, Y. L., Guo, Y., Honda, Y., Huber, V., Kyselý, J., Lavigne, E., Royé, D., Ryti, N., Silva, S., Urban, A., Gasparrini, A., Bresch, D. N., & Vicedo-Cabrera, A. M. (2023). Rapid increase in the risk of heat-related mortality. *Nature Communications, 14*(1), Article 4894. https://doi.org/10.1038/s41467-023-40599-x

Lyons, B. A., Hasell, A., & Stroud, N. J. (2018). Enduring extremes? Polar vortex, drought, and climate change beliefs. *Environmental Communication, 12*(7), 876–894. https://doi.org/10.1080/17524032.2018.1520735

Marlon, J. R., Wang, X., Mildenberger, M., Bergquist, P., Swain, S., Hayhoe, K., Howe, P. D., Maibach, E., & Leiserowitz, A. (2021). Hot dry days increase perceived experience with global warming. *Global Environmental Change, 68*, Article 102247. https://doi.org/10.1016/j.gloenvcha.2021.102247

McClure, J., Noy, I., Kashima, Y., & Milfont, T. L. (2022). Attributions for extreme weather events: Science and the people. *Climatic Change, 174*(3–4), Article 22. https://doi.org/10.1007/s10584-022-03443-7

McCright, A. M., & Dunlap, R. E. (2011). The politicization of climate change and polarization in the American public's views of global warming, 2001–2010. *Sociological Quarterly, 52*(2), 155–194. https://doi.org/10.1111/j.1533-8525.2011.01198.x

Naveau, P., Hannart, A., & Ribes, A. (2020). Statistical methods for extreme event attribution in climate science. *Annual Review of Statistics and Its Application, 7*, 89–110. https://doi.org/10.1146/annurev-statistics-031219-041314

Newman, R., & Noy, I. (2023). The global costs of extreme weather that are attributable to climate change. *Nature Communications, 14*(1), Article 6103. https://doi.org/10.1038/s41467-023-41888-1

Painter, J., Thaker, J., Borwankar, V., Jain, G., & Negi, K. (2024). *The 2022 Indian heatwaves: Exploring media coverage in English, Hindi, Marathi, and Telugu.* Climate Trends. https://doi.org/10.13140/RG.2.2.12241.30562

Pelham, B. W., Sumarta, T. T., & Myaskovsky, L. (1994). The easy path from many to much: The numerosity heuristic. *Cognitive Psychology, 26*(2), 103–133. https://doi.org/10.1006/cogp.1994.1004

Poluektova, O., Julienne, H., Robertson, D. A., Braiden, A. K., & Lunn, P. D. (2024). Primacy effects in the formation of environmental attitudes: The case of mineral exploration. *Journal of Environmental Psychology, 94*, Article 102248. https://doi.org/10.1016/j.jenvp.2024.102248

Rataj, E., Kunzweiler, K., & Garthus-Niegel, S. (2016). Extreme weather events in developing countries and related injuries and mental health disorders — A systematic review. *BMC Public Health, 16*(1), Article 1020. https://doi.org/10.1186/s12889-016-3692-7

Rohini, P., Rajeevan, M., & Srivastava, A. K. (2016). On the variability and increasing trends of heat waves over India. *Scientific Reports, 6*, Article 26153. https://doi.org/10.1038/srep26153

Roger, T., Roger, P., & Schatt, A. (2018). Behavioral bias in number processing: Evidence from analysts' expectations. *Journal of Economic Behavior & Organization, 149*, 315–331. https://doi.org/10.1016/j.jebo.2018.02.026

Roxy, M. K., Ghosh, S., Pathak, A., Athulya, R., Mujumdar, M., Murtugudde, R., Terray, P., & Rajeevan, M. (2017). A threefold rise in widespread extreme rain events over Central India. *Nature Communications, 8*, Article 708. https://doi.org/10.1038/s41467-017-00744-9

Shukla, J. (2013). Extreme weather events and mental health: Tackling the psychosocial challenge. *International Scholarly Research Notices, 2013*, Article 127365. https://doi.org/10.1155/2013/127365

