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LETTER

Bayesian versus politically motivated reasoning in human perception of climate anomalies

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Abstract

In complex systems where humans and nature interact to produce joint outcomes, mitigation, adaptation, and resilience require that humans perceive feedback—signals of health and distress—from natural systems. In many instances, humans readily perceive feedback. In others, feedback is more difficult to perceive, so humans rely on experts, heuristics, biases, and/or identify confirming rationalities that may distort perceptions of feedback. This study explores human perception of feedback from natural systems by testing alternate conceptions about how individuals perceive climate anomalies, a form of feedback from the climate system. Results indicate that individuals generally perceive climate anomalies, especially when the anomalies are relatively extreme and persistent. Moreover, this finding is largely robust to political differences that generate predictable but small biases in feedback perception at extreme ends of the partisan spectrum. The subtlety of these biases bodes well for mitigation, adaptation, and resilience as human systems continue to interact with a changing climate system.

1. Introduction

Although researchers debate whether Earth has transitioned from the Holocene to a new 'Anthropocene' geologic epoch, there is broad agreement that human actions have wide-ranging effects on natural systems that, in turn, have far-reaching effects on human systems [1–3]. In this context, mitigation, adaptation, and achieving resilience require that humans accurately perceive feedback—signals of health and distress—from natural systems [4]. Climate change represents a classic example of this complex coupling of human and natural systems. Human activities contribute to climate change, which alters ecosystems, and, consequently, the ecosystem services that sustain human life (e.g. food and water production) [5]. To preserve these services or develop viable alternatives, humans must recognize feedback—signals of climate change and ecosystem decline—from natural systems.

In many instances, humans readily perceive feedback from natural systems. Farmers, for example, recognize when irrigation and planting practices increase production and residents of riverine communities notice changes in marine life that accompany water pollution. In other instances, feedback is more difficult to perceive; it is subtle, variable, and subject to distortion. Again, climate change represents a classic example. Signals of climate change, such as unusually warm temperatures and/or less precipitation than average (drought), manifest over time and space, but are nested in weather fluctuations that exhibit high variance in both time and space. This makes it difficult for humans to perceive climate signals by way of direct experience [6–10].

Figure 1(*a*) illustrates this process with a Bayesian logic where individuals revise perceptions of natural systems in accordance with feedback from those systems [11]. When signals are large and consistent, such

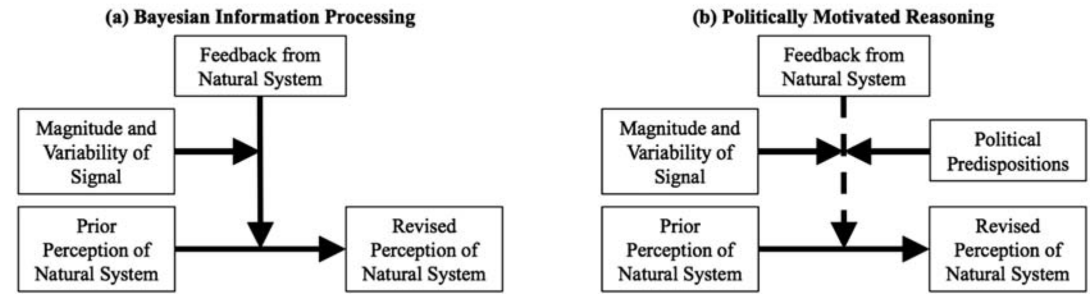

Figure 1. Modes of perception. Alternate conceptions about how individuals perceive feedback from natural systems.

as a string of hot summer days when temperatures are routinely 5+ °F above average, individuals are more likely to detect feedback and revise perceptions. When signals are small and variable, such as a wet spring when a few high precipitation days cause a modest departure from average, individuals are less likely to detect feedback and revise perceptions. Instead, they may rely on perceived experts (e.g. scientists, journalists, or commentators), heuristics, biases, and/or identity protective rationalities when assessing feedback.

