Drought exposure and accuracy: Motivated reasoning in climate change beliefs

Guglielmo Zappalà*

Abstract

The lack of stringent policies to avert climate change has increased the importance of effective and timely adaptation. Adequate adaptation is particularly important for agricultural communities in developing countries, which may most suffer the consequences of climate change. Evidence is still scarce on how people in the most vulnerable areas form climate change beliefs and whether such beliefs exhibit cognitive biases. Using survey data from rural households in Bangladesh together with a meteorological measure of excess dryness relative to historical averages, I study the effect of long-term average drought exposure and short-term deviations on beliefs about drought frequency and the interpretation of drought events. To explore how individuals interpret past droughts, I use an instrumental variable approach and investigate whether individual beliefs lead to asymmetric distortion of objective information. The results show that individuals recollect and overweight evidence tilted towards their prior beliefs, providing evidence of confirmation bias as a directional motivated reasoning mechanism. The findings highlight the need for models that account for behavioral factors and cognitive biases in the study of climate change beliefs for effective communication and adaptation policies.

Keywords: Beliefs, Climate change, Droughts, Expectation formation, Motivated reasoning

JEL Classification: D10, D80, Q12, Q51, Q54

---

*Paris School of Economics and Université Paris 1 Panthéon-Sorbonne, 48 Boulevard Jourdan, 75014, Paris, France. Email: guglielmo.zappala@psemail.eu. I am extremely grateful to Katrin Millock for invaluable advice throughout this project. I am thankful to Tamma Carleton for her hospitality and guidance during my stay at UC Santa Barbara. I thank Andrew Clark, Tatyana Deryugina, Fabrice Etilé, Nicolas Jacquemet and an anonymous referee for the FAERE Working Paper Series for their useful comments, as well as seminar participants at the Paris School of Economics. I am also indebted to the Editor and two anonymous referees for their insightful feedback. All remaining errors are mine. This work has been funded by a French government subsidy managed by the Agence Nationale de la Recherche under the framework of the *Investissements d'avenir programme* (ANR-17-EURE-001) and by the Université Paris 1 Panthéon-Sorbonne Economics Doctoral School (ED 465).

1 Introduction

Climate change threatens to alter the frequency, timing, duration, intensity and spatial distribution of extreme weather events, including droughts (IPCC, 2021). Despite broad scientific consensus that human activities are causing climate change (Oreskes, 2004), there is ample disagreement among the general public in the beliefs about climate change and its causes (Lee et al., 2015). The inertia of policies to avert significant climate change has increased the importance of adaptation. Effective adaptation is particularly important in developing countries and rural areas (Mertz et al., 2009). The relationship between meteorological conditions and agricultural yields has been extensively empirically documented (Auffhammer & Schlenker, 2014; Carleton & Hsiang, 2016; Hultgren et al., 2022) with implicit models of adaptation that assume agents react to objectively interpreted new information conditional on prior beliefs, fully accounted for by meteorological conditions. Understanding the determinants of beliefs and the existence of cognitive biases among the most vulnerable communities, whose activities heavily rely on natural resources and climate, is of paramount importance since it may have direct implications for adaptive behavioral responses (Zappalà, 2022).

This paper studies the effect of drought exposure on beliefs about climate change and investigates whether individuals adopt directional motivated reasoning, according to which they tend to overweight evidence that confirms their prior beliefs. I combine a two-wave survey of rural households in Bangladesh with a meteorological measure of dryness at the union-level[1], the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010). First, I document how long-term average exposure to dryness and short-term deviations affect individuals' beliefs about drought frequency and their accuracy in interpreting these events. To define accuracy, I compute the deviation between the self-reported number of droughts and meteorological events measured using climatological cut-offs (McKee et al., 1993; Paulo et al., 2012). A positive difference indicates overestimation in the recollection of droughts. Second, I examine the potential cognitive heuristics adopted in the interpretation of droughts. I test whether individuals asymmetrically distort objective information overweighting evidence that confirms their prior beliefs,

[1]Unions are the smallest rural administrative and local government unit in Bangladesh. Administrative units are structured as follows: Division ⊃ District (*Zila*) ⊃ Sub-district (*Upazila*) ⊃ Union. There are 5,158 unions, that have an average size of approximately 10–20 km^2.

showing evidence of confirmation bias (Kahneman & Tversky, 1982; Rabin & Schrag, 1999). To identify the causal effect of prior beliefs on how information from drought events is distorted, I adopt an instrumental variable approach using as instrument the twenty-year long-term average exposure to dryness, which exploits quasi-random variation in the SPEI realizations within unions over time. The exogeneity of the instrument relies on the assumption that accounting for time- and individual-specific unobserved heterogeneity, deviations in meteorological conditions of dryness do not affect the accuracy of recollecting drought events via other channels than beliefs. To assess the validity of this assumption, I perform several checks ruling out other channels such as adaptation, recent deviations in terms of dryness, and information.

The analysis yields two main findings. First, twenty-year long-term average exposure to dryness predicts beliefs of increase in droughts and the interpretation of drought events, whereas short-term deviations in exposure do not matter. Individuals form beliefs based on exposure to their average climatic conditions and beliefs about slow-onset environmental changes are inelastic to short-term deviations. Second, I document that individuals overestimate the number of drought events when they believe that droughts have increased. This result shows that individuals adopt directional motivated reasoning, with the interpretation of droughts biased towards their priors. This finding differs from objective processing of information in a Bayesian setting, where individual prior beliefs do not affect the interpretation of information (Druckman & McGrath, 2019).

The paper makes several contributions to the literature. First, it relates to the branch analysing the determinants of climate change beliefs, widely investigated in developed countries and identified in political orientation, education, and personal experience of weather shocks (e.g., Carlsson et al., 2021; Czarnek et al., 2021; Hoffmann et al., 2022; Poortinga et al., 2019).[2] A growing attention has been devoted to individuals whose economic livelihood depends on climate, including farmers or fishers. Most evidence is based on US data (Arbuckle, Morton, et al., 2013; Arbuckle, Prokopy, et al., 2013; Gramig et al., 2013; Rejesus et al., 2013), whereas it is yet understudied the formation process in developing countries. Understanding climate change awareness in Bangladesh is of paramount importance, where, according to the 2007-2008 Gallup World Poll representative survey, more than 65% of respondents had never heard of climate change, in contrast with the

[2] A more exhaustive list includes Beattie et al. (2019), Carlton et al. (2016), Hansen et al. (2012), Howe et al. (2014), Kaufmann et al. (2017), Konisky et al. (2016), McCright et al. (2014), Moore et al. (2019), and Weber (2010).

low levels (below 10%) of climate change *skepticism* in high-income countries (Lee et al., 2015). More than a decade later, in the 2019 Gallup World Risk Poll, more than one-third of the population in Bangladesh was still unable to provide an answer to the potential effects of climate change (Rzepa & Ray, 2020). The paper provides empirical evidence of the determinants of beliefs on the consequences of climate change in a developing country, focusing on slow-onset environmental changes. Importantly, I exploit the unique longitudinal dimension of the survey to account for individual-specific unobserved heterogeneity and study within-individual changes in beliefs.