Sippel, S., Meinshausen, N., Fischer, E. M., Székely, E., & Knutti, R. (2020). Climate change now detectable from any single day of weather at global scale. *Nature Climate Change, 10*(1), 35–41. https://doi.org/10.1038/s41558-019-0666-7

Swain, D. L., Singh, D., Touma, D., & Diffenbaugh, N. S. (2020). Attributing extreme events to climate change: A new frontier in a warming world. *One Earth, 2*(6), 522–527. https://doi.org/10.1016/j.oneear.2020.05.011

Taylor, A., de Bruin, W. B., & Dessai, S. (2014). Climate change beliefs and perceptions of weather-related changes in the United Kingdom. *Risk Analysis: An Official Publication of the Society for Risk Analysis, 34*(11), 1995–2004. https://doi.org/10.1111/risa.12234

Thomas-Walters, L., Goldberg, M. H., Lee, S., Lyde, A., Rosenthal, S. A., & Leiserowitz, A. (2024). Communicating the links between climate change and heat waves with the Climate Shift Index. *Weather, Climate, and Society, 16*, 511–520. https://doi.org/10.1175/WCAS-D-23-0147.1

Thomas-Walters, L., Goldberg, M. H., Scheuch, E., Lee, S., Thaker, J., Lyde, A., Rosenthal, S. A., & Leiserowitz, A. (2025). *Communicating the impact of climate change on extreme weather in India, the United Kingdom, and the United States* [OSF project page containing code, codebook, data, survey and materials, preregistration]. Open Science Framework. https://doi.org/10.17605/OSF.IO/MPQ8V

Thomas-Walters, L., Goldberg, M. H., Scheuch, E., Lee, S., Thaker, J., Lyde, A., Rosenthal, S. A., & Leiserowitz, A. (2026). *Supplementary Materials to* "Communicating the impact of climate change on extreme weather in India, the United Kingdom, and the United States"

[Supplementary charts and tables]. PsychOpen GOLD https://doi.org/10.23668/psycharchives.21874

Trottier, N., Groeneveld, E., & Lavoie, C. (2017). Giant hogweed at its northern distribution limit in North America: Experiments for a better understanding of its dispersal dynamics along rivers. *River Research and Applications, 33*(7), 1098–1106. https://doi.org/10.1002/rra.3149

Turner, M. G., Calder, W. J., Cumming, G. S., Hughes, T. P., Jentsch, A., LaDeau, S. L., Lenton, T. M., Shuman, B. N., Turetsky, M. R., Ratajczak, Z., Williams, J. W., Park Williams, A., & Carpenter, S. R. (2020). Climate change, ecosystems and abrupt change: Science priorities. *Philosophical Transactions of the Royal Society B, 375*(1794), Article 20190105. https://doi.org/10.1098/rstb.2019.0105

USGCRP. (2023). *Fifth National Climate Assessment*. US Global Change Research Program. https://nca2023.globalchange.gov/chapter/2/

Valentim, A. (2021). Imperfect information and party responsiveness: Evidence from extreme weather events and the Green Party in England. *SSRN*. https://doi.org/10.2139/ssrn.3960045

Vlasceanu, M., Doell, K. C., Bak-Coleman, J. B., Todorova, B., Berkebile-Weinberg, M. M., Grayson, S. J., Patel, Y., Goldwert, D., Pei, Y., Chakroff, A., Pronizius, E., van den Broek, K. L., Vlasceanu, D., Constantino, S., Morais, M. J., Schumann, P., Rathje, S., Fang, K., Aglioti, S. M., . . .Van Bavel, J. J. (2024). Addressing climate change with behavioral science: A global intervention tournament in 63 countries. *Science Advances, 10*(6), Article eadj5778. https://doi.org/10.1126/sciadv.adj5778

Voskamp, I. M., & Van de Ven, F. H. (2015). Planning support system for climate adaptation: Composing effective sets of blue-green measures to reduce urban vulnerability to extreme weather events. *Building and Environment, 83*, 159–167. https://doi.org/10.1016/j.buildenv.2014.07.018

Zanocco, C., Mote, P., Flora, J., & Boudet, H. (2024). Comparing public and scientific extreme event attribution to climate change. *Climatic Change, 177*, Article 76. https://doi.org/10.1007/s10584-024-03735-0