In the climate domain, politically motivated reasoning [12, 13], illustrated in figure 1(*b*), represents an alternative to Bayesian information processing [14–16]. Here, individuals fit perceptions of feedback to beliefs that cohere with their political predispositions. In extreme cases, such predispositions overwhelm feedback, causing individuals to ignore signals completely. In less extreme cases, predispositions distort the feedback that individuals perceive, causing them to accept signals that comport with predispositions and reject signals that do not. On climate change, for example, this propensity may cause strong partisans to overlook feedback altogether or engage in selective perception. Given the well-documented relationship between political predispositions in the United States and beliefs about climate change [16], Liberal Democrats may not perceive unusually cold seasons that are inconsistent with global warming, whereas Conservative Republicans will. The opposite may be true of dry seasons that are consistent with warming—Liberal Democrats will notice them, whereas Conservative Republicans will not[6].

Do individuals engage in Bayesian information processing, politically motivated reasoning, or some combination of both when they encounter feedback from natural systems? A key challenge to answering this question is the lack of dynamic data. Both conceptions of human perception are dynamic: they posit that individuals formulate and revise (or fail to revise) perceptions as they encounter new information. To date, most research on perceptions of feedback—including on climate change—uses static data to make inferences about these dynamics. For instance, numerous studies compare perceptions with climatic conditions at a single point in time across varying geographic areas (e.g. counties, ZIP codes, and states) [6, 10, 19–31]. While valuable, these efforts to identify relationships between climate signals and perceptions assume rather than demonstrate a dynamic process of perception change in response to feedback, and they have yielded divergent findings that complicate empirical generalizations [14, 16].

2. Data and methods

In this study, we overcome this challenge with dynamic data from the Meso-Scale Integrated Socio-geographic Network (M-SISNet), a longitudinal (panel) survey that continuously measures public perceptions of climatic conditions in Oklahoma, a conservative state where a large fraction of the population is skeptical about human-caused climate change [32][7]. M-SISNet surveys are administered at the end of each season (winter, spring, summer, fall) and begin with recurrent questions about climate anomalies in the respective seasons. Basic values, beliefs, and political predispositions are measured once a year on the winter survey.

The M-SISNet employs an address-based sampling frame that we geospatially and temporally integrate with the Oklahoma Mesonet, a network of 120 stations that continuously monitor environmental conditions throughout the state [33, 34]. For example, each Mesonet station measures air temperature and precipitation every 5 min. At the end of each day, Mesonet

[6] Climate projections indicate that the impacts of climate change will vary by region. Projections for Oklahoma and neighboring states in the Southern Plains indicate that climate change will, on average, cause temperatures to increase, precipitation to decrease, and drought to increase [17, 18].

[7] The M-SISNet was created by a team of scientists in meteorology, ecology, political science, sociology, economics, geography, and anthropology at the University of Oklahoma and Oklahoma State University. Each quarterly survey begins with a set of questions that measure perceptions of climate anomalies. These questions use the exact same language (listed in table 1) and repeat every season. Because of this, we believe that the measures are highly reliable—they are consistent over time and across survey instruments. We are also confident in the validity of the measures. In multiple interviews and pre-tests, subjects demonstrated a high understanding of the questions and their relation to the concept that we are trying to measure—perception of climate anomalies.

Table 1. Measures and descriptive statistics.

Construct	Source	Measure	Scale/Units	Mean	SD
Perception of seasonal precipitation anomaly	M-SISNet	Would you say that the amount of precipitation that fell this [season] was more, less, or about the same amount as in previous [seasons]?	More = 3 About the same = 2 Less = 1	2.09	0.86
Perception of seasonal temperature anomaly	M-SISNet	Would you say that this [season] has been warmer, cooler, or about the same as previous [seasons]?	Warmer = 3 About the same = 2 Cooler = 1	2.13	0.85
Seasonal precipitation anomaly	Mesonet	Interpolated departure from 15 year average total daily rainfall by season by respondent	Inches	1.92	4.19
Seasonal temperature anomaly	Mesonet	Interpolated departure from 15 year average daily air temperature by season by respondent	Degrees Fahrenheit	0.82	2.00
Daily precipitation variability	Mesonet	Interpolated standard deviation of total daily rainfall by season by respondent	Standard deviation[a]	0.35	0.15
Daily temperature variability	Mesonet	Interpolated standard deviation of average daily air temperature by season by respondent	Standard deviation[a]	9.33	3.15
Political predisposition	M-SISNet	[Combination of three questions] With which political party do you most identify? As of today, do you lean more to the Democratic Party or the Republican Party? On a scale of political ideology, individuals can be arranged from strongly liberal to strongly conservative. Which of the following categories best describes your views?	Liberal Democrat = −7... Moderate = 0... Conservative Republican = 7	1.71	4.81