Second, this paper relates to the strand of literature that investigates cognitive heuristics associated with climate change beliefs, including anchoring, availability, representativeness or motivated reasoning (Joireman et al., 2010; Li et al., 2011; Zaval et al., 2014). This paper contributes to this literature testing the confirmation bias hypothesis. Individuals exhibit confirmation bias as a form of directional motivated reasoning if they misread the new evidence as supportive of existing hypotheses, interpreting information and overweighting evidence that confirms their beliefs (Agnew et al., 2018b; Faia et al., 2021; Fryer et al., 2019). Notwithstanding previous theoretical discussions of directional motivated reasoning mechanisms (Druckman & McGrath, 2019) and other cognitive biases (Zhao & Luo, 2021) in climate change beliefs, former empirical studies have focused on other types of cognitive biases, including availability bias (Gallagher, 2014), representativeness and spreading activation (Deryugina, 2013) in the US. The sole exception in rural communities in developing countries finds recency bias among Indian farmers (Kala, 2017).

The literature on motivated reasoning has concluded that prior climate beliefs influence the interpretation of environmental changes (Goebbert et al., 2012; Zanocco et al., 2018). Previous empirical studies testing motivated reasoning neglect potential endogeneity concerns between the interpretation of evidence and beliefs (Howe & Leiserowitz, 2013; Myers et al., 2013; Shao, 2016). I build on studies of motivated reasoning in climate change beliefs (Osberghaus & Fugger, 2022; Stahlmann-Brown & Walsh, 2022; Weber, 1997) to estimate the effect of beliefs on the interpretation of weather events in a developing country. In Bangladesh, where climate change awareness is particularly low (Lee et al., 2015; Rzepa & Ray, 2020) and drought vulnerability extremely high (Shahid, 2011), examining the drivers of the interpretation of droughts and the presence of cognitive biases is fundamental. This is, to the best of my knowledge, the first study that tests whether individuals display directional motivated reasoning in a developing country, identifying the causal effect of beliefs on how information from weather events is distorted in a quasi-experimental setting.

The remainder of the paper is organized as follows. Section 2 describes the data used in the empirical analysis. Section 3 defines the conceptual framework for the propositions that I test empirically. Section 4 presents the empirical approach. Section 5 discusses the results and their robustness. Section 6 concludes.

2 Data

I combine data from two main sources to measure beliefs and self-reported incidence of drought events at the individual level on the one hand, and meteorological measures of exposure to dryness and occurrence of drought events computed at the union level, on the other.

Beliefs about droughts and self-reported drought events. I measure individual beliefs and self-reported frequency of drought events from the Bangladesh Climate Change Adaptation Survey (BCCAS). The data consist of a two-wave survey by the International Food Policy Research Institute (2014a), collecting information from 800 agricultural households in 40 randomly selected unions in Bangladesh (Table A1). The first wave was conducted in January 2011 and previously analysed in Delaporte and Maurel (2018). A follow-up wave (International Food Policy Research Institute, 2014b) was conducted in September 2012. More than 97%, i.e., 766 out of 800 households, were reinterviewed in the second wave.[3] I construct a binary variable, *Belief of Increase in Droughts*, or simply *Belief*, equal to one if the respondent answers "Longer periods of droughts" to the question "Have you noticed any changes in climate over the last 20 years? If yes, please specify what changes you have noticed."

Prior to being asked about their beliefs, individuals are asked a series of questions about their memories of weather events in recent years, as in Weber (1997). I construct the variable *self-reported # droughts* using the question in the first wave "In the last five years, have the household's properties and productivity been affected by droughts? How many times did it occur?". The same question in the second wave asks respondents to report the number of droughts since the last interview. This variable is then used to measure the accuracy of recollection of drought events

[3] The remaining 34 households could not be interviewed because they migrated (15 households) or were not at home at the time of the survey.

as explained below. Table A2 reports the exact wording and formulation of each question in the two waves.[4] Although the survey does not provide a formal definition of droughts and does not record differently the intensity of perceived weather events, different interpretation of droughts by different respondents does not pose a challenge to the validity of the empirical analysis that exploits within-individual variation in beliefs over time.[5]

Dryness exposure. To construct a measure of exposure to dryness, I use a climatological measure, the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010), which provides information about drought conditions at the global scale, with a 0.5° spatial resolution (≈ 55km at the Equator) and a monthly time resolution. The SPEI-1 compares the amount of precipitation and potential evapotranspiration to obtain a measure of drought based on water balance accumulated over one month and is constructed using data from the Climatic Research Unit of the University of East Anglia (CRU TS version 4.03). The index is a standardized probability measuring the deviation in dryness relative to the average observed during the available 1901-2018 time period in each grid cell. A value of zero indicates the median amount (half of the historical amounts are below the median, and half are above the median), and the index is negative for dry, and positive for wet conditions. For instance, a value equal to -1 indicates that the difference between precipitation and potential evapotranspiration is one standard deviation lower than the historical average for a given grid cell.

I build two measures of exposure to dryness at the union level to account for long-term average and short-term deviation (Bento et al., 2020; Guiteras et al., 2015; Hsiang & Jina, 2014).[6] I construct union-level SPEI monthly realizations as a weighted average of the union surface over each grid cell. Figure A1 displays the relationship between the union boundaries and the SPEI gridded dataset. The long-term exposure is the average of the monthly SPEI across the previous twenty years, indicating whether this period was relatively drier or wetter than the historical average for each union. This measure is constructed as the "objective counterfactual" of the individual beliefs

[4]From the BCCAS, I also collect individual and union characteristics from the community questionnaire that I use in subsequent robustness exercises.

[5]The underlying assumption is that individuals do not differentially change their internal definition of droughts between the two survey waves.

[6]For ease of interpretation of the coefficients in the empirical analysis, these measures are taken in their additive inverse form, meaning that higher values are associated with drier conditions.

that droughts have increased in the previous twenty years. Beliefs are assumed to be formed from the long-term average exposure in the union of residence.[7]

I construct a short-term deviation measure from the long-term average, as the difference between the average SPEI monthly realizations over the previous five years and the twenty-year long-term average, for the first wave, and the difference between the average SPEI monthly realizations between the two waves and the twenty-year long-term average, for the second wave.[8]

Drought events. To have a measure of individual accuracy of recollection of droughts, I compare the self-reported number with the objectively recorded number of drought events. The climatology literature defines a drought event as the period of consecutive time points in which the SPEI is below certain thresholds (Spinoni et al., 2014). Specifically, there are five classes of droughts: i) non-drought (SPEI > -0.5); ii) mild droughts ($-1 <$ SPEI ≤ -0.5); iii) moderate droughts ($-1.5 <$ SPEI ≤ -1); iv) severe droughts ($-2 <$ SPEI ≤ -1.5); v) extreme droughts (SPEI ≤ -2) (McKee et al., 1993; Paulo et al., 2012). Since the SPEI is normally distributed, each of the five classes respectively accounts for about 69.1%, 15%, 9.2%, 4.4% and 2.3% of the set of historical values for each grid cell.

Based on this classification, I compute for each union the number of extreme drought events that have occurred in the five years before the first wave of the survey and between the first and the second wave.[9] To test the robustness of the results, I employ other cut-offs to define the objective number of droughts, including moderate (SPEI ≤ -1) and severe (SPEI ≤ -1.5) droughts. Figure A2 shows the timeline of the survey compared to the construction of the measures of dryness and drought events.

Following this approach, I create a measure of accuracy of recollection of past drought events:

$$\Delta_{it}^{type} = \text{self-reported } \# \text{ droughts}_{it} - \text{objective } \# \text{ droughts}_{ut}^{type} \tag{1}$$

where Δ_{it}^{type} ($type \in \{$moderate; severe; extreme$\}$) measures the deviation between the self-

[7]Since the survey does not provide information on the place of residence of the respondents over the twenty years before the first wave, I assume they have not moved and have been exposed to the union-average dryness conditions.

[8]This methodology is adopted in order to create a continuous measure of wave-specific variation in exposure to dryness that matches the time period covered by the self-reported number of drought events in the BCCAS.

[9]The choice of the time periods mirrors the time period covered by the survey questions on the number of drought events experienced.

reported number of droughts by individual i in survey wave t with the number of droughts recorded using the SPEI in union u over the same time period. These wave-specific measures of interpretation infer whether respondents overestimate or underestimate the number of drought events that they have experienced. For instance, a positive value shows that individuals overestimated the number of drought events. By matching households with objectively recorded drought events at the union level, I measure asymmetric changes in the recollection of drought events for individuals that faced the same course of events and have been exposed to the same set of objective information. I acknowledge that meteorological data are not necessarily the "truth", but I use them to study a systematic pattern to individual interpretation of drought events as a function of their beliefs.[10]

Descriptive statistics. The final sample is composed of 714 individuals. Since the focus is on personal experience, the sample includes only households who have been surveyed in both waves and did not move, and for which the respondent was the same. This setting accounts for individual-level unobserved heterogeneity (including different interpretation of the questions) and allays concerns about the biasedness of the coefficients associated with self-reported subjective measures. Table A3 tests for differences in means for the main variables between the sample of attritors and non-attritors in the first wave and finds no statistically significant differences.

Tables A4 and A5 provide, respectively, summary statistics on self-reported variables and objective measures of drought exposure. On average, half of the sample believes that droughts have increased over the past twenty years. All unions have experienced at least one moderate drought event in both time periods considered in the first and second waves. Although between the two waves only one extreme drought event is recorded in Chaklarhat, in the northwest region of Bangladesh, an area historically prone to drought events (Alamgir et al., 2015), the share of individuals believing that droughts have increased is 46 percentage points higher in the second wave.

Table A4 shows that respondents on average underestimate the number of droughts when the accuracy measure Δ includes moderate and severe droughts. On the contrary, Δ is on average

[10]Despite the recurrent and devastating nature of droughts, previous studies in Bangladesh have more often focused on floods (Chen et al., 2017; Gray & Mueller, 2012; Guiteras et al., 2015). In spite of data availability on individual beliefs and personal experience of floods in the survey, I focus on droughts since there exist meteorological measures both of exposure to dryness and drought events. Rainfall measures have been shown to be weak proxies for flood exposure, and flood extent is nowadays commonly measured using remote-sensing data from the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) (Chen et al., 2017; Guiteras et al., 2015). Nevertheless, differently from drought event recording, to the best of my knowledge, there is no classification for the meteorological number of flood events.

positive, but close to zero, using only meteorological extreme drought events. Figure A3 displays the frequency distribution of Δ with the three cut-offs for the objective measure. A large share of respondents underestimates droughts with moderate (98.6%) and severe cut-offs (68.6%). There may thus be a systematic upward bias when including these two types of drought events as objective counterfactual of the self-reported number of droughts to construct Δ. This would translate into a downward bias in Δ. Therefore, I construct Δ only including extreme droughts. In this case, most of the respondents (65%) are accurate ($\Delta = 0$) and the distribution is right-skewed with more than 25% of the respondents overestimating. Generally, droughts are shown to have substantial impacts on agriculture when the SPEI is below -1.5, i.e., if the drought is at least severe (Zargar et al., 2011). Hence, extreme drought events may be a valid objective counterfactual for the self-reported droughts, although I test for the robustness of the results including moderate and severe droughts.

3 Conceptual Framework

This section describes a conceptual framework, whose objective is two-fold. First, it models the relationship between objective exposure to dryness and self-reported individual beliefs and the way individuals recollect drought events. Second, it sets as a benchmark the Bayesian updating framework in the context of drought events, defining how a Bayesian updater would interpret new information as independent from her prior belief and use both available evidence and prior belief to form a posterior. This is used in comparison to an agent who adopts directional motivated reasoning and interprets evidence as tilted towards her prior beliefs.

3.1 Objective Exposure, Beliefs and Accuracy

In the climate impact literature, an outcome of interest y is related to the environmental exposure E, whose functional form f is ex-ante unknown and requires accurate data in order to be unbiased and precisely estimated. The use of accurate data is even more relevant for extreme weather events, where self-reported survey data have been predominantly used in the literature, despite potentially subject to endogeneity concerns (Guiteras et al., 2015). The baseline equation is

$$y = f(E) + \varepsilon \tag{2}$$

where y represents the outcome of interest, in this case, the belief of increase in droughts and the interpretation of drought events, and E represents dryness exposure. The use of objectively measured right-hand side variables allays the concern about the presence of correlated measurement error between the explanatory and the outcome variable. Self-reported environmental exposure E would provide little information about the relationship of interest between beliefs and exposure to dryness. For example, poorer households may be more exposed to droughts but less able to assess damages accurately.

Individuals may form their beliefs of increase in droughts using their long-term average exposure to dryness as a reference point to judge deviations from the average. In this case, a household frequently exposed to larger droughts and one not frequently exposed would consider a drought of the same magnitude differently. For this reason, a priori, it is uncertain whether beliefs and the recollection of drought events depend on the average conditions of exposure to dryness, deviations from the average, or both. Low-exposure households may be more likely to change their beliefs if they experience a larger drought, whereas households with a larger long-term average exposure to excess dryness may have a more inelastic reaction to deviations from the mean. The following proposition formulates a first initial prediction about the relationship between drought exposure and beliefs.

Proposition 1: Exposure to excess dryness positively affects the belief of increase in droughts and the recollection of drought events, i.e. $\partial y/\partial E = \partial f(E)/\partial E \geq 0$.

3.2 Bayesian Framework

Bayes' rule is commonly used for modeling the belief updating process. In a Bayesian updating framework, new information is embodied into prior beliefs to reach an updated posterior belief. Using the standard law of large numbers, a Bayesian updater who forms beliefs conditional on the full sequence of signals would form with probability equal to one a posterior belief of the correct state of nature.

Consider an agent with a prior belief $\pi(\mu)$, where π denotes the function of belief μ as the probability distribution regarding the true state $\pi(\mu) \sim \mathcal{N}(\widehat{\mu_0}, \widehat{\sigma_0}^2)$, with $\widehat{\mu_0}$, the agent's best guess about the true state of the world, and $\widehat{\sigma_0}^2$, the individual's uncertainty around her guess, where a $\frown$ denotes anything related to perceptions (Druckman & McGrath, 2019). In this study, the individual belief about an increase in droughts in the past twenty years $\pi(\mu)$ includes her estimate of the increase in droughts $\widehat{\mu_0}$ and the confidence in that estimate $\widehat{\sigma_0}^2$.