[a] Centered at mean = 0 for the regression analysis.

operators aggregate these measures to provide daily summaries that indicate the average air temperature and total precipitation each day at each station.

Together, the geographic resolution and temporal structure of these data streams allow for a dynamic assessment of the relative roles of Bayesian information processing and politically motivated reasoning in human perception of climate anomalies. We conduct this assessment by examining the extent to which 1760 M-SISNet panelists perceive departures from average precipitation and temperature over the course of 11 consecutive seasons, summer 2014 to winter 2017. Table 1 describes the measures we use for this analysis.

We capture perceptions and political predispositions with responses to M-SISNet questions. We measure climate anomalies in two steps. First, we use daily summaries from the Mesonet to calculate 15 year (2002–2016) precipitation and temperature averages and departures from average (anomaly) at each station in each season. Then, we use ordinary kriging interpolation to match these values to the geolocation of each panelist in the M-SISNet sample. We measure variability using a similar approach. We use Mesonet data to calculate daily variability in precipitation and temperature at each station in each season and ordinary kriging to interpolate these values to the address of each panelist in the sample, providing a level of accuracy greatly exceeding that employed in previous (static) studies matching perceptions with climatic conditions at the level of counties, ZIP codes and states.

In the analysis that follows, we use variation within individuals across seasons to estimate the causal effect of precipitation and temperature anomalies on perception formulation and revision over time. We begin by assessing the Bayesian conception of information processing. Then, we look for evidence of politically motivated reasoning.

3. Analysis and results

3.1. Bayesian information processing

Figure 2 provides a graphic indication of the dynamic relationship between feedback and perceptions. The grey lines indicate climate anomalies and perceptions of those anomalies for each M-SISNet panelist in each season; the black lines track sample means by season. A comparison of the trends shows that individuals generally perceive both forms of feedback, especially when anomalies are sizable. It is notable, however, that perceptions of temperature anomaly look to be more responsive to feedback than do perceptions of precipitation anomaly. This difference likely stems from the relative magnitudes of the respective signals. Apart from spring 2015, the temperature anomalies in Oklahoma were more extreme than the precipitation anomalies.

Statistically, we use ordinary least squares (OLS) regression and a fixed effects estimator (the *within* transformation) to test the Bayesian conception of perception change within individuals over time. We estimate separate models for precipitation and temperature perceptions that take the following form:

$$Y_{it} = \alpha_i + \rho D_{it} + \delta V_{it} + \lambda(D_{it} * V_{it}) + \varepsilon_{it},$$