Bayesian updating occurs when new information, x, is provided to the individual as a draw from the distribution $\mathcal{N}(\mu, \widehat{\sigma_x}^2)$, centered at the true state of the world μ and with variance in the individual perception of the credibility of the new information, $\widehat{\sigma_x}^2$. Agents embody the new information and form an updated posterior belief, $\pi(\mu|x)$. Here, new information x corresponds to the number of drought events in the union of residence of households.

Druckman and McGrath (2019) discuss the accuracy-driven motivated reasoning in climate change preference formation in the Bayesian framework. Individuals aim at arriving at a correct conclusion, evaluating new information x to maximize the likelihood that the posterior belief is an accurate estimate of the true state of nature. Therefore, the evaluation of x is independent of the individual's prior belief $\pi(\mu)$. The individual's prior belief $\pi(\mu)$ does not affect the interpretation of the new information $\widehat{x}$, here the self-reported number of drought events.

Estimating every component of Bayes' formula and the posterior belief is not feasible in this empirical setting due to the lack of available data. Nevertheless, this theoretical result is used to compare how an accuracy-motivated Bayesian agent would differ from an agent that displays directional motivated reasoning. In the latter case, the individual belief would distort the interpretation of new evidence and bias it towards it.

3.3 Directional Motivated Reasoning

In psychology, a "heuristic" is a simplified model for making inferences. Individuals who apply cognitive heuristics may not use all available information or may oversimplify such information when processing it. These cognitive biases are departures from Bayesian updating and some of them have already been documented in the context of climate change belief formation (Deryugina, 2013; Fryer et al., 2019; Gallagher, 2014). Druckman and McGrath (2019) summarize three mechanisms of directional motivated reasoning in climate change preference formation. Under motivated reasoning, the interpretation of personal experience of climatic changes stems from prior beliefs rather than from impartially detecting changes in their local environment (Palm et al., 2017). The first and foremost mechanism is the confirmation bias (Lodge & Taber, 2013).

Individuals subject to confirmation bias are motivated to maintain their prior belief $\pi(\mu)$ after elaborating new information and thus they seek out information that confirms their prior belief. The distribution from which the individual draws the new information x is no longer $\mathcal{N}(\mu, \widehat{\sigma_x}^2)$ but $\mathcal{N}(\widehat{\mu_0}, \widehat{\sigma'_x}^2)$, centered at the mean of the individual's prior beliefs and not at the true state of the world. The individual belief $\pi(\mu)$ thus affects the perceived new information $\widehat{x}$, the self-reported number of drought events.

The interpretation of the information is accurate if $\widehat{x} - x = 0$. Using Equation (1), individuals are accurate if self-reported and objective number of drought events coincide, i.e. $\Delta = 0$. Following Fryer et al. (2019), the functional form of the confirmation bias and distortion of information relates the interpretation of objective information x compared to the perceived information $\widehat{x}$, as a function of the prior belief μ. Under confirmation bias, the interpretation of information is distorted in the direction of individual beliefs for a given objective information x. This implication is formulated in the form of the following proposition.

Proposition 2: Individuals display directional motivated reasoning and are subject to confirmation bias if the prior belief μ affects and distorts the interpretation of the information x. Under directional motivated reasoning, the interpretation of drought events measured as the deviation between the self-reported and recorded number of droughts is a function of individual beliefs of increase in droughts μ:

$$\widehat{x} - x = \pi(\mu) \tag{3}$$

4 Empirical Approach

4.1 Objective Exposure, Beliefs and Accuracy

I first examine the effect of objective exposure to dryness on the belief of increase in droughts and on how individuals self-report drought events compared to the objectively recorded number. The probability of overestimating the number of droughts is defined as a dummy equal to one if the self-reported number is greater than the number of objectively recorded extreme drought events with the SPEI (i.e., $\Delta > 0$), and zero otherwise. Afterward, I shift the focus to the extent of overestimation, using the Δ measure that takes negative values if individuals underestimate, null if they are accurate and positive if they overestimate the number of drought events.

I employ an OLS regression in a panel setting using individual-specific and year-specific fixed effects. I estimate beliefs of increase in droughts over the previous twenty years and interpretation of droughts as a function of the long-term average exposure, the deviation from long-term average, and their interaction to account for the heterogeneous effect of deviations. This functional form $f(E)$ is adopted since individuals perceive exposure relative to their average environment and use it as a reference point to judge deviations from that average. The full specification is written as:

$$y_{it} = \beta_1 \text{LT Exposure}_{ut} + \beta_2 \text{Deviation}_{ut} + \beta_3 \text{LT Exposure}_{ut} \times \text{Deviation}_{ut} + \alpha_i + \lambda_t + \varepsilon_{it} \tag{4}$$

where y_{it} is the belief of increase in drought or the interpretation of drought events for individual i in survey wave t. The coefficients on all weather variables can be interpreted causally since within-union realizations of weather are plausibly exogenous (Auffhammer & Carleton, 2018; Carleton & Hsiang, 2016). I exploit within-individual variation by accounting for time-invariant individual-specific and year-specific characteristics to identify the effect of drought exposure. Individual-specific fixed effects absorb the effect of all time-invariant factors that differ between individuals, including unobservable characteristics that could not be accounted for in a cross-sectional empirical design, such as personality traits, gender, location, education level, interpretation of droughts (Hsiang, 2016). Similarly, λ_t controls for unobserved shocks common to all individuals in a given year.

In five cases out of the 40 sampled unions, the 0.5° grid cells of the SPEI data embed more than one union. Standard errors clustered at the union-level would be underestimated. For this reason, I cluster standard errors at the grid cell level to account for correlation and heteroskedasticity across unions, and *a fortiori* individuals, within the same cell.[11]

[11] Union, or grid-cell, fixed effects are superfluous since all individuals in the estimation sample never change place of residence and therefore union-specific unobserved heterogeneity is taken into account by individual-specific fixed effects.

4.2 Directional Motivated Reasoning

To examine whether individuals exhibit confirmation bias, I formulate a new specification that relates beliefs of increase in droughts to their interpretation. This approach empirically tests Equation (3): individuals who display directional motivated reasoning distort the interpretation of new information as a function of their beliefs. Figure A4 provides stylized evidence of this mechanism. The frequency distribution of the measure Δ for individuals holding beliefs that droughts have increased is more left-skewed than for individuals who do not hold such beliefs. The t-test of a difference in means between the two samples is -11.26: Δ has an average of -0.12 among the *non-believers*, and an average of 0.47 among the *believers*, implying a statistical difference between the two samples (p-value < 0.001). This is confirmed by a Kolmogorov-Smirnov test conducted under the null hypothesis of equal distribution of Δ by beliefs, which I fail to accept (p-value < 0.001).

I design an econometric specification that uses as outcome both the probability and the extent to which individuals overestimate. The baseline equation writes

$$\text{Overestimation}_{it} = \gamma \text{Belief}_{it} + \beta \text{Deviation}_{ut} + \alpha_i + \lambda_t + u_{it} \tag{5}$$

where Belief_{it} is the binary variable indicating whether individual i in survey wave t believes that droughts have increased over the past twenty years. Deviation_{ut} refers to the short-term deviation in dryness from the LT Exposure and α_i and λ_t are individual and year fixed effects. Standard errors are clustered at the grid cell level.

Even when accounting for the fixed effects, the OLS regression may yield biased estimates of the effect of beliefs on accuracy for several reasons. First, individuals may alter their long-lasting beliefs after receiving new information and therefore beliefs could change as a consequence of the interpretation of drought events. Equation (5) may be subject to simultaneity bias and the estimates of the effect of beliefs on the interpretation of drought events would be biased downwards. Second, the estimate of the coefficient may also be biased because of classical measurement error. This would lead to an attenuation bias and thus $\hat{\gamma}$ would again be biased towards zero. The errors in measurement of the belief may be correlated with the noise u_{it}, which represents other unobservable determinants of outcomes, for example, poorer households might be more exposed to droughts but less able to assess damages accurately. Finally, other omitted time-varying individual-specific characteristics such as risk perceptions may be simultaneously correlated with changes in individuals' beliefs about droughts and in the recollection of drought events.

To address the concerns on endogeneity, I adopt an instrumental variable approach using as an instrument the average long-term exposure to dryness over the previous twenty years. This variable complies with the two restrictions for a valid instrument. The variable is relevant as shown from the estimation of Equation (4) (Table 1, column 3). A household frequently exposed to large extreme weather events and one not frequently exposed may differently interpret an event of the same magnitude (Guiteras et al., 2015). Average long-term exposure is expected to satisfy the exclusion restriction, by determining individuals' interpretation of past drought events only through their beliefs about these events. The validity of the instrument and the identifying assumption is discussed below. Testing whether the interpretation of new information is tilted towards the beliefs provides evidence of confirmation bias if the estimated coefficient $\hat{\gamma}$ is positive and statistically significant.

4.2.1 Identifying Assumption and Instrument Validity

In an OLS regression, the identification of the effect of beliefs on individuals' interpretation of drought events is threatened by reverse causality, omitted variable bias and classical measurement error. To address these and similar concerns, I adopt an instrumental variable approach and use the twenty-year long-term average exposure to dryness as an instrument for beliefs of increase in droughts. The instrumental variable approach strengthens the causality argument under the exclusion restriction that exposure to dryness does not affect the accuracy of recollecting drought events via other channels besides beliefs.

The variation underlying the instrument, relative changes in long-term exposure to excess dryness, is plausibly as good as random and hence likely exogenous to within-individual variation over time. By retaining only variation in beliefs generated by the quasi-experimental variation in long-term dryness, this approach exploits the rational component of changes in beliefs estimated from variation in dryness exposure. If individuals did not exhibit confirmation bias, using an instrumental variable approach, beliefs should have a null effect on the interpretation of weather events.

There are three major concerns that may violate the exclusion restriction. In what follows, I describe additional tests that assuage concerns on its validity. First, variation in the instrument may have an indirect effect on self-reported evidence through the omitted variable of subjective well-being and mood (Mellon, 2021). According to the empirical evidence on self-reported life satisfaction (Maddison & Rehdanz, 2011), the estimates of beliefs on recollection of droughts may be downward biased. Droughts have a negative effect on happiness (Keshavarz & Karami, 2012; Sekulova & van den Bergh, 2013) and life satisfaction (Carroll et al., 2009), which could positively affect the overestimation of past weather events (Forgas et al., 2009) and thus threaten the exclusion restriction. Nevertheless, studies using an individual fixed-effect empirical setting (Feddersen et al., 2016) do not detect a relationship between climate and self-reported life satisfaction and find an effect close to zero. These findings allay potential concerns about the validity of the instrument.

Second, objective drought exposure may affect the individual's recollection of past drought events through past adaptation. This concern would arise if past environmental conditions affected past actions, which would in turn impose "historical restraints" on current actions (Lemoine, 2021). Households that adapted due to changes in dryness might experience fewer droughts, and thus underestimate them, than if they had not adapted. For this reason, this potential channel would bias downwards the 2SLS estimates. In order to allay the potential concern about the validity of the instrument, the econometric specification includes a history of transient shocks proxied by the short-term deviation from the long-term exposure to dryness. This should reduce the bias introduced by historical restraints. In Section 5, additional robustness checks show that the adaptation channel does not threaten the identification of the effect of beliefs.

Finally, the instrument may be positively correlated with the propensity of individuals to seek weather information and listen to weather forecasts. The literature exploring this channel uses internet search activity data to examine if local short-run weather fluctuations cause people to seek information about climate change, finding that they have an effect on search behavior (Choi et al., 2020), but not always consistent with the projected impacts of climate change (Lang, 2014). The main difference between the previous findings and my design stands in the use of a long-term average in place of short-term fluctuations. The use of long-term exposure to dryness should allay the concern on its potential correlation with seeking information on climate change. Furthermore, if this channel existed, seeking and receiving more weather information would be negatively correlated with the recollection of drought events. A more informed individual would be able to reduce the distance between the self-reported and objective number of droughts. Therefore, this channel would underestimate the effect of beliefs on the overestimation of drought events. The survey does not contain explicit information on the individual use of weather information, however, in Section 5, I discuss additional robustness checks that assuage concerns about the validity of the instrument. Table A6 shows the correlations between the instrument and the additional controls included in the robustness exercises. Out of the ten estimates, I find that only one is statistically significant at the 10% level, which is consistent with sampling variation given the multiple tests carried out, thus strengthening the exogeneity hypothesis of the instrument.

5 Results

5.1 Objective Exposure, Beliefs and Accuracy

Table 1 displays the results for the effect of objective exposure to dryness on beliefs and recollection of drought events. Columns (1) and (2) separately investigate whether short-term deviations and long-term exposure predict self-reported beliefs and the measure of accuracy. Column (3) includes them both, and in column (4) I include their interaction, as in Equation (4).

When considering the belief of increase in droughts, both the long-term average exposure (column 1) and the short-term deviation from the reference environment (column 2) have a positive statistically significant effect. The effect of long-term average exposure is more than ten times larger than the effect of short-term deviations. A one standard deviation (SD) increase in long-term exposure is associated with approximately a 1.2 SD increase in the probability of believing that droughts have increased over the previous twenty years ($15.13 \times 0.04/0.5$).[12] In contrast, a one SD increase in deviations from the average drought exposure increases the probability of believing in an increase in droughts by around 0.14 SD ($0.729 \times 0.10/0.5$). When considering the effect of both LT Exposure and Deviation in column (3) and including their interaction (column 4), only the coefficient associated with long-term exposure is statistically significant.

When regressing the probability of overestimating the number of drought events and the extent

[12]Respondents' median age is 45. Baseline results are robust if excluding individuals below 30 years old (around 7% of the sample).

of overestimation on the full specification, the effect of short-term deviation and of the interaction term are not statistically different from zero (columns 8 and 12). Long-term exposure continues to have a sizeable positive and statistically significant effect on individuals' overestimation of drought events across all specifications.