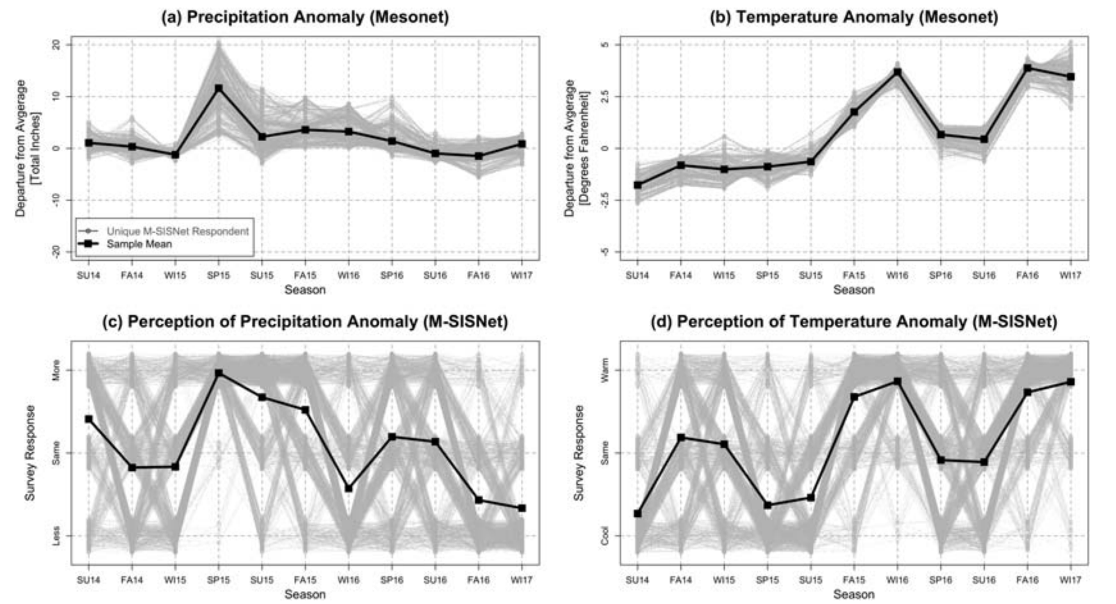

Figure 2. Anomalies and perceptions by respondent and season. The horizontal axes represent seasons. The vertical axes in (*a*) and (*b*) represent departures from average; the vertical axes in (*c*) and (*d*) represent survey responses (perceptions). The grey lines indicate anomalies and perceptions for each respondent in each season; the black lines indicate sample means by season. We add random noise to the grey lines in (*c*) and (*d*) to prevent overplotting.

where Y_{it}, the outcome variable, is a perception about the climate for panelist i in season t, α_i is an intercept term ('fixed effect') for each panelist in the sample, ρD_{it} is the climate anomaly that each panelist experienced in each season, δV_{it} is the climate variability that each panelist experienced in each season, $\lambda(D_{it} * V_{it})$ is an interaction term that multiplies the anomaly by the variability that each panelist experienced in each season, and ε_{it} is the error term. The coefficients for the anomaly terms estimate the main effects of feedback on perceptions when variability is average (the sample mean) and the coefficients for the interaction terms show how this relationship changes when variability increases (or decreases), relative to average. These estimates are shown in table S1 available at stacks.iop.org/ERL/12/114004/mmedia.

Consistent with figure 2, the estimates show a statistically significant relationship between anomalies and perceptions ($p < 0.001$). At average levels of daily variability (0.0), a 1 inch departure from average precipitation in a season increases (or decreases) perceptions of precipitation in that season by approximately 0.04 on the 1–3 scale. A more extreme, but not uncommon 10 inch departure causes perceptions to change by almost half a point. Perceptions of temperature anomalies are more sensitive to feedback. At average levels of daily variability (0.0), a 1 °F departure from the average temperature in a season produces a 0.22 change on the scale of perceptions; a 5 °F departure causes individuals to revise perceptions by a full point.

The estimates also show that daily variation significantly moderates the relationship between anomalies and perceptions ($p < 0.001$). A standard deviation increase in daily precipitation variability reduces the anomaly effect by 0.09. A standard deviation increase in temperature variability reduces the effect of the anomaly on perceptions by 0.01. Figure S1 shows this moderation at different levels of variability. When daily variation is low (−0.2), a 1 inch departure from average precipitation causes a 0.06 change in perceptions. When daily variation is high (0.2), an equivalent departure from average precipitation produces a smaller change in perceptions (0.02). The same is true for temperatures. When daily temperatures in a season are consistent (−4.0), temperature anomalies exert a relatively large influence on perceptions (0.26); when temperatures are more variable (4.0), the influence of anomalies on perceptions declines (0.16).

These results are consistent with Bayesian information processing. On average, individuals revise perceptions about climate systems in accordance with feedback from those systems. This is especially true when the signals are large and consistent. Nevertheless, the range of grey lines around the sample means in figure 2 indicates that perceptions are heterogeneous. When it was unusually wet, some respondents said it was dry; when it was unseasonably cool, some said it was warm. Politically motivated reasoning may explain this heterogeneity. In place of signals, partisans may rely on political predispositions when processing climate anomalies.