The findings suggest that objective exposure matters for climate change belief formation in Bangladesh. Long-term average exposure to dryness predicts beliefs about increases in droughts and overestimation of past droughts, whereas deviations from local average conditions do not matter. On the one hand, these results differ from previous findings that show that, although in a different geographical context, recent, local weather anomalies matter for the formation of climate change beliefs in the United States (Kaufmann et al., 2017; Konisky et al., 2016). On the other hand, these findings add empirical evidence to the result that the experience of a single drought event may not be enough to alter climate change beliefs and what matters is the average dryness condition in the long-term (Carlton et al., 2016). To corroborate this hypothesis, I regress beliefs on long-term average exposure and the average number of drought events experienced over the five years before the first wave and between the two waves including different types of droughts (moderate, severe, extreme). Table A7 shows that beliefs are only explained by long-term average exposure.

The results are robust to different estimation methods, using a logit method for the belief of increase in droughts and the probability of overestimating drought events (Table A8) and a Poisson method for the extent of overestimation (Table A9). The results are not specific to the cut-off used to compute the objective number of drought events. I re-estimate Equation (4) including moderate and severe drought events (Tables A10 and A11). Long-term exposure to dryness has a positive and statistically significant effect on the extent of overestimating drought events (Column 8). The coefficient is larger in magnitude when including also moderate droughts, smaller when considering severe droughts, but still larger than in the baseline specification in Table 1 that only records extreme droughts. An increase in long-term exposure makes the environment more drought-prone, affecting *in primis* the probability of a moderate drought event and thus increasing the probability of overestimating droughts.

Three additional tests check the robustness of the results to other measures of drought exposure. First, results are robust to measuring dryness and meteorological droughts using different time scales of the SPEI. Different time scales define the period considered over which water deficits accumulate.

I replicate the baseline results using the SPEI-4, SPEI-6 and SPEI-12 that, respectively, account for water deficits accumulated in the previous four, six and twelve months (Table A12). I also rescale the SPEI monthly realizations relative to each respondent's specific lifetime exposure to dryness conditions. To do so, I compute the individual-specific lifetime mean and standard deviation of dryness conditions using the SPEI and then normalize the SPEI monthly realizations used to construct long-term exposure and short-term deviations. This approach allows for the same SPEI realization in a given union to have different standardized probabilities with respect to each individual's lifetime exposure. Table A13 shows that results for different SPEI time scales are robust, providing suggestive evidence that individuals perceive exposure and form beliefs relative to their average environment based on their lifetime exposure. Figure A5 shows that individuals' beliefs are relatively inelastic to short-term deviations and beliefs depend on the relative long-term average exposure compared to their lifetime experience. Finally, instead of obtaining union-specific values of SPEI based on zonal statistics, I interpolate gridded data based on the inverse squared distance from the union centroids using as distance cut-offs 40, 80 and 120 km. Baseline results hold constructing dryness measures based on this approach (Table A14).

I also restrict the focus to the respondents who (weakly) overestimate the number of past drought events (Table A15). The sample size drops down to around 100 observations when considering those who overestimate severe drought events, therefore while the precision of the estimates deteriorates, the coefficients on deviations are never statistically significant and the coefficients on long-term exposure remain fairly stable across the estimations.

5.2 Directional Motivated Reasoning

Next, I shift the focus to the relationship between beliefs and interpretation of drought events. I test the hypothesis that individuals adopt directional motivated reasoning and are subject to confirmation bias. Under this hypothesis, individuals' interpretation of drought events would be biased towards their prior beliefs, such that holding beliefs that droughts have increased has a positive effect on the probability and extent of overestimating the number of droughts.

Since only beliefs of increase in droughts are recorded in the survey, I only focus on the overestimation of the number of past drought events. Further research should explore whether directional motivated reasoning is displayed also by individuals who hold beliefs about a decrease in droughts,

Table 1: Objective exposure, beliefs and overestimation of drought events

	Belief				Overestimation							
	Belief of Increase in Droughts				Probability				Extent			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LT Exposure	15.13***		14.60***	15.14***	10.48***		11.64***	12.44***	38.81**		59.12***	60.03***
	(2.129)		(3.132)	(3.386)	(1.934)		(2.871)	(3.078)	(16.96)		(16.70)	(18.26)
Deviation		0.729***	0.0711	-0.285		0.369*	-0.156	-0.683		-0.0576	-2.722***	-3.321
		(0.198)	(0.245)	(0.748)		(0.216)	(0.255)	(0.592)		(1.005)	(0.982)	(2.440)
LT Exposure × Deviation				2.411				3.569				4.058
				(4.024)				(2.950)				(14.93)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428	1428	1428	1428	1428	1428	1428
adj. R^2	0.281	0.253	0.280	0.279	0.155	0.133	0.155	0.155	0.198	0.128	0.235	0.234

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual believes that droughts have increased in the past twenty years (columns 1-4), a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 5-8) and the measure of overestimation Δ (columns 9-12). All regressions control for individual and year fixed effects. The measure Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

leading to a biased underestimation of drought events.

Panel A of Table 2 reports the OLS (columns 1 and 2) and 2SLS (columns 3 and 4) estimates of Equation (5) using as outcome the indicator that individuals overestimated the number of droughts ($\Delta > 0$) (columns 1 and 3), and the extent to which individuals overestimated droughts (Δ) (columns 2 and 4). Panel B reports the first stage estimates of the instrumental variable approach. The coefficient associated with Belief is positive and strongly statistically significant in both the OLS and 2SLS specifications. Consistent with Proposition 2, the belief of an increase in droughts increases the likelihood of overestimating drought occurrence by about 80 p.p. (column 3). When exploiting the extent of overestimation, beliefs have a positive and statistically significant effect, increasing the overestimation by four (column 4).

The magnitude of the 2SLS coefficient associated with Belief is significantly larger than the OLS estimate both in the probability and extent of overestimation. One potential explanation is that the OLS estimates suffer from reverse causality and attenuation bias due to measurement error.[13] A second possibility is that the 2SLS estimation identifies a local average treatment effect (LATE) for individuals that were more exposed to variation in excess dryness and thus more likely to update their beliefs about increases in droughts and overestimate their number.

These results provide suggestive evidence that individuals adopt directional motivated reasoning when interpreting drought events. The information is distorted, and changes in the perception of information for a given objective information set are driven by individual beliefs. Figure 1 plots the cumulative distribution functions of the predicted values of the extent of overestimation from Equation (5) for the two belief types. The gap between the two distributions shows that individuals with prior beliefs that droughts have increased exhibit confirmation bias and overestimate the number of drought events.

Same number of recorded droughts. Using objectively recorded droughts, all individuals within the same grid cell are exposed to the same set of objective information (the households in the sample do not change place of residence across the two waves). Any variation in the interpretation

[13]In an OLS setting undermined by reverse causality, the coefficient associated with beliefs would be biased downwards, and under the classical error-in-variables assumption, OLS estimates would suffer from attenuation bias due to measurement error. As shown in Panel B of Table 2, long-term average exposure to dryness has a positive, significant effect on belief and the Kleibergen-Paap (K-P) Wald F-statistic for weak identification is 21.736, higher than any critical value reported by Stock and Yogo (2005).

Table 2: Directional motivated reasoning. OLS and 2SLS estimates.