3.2. Politically motivated reasoning

We test for politically motivated reasoning both descriptively and statistically. Figure 3 duplicates figure 2, but adds two lines to each plot. The blue lines track the sample mean for Liberal Democrats

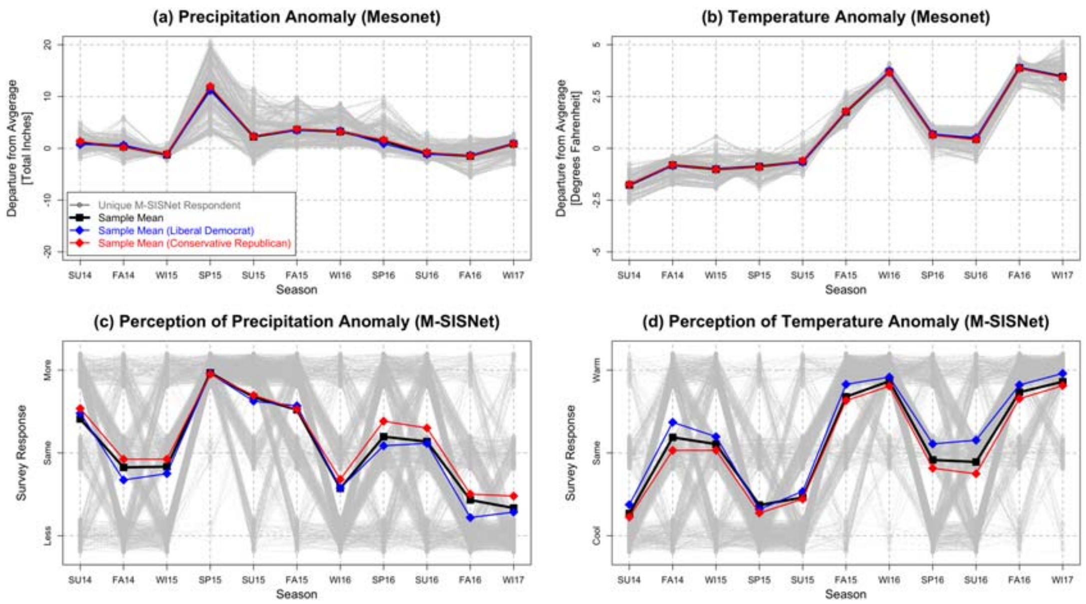

Figure 3. Anomalies and perceptions by respondent, season, and partisan identification. The horizontal axes represent seasons. The vertical axes in (*a*) and (*b*) represent departures from average; the vertical axes in (*c*) and (*d*) represent survey responses (perceptions). The grey lines indicate anomalies and perceptions for each respondent in each season; the black lines indicate sample means by season; the red and blue lines indicate sample means by season among Conservative Republicans (red) and Liberal Democrats (blue). We add random noise to the grey lines in c and d to prevent overplotting.

in each season; the red lines do the same for Conservative Republicans[8]. A comparison of the trends shows that the precipitation and temperature anomalies experienced by Liberal Democrats and Conservative Republics were nearly identical, but their respective perceptions of these anomalies differed systematically. Conservative Republicans exhibit a bias towards perceiving greater precipitation and cooler temperatures. Liberal Democrats exhibit an opposite bias, towards perceiving less precipitation and warmer temperatures. Though apparent, this politically motivated bias does not overwhelm the Bayesian process; both groups incorporate feedback when revising perceptions, especially when the signals are sizable.

Statistically, these findings imply that the difference between Conservative Republicans and Liberal Democrats is in the intercepts rather than slopes that define the relationship between feedback and perceptions. We assess this prospect by examining the distribution of intercept estimates (α_i) for each respondent in the models we describe above. These estimates denote the average distance of each respondent from the sample mean. As shown in figure S2, most respondents were relatively close to the mean, especially in their perception of temperature anomalies. Nevertheless, a portion of respondents exhibit bias.