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Panel A:	Probability	Extent	Probability	Extent
Belief	0.166***	0.368***	0.797***	4.049**
	(0.0491)	(0.115)	(0.232)	(1.541)
Deviation	0.248	-0.326	-0.213	-3.010**
	(0.211)	(0.997)	(0.335)	(1.421)
F-stat			21.736	21.736
Panel B:			*Belief of Increase in Droughts*	
LT Exposure			14.60***	14.60***
			(3.135)	(3.135)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428

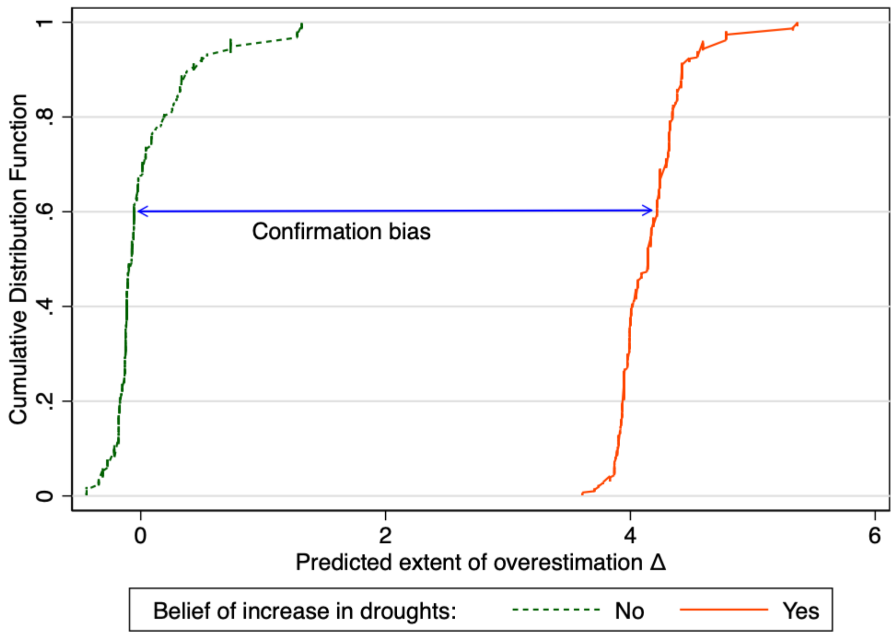
Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-3) and the measure of overestimation Δ (columns 2-4). The measure Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The table reports the OLS estimates of Equation (5) in columns (1) and (2) and the 2SLS estimates in columns (3) and (4) in Panel A. Panel B reports the first stage associated with 2SLS regressions, controlling for Deviation. The main regressor of interest is Belief, which is instrumented with the LT Exposure in columns (3) and (4). All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

of droughts stems from asymmetric changes in beliefs. To corroborate this hypothesis, I restrict the sample to the unions that experienced the same objective number of drought events. This setting is similar to an experiment in which all participants are given the same objective evidence (with the clear difference that in this setting the evidence cannot be controlled by the experimenter).

Since there is substantial heterogeneity across unions in the number of extreme droughts experienced, this analysis can only be performed for the unions that have not experienced any extreme drought event.[14] With this restriction, all households in the sub-sample did not face any drought in the years before each survey wave, and any residual asymmetric variation in interpretation is

[14]Since the SPEI values are normally distributed, extreme drought events (SPEI ≤ -2) account for about 2.3% of all available historical values. On average, such SPEI values would then be recorded once every 44 months, explaining why no extreme droughts is the only case that brings together several unions.

Figure 1: Differential cumulative distribution functions of predicted overestimation of droughts



Notes: Figure shows the cumulative distribution function (CDF) for the extent of overestimation predicted from Equation (5) using a 2SLS approach. The dashed green line shows the CDF for individuals in the estimation sample that did not report that droughts have increased. The solid red line shows the CDF for individuals in the estimation sample with a belief that droughts have increased. The extent of overestimation Δ is computed as explained in Equation (1): I use the cut-off for extreme drought events (SPEI $\leq$ -2) to compute the number of objective drought events in a given union and subtract it from the number of self-reported drought events over the same time period.

explained by changes in individual beliefs (accounting for short-term deviation in excess dryness and individual-specific and year-specific fixed effects). The marginal effect of believing in an increase in drought increases the probability of overestimating droughts by 95 p.p. (Table A16). This result demonstrates that individuals with prior beliefs of increases in droughts, although not recently exposed to extreme droughts, will distort their interpretation and overestimate them.

Measures of drought exposure. I also test for the robustness of the results using different SPEI time scales to construct drought exposure based on different periods over which water deficits accumulate. Table A17 shows similar 2SLS estimates using the SPEI-4, SPEI-6 and SPEI-12. I also normalize the SPEI to individual-specific lifetime exposure to dryness conditions and obtain a robust positive effect of beliefs on the probability and the extent of overestimating droughts across different SPEI temporal scales (Table A18). Finally, the results are robust to the construction of drought exposure based on the interpolation of gridded data weighted by the inverse squared distance from the union centroids using as distance cut-offs 40, 80 and 120 km (Table A19).

Drought cut-offs. The findings are robust to different drought cut-offs to construct Δ (Table A20). The effect of beliefs is larger including moderate droughts (14.03, column 3) and severe droughts (6.92, column 4), compared to the effect on recollection of extreme droughts (4.05, column 4 in Table 2). This result suggests that the more ambiguous the signal, the more the evidence is open to interpretation. This situation creates room for the learner to adopt directional motivated reasoning and interpret ambiguous new information as a reinforcement of prior beliefs (Agnew et al., 2018a, 2018b). I also limit the analysis to the sub-sample of individuals who overestimate droughts using the cut-offs of severe and extreme droughts (Table A21). Using extreme drought events, the OLS and 2SLS coefficients are positive, suggesting that individuals distort their interpretation of information due to their beliefs and exhibit directional motivated reasoning.

Historical restraints. As discussed in Section 4.2.1, a potential threat to the validity of the instrument concerns individuals exposed to more harmful conditions of dryness who may be more prone to adapt. Past weather affects past actions (i.e., adaptation), imposing historical restraints on current actions (i.e., interpreting drought events). The inclusion of short-term deviations from long-term average exposure in the baseline specification as a measure of transient shock is a first way to allay the concerns about this potential threat (Lemoine, 2021). Below, I discuss two additional robustness checks to deal with this concern.

Short-term deviations. First, I vary the definition of short-term deviations and include one-year and two-year lagged annual deviation measures from the long-term average exposure to dryness and I also extend the time horizon up to five years. Using a longer history of transient shocks reduces the bias introduced by historical restraints (Lemoine, 2021). The coefficient associated with belief is consistently statistically significant across all specifications and larger in magnitude than in the baseline estimates (Table A22).

Adaptation. Second, I account for different measures at the union-level that proxy for variations in the cost of adaptation(Tables A23 and A24).[15] I include measures of the presence of different types of banks (state-owned Krishi bank, Commercial bank, Grameen bank, or any of the three) that could affect adaptation by relaxing households' financial constraints (columns 1-4). Similarly,

[15] I use the community questionnaire that asks questions regarding each village. Table A2 reports the exact wording and formulation of each question in the two waves.

I include an indicator of the presence of agricultural extension or a block officer (column 5), which may alter the weather information set of households. I also account for access to electricity (column 6), which could facilitate the use of electricity-dependent irrigation techniques, and for the presence of a shop for fertilizers or pesticides (column 7), which may influence the input use in agricultural production. The coefficients on beliefs are consistently positive, with no considerable variations in magnitude. When including all controls in column (8), the estimates are larger in magnitude, suggesting that the baseline estimates could be underestimating the effect of beliefs.