We examine this bias using OLS regression models with orthogonal polynomial terms to define the relationship between individual intercept estimates (an indication of bias) and political predispositions. Again, we estimate separate models for precipitation and temperature perceptions that take the following form:

$$Y_i = \alpha + \beta P_i + \beta P_i^{\,2} + \beta P_i^{\,3} + \varepsilon_i,$$

where Y_i, the outcome variable, is the intercept estimate ('fixed effect') for each panelist in the sample, α is an intercept term for the entire sample, and βP_i is the political predisposition of each panelist in the sample, and ε_i is the error term. We use a cubic form of βP_i because it allows for two inflection points in the line that identifies the relationship between perceptions and anomalies, one on the left and one on the right side of the partisan scale. For these models, we use the political predisposition that M-SISNet panelists listed in winter 2017 (the most recent wave), but the results are robust to measurement in other waves. The estimates from these models are shown in table S2.

Consistent with figure 3, the estimates indicate a statistically significant political bias in the intercept estimates ($p < 0.001$). On average, Conservative Republicans are more likely to perceive less precipitation and cooler temperatures than are Liberal Democrats. Moreover, the second and third degree polynomials are statically significant, indicating that partisan bias manifests at increasing rates on opposing ends of the political spectrum ($p < 0.05$; $p < 0.001$).

Figure 4 shows this tendency by plotting predictions from the models as predispositions range from Liberal Democrat to Conservative Republican. At the extreme, perceptions of precipitation anomaly among Liberal Democrats are approximately 0.1 points below the sample mean; Conservative Republicans are 0.05 points above the sample mean. The opposite is true

[8] The plot compares highly partisan groups, where Liberal Democrat = −7 and Conservative Republican = 7. The difference between the groups is even smaller when less partisan groups are included.

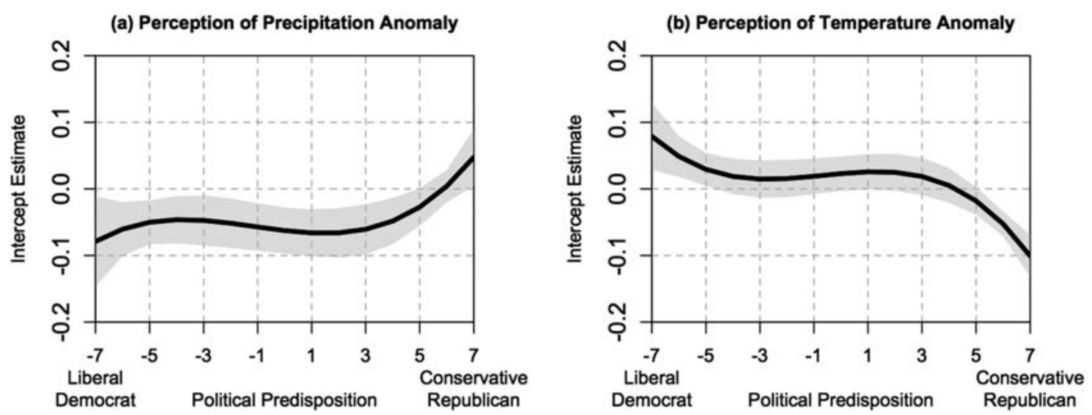

Figure 4. The relationship between political predispositions and individual intercept estimates. The vertical axes represent intercept estimates and the horizontal axes represent political predispositions. The black lines represent predicted intercept estimates as political predispositions go from Liberal Democrat to Conservative Republican. The grey regions represent 95% confidence intervals around the predictions. The predictions come from the parameter estimates in table S2.

for perceptions of temperature anomaly; Liberal Democrats are 0.1 points above the sample mean and Conservative Republicans are 0.1 points below. These patterns indicate a bias consistent with politically motivated reasoning. Conservative Republicans perceive signals that are inconsistent with global warming—more precipitation than average and relatively cool temperatures. Liberal Democrats perceive signals that are generally consistent with global warming—less precipitation (drought) and unseasonably warm temperatures. Note, however, that these biases are relatively small (less than 0.1 points on a 3 point scale) and tend to be concentrated among individuals at the extreme ends of the political spectrum (political predisposition = −7 and 7). In other words, politically motivated reasoning does not overwhelm the Bayesian process whereby both groups incorporate feedback when revising perceptions, especially when the signals are sizable. This is true of even the strongest partisans.

4. Conclusion

Most conceptions of human perception imply a dynamic process whereby perceptions change (or fail to change) in response to feedback from natural systems. While researchers often agree with these conceptions, data limitations have made it difficult to evaluate and compare them. For example, previous research on human perception of climate anomalies generally uses static data to compare dynamic processes like Bayesian information processing and politically motivated reasoning. These studies have yielded divergent findings that complicate our understanding of how individuals perceive feedback from the climate system. We have addressed this complication by matching high-resolution data on climate conditions to dynamic (panel) data that track changes in perceptions over time. Our results show that residents of Oklahoma, a US state where 'global warming' gets a chilly reception, generally perceive climate anomalies, especially when they are relatively extreme and persistent. Moreover, our findings indicate that this pattern is largely robust to political differences that generate predictable but small biases in perception at extreme ends of the partisan spectrum. This finding adds important nuance to our understanding of politically motivated reasoning. Cognitive processes like biased assimilation [35] and confirmation bias [36] influence perception, but the influence is not so strong that it causes partisans to completely miss or ignore feedback from the climate system.

We take these results to be reasonably heartening, but more work is necessary on the values, beliefs, and identities that may induce motivated reasoning. Here, we focus on political predispositions, but it is quite possible that geographic identities, cultural worldviews, religious beliefs, economic interests and a variety of other factors cause humans to perceive and/or misperceive feedback from the climate system. More work is also necessary to understand how human perception of climate anomalies relates to broader beliefs about climate change and public policy. Research in this direction will continue to advance our understanding of complex systems, where efforts to promote mitigation, adaptation, and resilience require that humans perceive feedback from the environment.

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References

[1] Crutzen P J 2002 Geology of mankind *Nature* **415** 23–3

[2] Liu J *et al* 2007 Complexity of coupled human and natural systems *Science* **317** 1513–16

[3] Waters C N *et al* 2016 The Anthropocene is functionally and stratigraphically distinct from the Holocene *Science* **351** 6269

[4] Pachauri R K and Meyer L A 2014 *IPCC Climate Change 2014: Synthesis Report* (Cambridge: Cambridge University Press)

[5] Berkes F, Colding J and Folke C 2008 *Navigating Social-Ecological Systems: Building Resilience for Complexity and Change* (Cambridge: Cambridge University Press)

[6] Akerlof K, Maibach E W, Fitzgerald D, Cedeno A Y and Neuman A 2013 Do people personally experience global warming, and if so how, and does it matter? *Glob. Environ. Change* **23** 81–91

[7] Marx S M *et al* 2007 Communication and mental processes: Experiential and analytic processing of uncertain climate information *Glob. Environ. Change* **17** 47–58

[8] McDonald R I, Chai H Y and Newell B R 2015 Personal experience and the psychological distance of climate change: an integrative review *J. Environ. Psychol.* **44** 109–18

[9] Weber E U 2016 What shapes perceptions of climate change? new research since 2010 *WIREs Clim. Change* **7** 125–134

[10] Kaufmann R K *et al* 2017 Spatial heterogeneity of climate change as an experiential basis for skepticism *Proc. Natl Acad. Sci.* **114** 67–71

[11] Deryugina T 2013 How do people update? the effects of local weather fluctuations on beliefs about global warming *Clim. Change* **118** 397–416

[12] Bolsen T, Druckman J N and Cook F L 2014 The influence of partisan motivated reasoning on public opinion *Polit. Behav.* **36** 235–62

[13] Kahan D M 2016 The politically motivated reasoning paradigm, Part 1: what politically motivated reasoning is and how to measure it *Emerg. Trends Soc. Behav. Sci.*

[14] Dunlap R E, McCright A M and Yarosh J H 2016 The political divide on climate change: partisan polarization widens in the US *Environ.: Sci. Policy Sustain. Dev.* **58** 4–23

[15] McCright A M and Dunlap R E 2011 The politicization of climate change and polarization in the American public's views of global warming, 2001–2010 *Sociol. Quart.* **52** 155–94

[16] McCright A M, Marquart-Pyatt S T, Shwom R L, Brechin S R and Allen S 2016 Ideology, capitalism, and climate: explaining public views about climate change in the United States *Energy Res. Soc. Sci.* **21** 180–9

[17] Melillo J M, Richmond T C and Yohe G W 2014 *Climate Change Impacts in the United States: The Third National Climate Assessment* (Washington, DC: US Global Change Research Program)

[18] Wuebbles D, Fahey D and Hibbard K 2017 *Climate Science Special Report (CSSR)* (Washington, DC: US Global Change Research Program)

[19] Bohr J 2017 Is it hot in here or is it just me? Temperature anomalies and political polarization over global warming in the American public *Clim. Change* **142** 271–85

[20] Donner S D and McDaniels J 2013 The influence of national temperature fluctuations on opinions about climate change in the US since 1990 *Clim. Change* **118** 537–550

[21] Goebbert K, Jenkins-Smith H C, Klockow K, Nowlin M C and Silva C L 2012 Weather, climate, and worldviews: the sources and consequences of public perceptions of changes in local weather patterns *Weath. Clim. Soc.* **4** 132–44

[22] McCright A M, Dunlap R E and Xiao C 2014 The impacts of temperature anomalies and political orientation on perceived winter warming *Nat. Clim. Change* **4** 1077–81

[23] Li Y, Johnson E J and Zaval L 2011 Local warming: daily temperature change influences belief in global warming *Psychol. Sci.* **22** 454–9

[24] Ruddell D, Harlan S L, Grossman-Clarke S and Chowell G 2012 Scales of perception: public awareness of regional and neighborhood climates *Clim. Change* **111** 581–607

[25] Hamilton L C and Stampone M D 2013 Blowin' in the wind: short-term weather and belief in anthropogenic climate change *Weath. Clim. Soc.* **5** 112–9

[26] Egan P J and Mullin M 2012 Turning personal experience into political attitudes: the effect of local weather on Americans' perceptions about global warming *J. Polit.* **74** 796–809

[27] Howe P D, Markowitz E M, Lee T M, Ko C-Y and Leiserowitz A 2013 Global perceptions of local temperature change *Nat. Clim. Change* **3** 352–6

[28] Howe P D and Leiserowitz A 2013 Who remembers a hot summer or a cold winter? the asymmetric effect of beliefs about global warming on perceptions of local climate conditions in the US *Glob. Environ. Change* **23** 1488–500

[29] Howe P D, Mildenberger M, Marlon J R and Leiserowitz A 2015 Geographic variation in opinions on climate change at state and local scales in the USA *Nat. Clim. Change* **5** 596–603

[30] Shao W 2016 Are actual weather and perceived weather the same? understanding perceptions of local weather and their effects on risk perceptions of global warming *J. Risk Res.* **19** 722–42

[31] Cutler M J 2015 Seeing and believing: the emergent nature of extreme weather perceptions *Environ. Sociol.* **1** 293–303

[32] Jenkins-Smith H C, Ripberger J T, Silva C L, Gupta K, Carlson N, Henderson M and Goodin A 2017 The Oklahoma Meso-Scale Integrated Socio-Geographic Network: A Technical Overview Center for Risk and Crisis Management *Technical Report* (http://crcm.ou.edu/epscor/codebooks/MSISNet-TechnicalOverview.pdf)

[33] Brock F V *et al* 1994 The Oklahoma mesonet: a technical overview *J. Atmos. Oceanic Technol.* **12** 5–19

[34] McPherson R A *et al* 2007 Statewide monitoring of the mesoscale environment: a technical update on the Oklahoma mesonet *J. Atmos. Oceanic Technol.* **24** 301–21

[35] Rachlinski J J 2000 The psychology of global climate change *U. Ill. L. Rev.* **1** 299–319

[36] Whitmarsh L 2011 Scepticism and uncertainty about climate change: dimensions, determinants and change over time *Glob. Environ. Change* **21** 690–700