Weather information. As explained in Section 4.2.1, the validity of the instrument may be threatened if individuals more exposed to dryness are more likely to seek weather information. This channel would downward bias the effect of beliefs since more informed individuals would be more accurate. Although the survey does not contain detailed information on the propensity of individuals to listen to weather forecasts, I use data on the type of information on agricultural practices that could relate to droughts received from extension agents and whether individuals receive information from other sources besides the extension worker, in particular TV, radio or newspapers.[16] When controlling for these variables, the 2SLS estimates of beliefs are positive, statistically significant and always larger in magnitude than the baseline estimates, suggesting that baseline estimates could be underestimating the true causal effect of beliefs (Table A25).

6 Discussion and Conclusion

Despite scientific consensus, beliefs about climate change and its causes vary widely across individuals, and awareness is still very low in the developing world (Lee et al., 2015). Understanding the determinants of beliefs and any potential biases that individuals may exhibit is essential for the design of more effective policies to help them adapt (Lemos et al., 2019). Particularly so for agricultural communities in developing countries, heavily exposed to the consequences of climate change and whose misinterpretation of weather signals may be considerably harmful. It is critical to understand if individuals misinterpret weather shocks because they lack information or because,

[16] I use the household questionnaire (module M) to construct different versions of a dummy variable of receiving information on soil and water conservation, crop protection, new crop varieties and crop utilization and a binary variable on the sources of information among which TV, radio and newspapers. Table A2 reports the exact wording and formulation of each question in the two waves.

instead of striving for accuracy, they pursue directional goals. Individuals may engage in motivated reasoning mechanisms when interpreting weather events and exhibit confirmation bias.

This paper studies the effect of dryness exposure on beliefs of increase in droughts and examines whether individuals adopt directional motivated reasoning in the interpretation of drought events. First, I investigate how long-term average exposure to dryness and short-term deviations affect beliefs and the accuracy of recollecting them, finding that only long-term average conditions matter. This result suggests that beliefs are longstanding, and hence shaped only by long-term conditions rather than short-term deviations and that one single drought event may not be enough to alter climate change beliefs. Second, I document that individuals engage in a form of directional motivated reasoning, adding the first empirical evidence in a developing country. Using an instrumental variable approach to tackle endogeneity concerns, I find that individuals distort the perception of information due to their beliefs. This result, robust to different specifications, provides suggestive evidence that individuals are subject to confirmation bias: they recollect and overweight evidence tilted towards their prior beliefs. From a normative perspective, individuals exhibiting motivated reasoning when it comes to slow-onset environmental changes suggest that policies should target individuals' beliefs to avert ignoring information countering prior beliefs.

Despite recent advancements in accurate estimates of climate impacts accounting for adaptation benefits and costs across sectors (Auffhammer, 2022; Carleton et al., 2022; Hultgren et al., 2022; Rode et al., 2021), the underlying conceptual framework still relies on perfectly informed and rational agents with unbiased beliefs measured by meteorological conditions (Deryugina & Hsiang, 2017). This paper empirically shows for the first time that climate beliefs can exhibit directional motivated reasoning, in support of previous theoretical arguments diverging from Bayesian agents, with asymmetric distortion of objective information as a result of climate beliefs (Druckman & McGrath, 2019). Integrating features of incomplete rationality of decision-makers and individual distortion of weather signals based on prior beliefs can have substantial consequences on climate impact estimates accounting for individual endogenous choices of adaptation.

These findings shed light on a cognitive bias that distorts the mental representation of climate change and may subsequently lead to erroneous interpretation of climate change consequences and prevent or facilitate behavioral responses (Zappalà, 2022). Drought frequency in Bangladesh is projected to increase in the future, particularly in regions historically considered less prone to droughts (Mohsenipour et al., 2018). Since beliefs are formed on long-run exposure rather than short-term deviations and drive the interpretation of weather events as a result of motivated reasoning, if individuals do not update them, they may not put in place timely adaptation to avert climate damage. Understanding how household beliefs about climate impact and cognitive biases impact adaptive decisions remain interesting questions for future work.

Against this background, it is essential to identify the nature of the bias to propose adequate debiasing tools for effective policies. A solution proposed by Zhao and Luo (2021) involves forward-looking techniques generating arguments for forward-looking options. Accurate information on historical and projected changes in climate may shape individuals' beliefs on climate change consequences and foster behavioral responses to put in place timely adaptation. Further work should focus on the role of information interventions exogenously varying the information set, and assessing how these affect beliefs and influence cognitive biases.

A limitation of this study opens avenues for future research. The data do not allow to test for the presence of directional motivated reasoning and confirmation bias among those who believe that droughts have decreased over time. Testing whether this prior belief, commonly associated with *climate change deniers*' or climate skeptics' position, leads to biased interpretation of weather events underestimating them, would be of particular interest. This question represents an important subject for future research.

References

Agnew, J. R., Bateman, H., Eckert, C., Iskhakov, F., Louviere, J. J., & Thorp, S. (2018a). First impressions matter: An experimental investigation of online financial advice. *Management Science*, *64*(1), 288–307.

Agnew, J. R., Bateman, H., Eckert, C., Iskhakov, F., Louviere, J. J., & Thorp, S. (2018b). Learning and confirmation bias: Measuring the impact of first impressions and ambiguous signals. *Wharton Pension Research Council Working Paper*, *15*.

Alamgir, M., Shahid, S., Hazarika, M. K., Nashrrullah, S., Harun, S. B., & Shamsudin, S. (2015). Analysis of meteorological drought pattern during different climatic and cropping seasons in Bangladesh. *Journal of the American Water Resources Association*, *51*(3), 794–806.

Arbuckle, J. G., Morton, L. W., & Hobbs, J. (2013). Farmer beliefs and concerns about climate change and attitudes toward adaptation and mitigation: Evidence from Iowa. *Climatic Change*, *118*(3), 551–563.

Arbuckle, J. G., Prokopy, L. S., Haigh, T., Hobbs, J., Knoot, T., Knutson, C., Loy, A., Mase, A. S., McGuire, J., Morton, L. W., Tyndall, J., & Widhalm, M. (2013). Climate change beliefs, concerns, and attitudes toward adaptation and mitigation among farmers in the Midwestern United States. *Climatic Change*, *117*(4), 943–950.

Auffhammer, M. (2022). Climate adaptive response estimation: Short and long run impacts of climate change on residential electricity and natural gas consumption. *Journal of Environmental Economics and Management*, 102669.

Auffhammer, M., & Carleton, T. (2018). Regional crop diversity and weather shocks in India. *Asian Development Review*, *35*(2), 113–130.

Auffhammer, M., & Schlenker, W. (2014). Empirical studies on agricultural impacts and adaptation. *Energy Economics*, *46*, 555–561.

Beattie, G., Han, Y., & La Nauze, A. (2019). Conservation spillovers: The effect of rooftop solar on climate change beliefs. *Environmental and Resource Economics*, *74*(3), 1425–1451.

Bento, A., Miller, N. S., Mookerjee, M., & Severnini, E. R. (2020). *A unifying approach to measuring climate change impacts and adaptation* (NBER Working Paper No. 27247). National Bureau of Economic Research.

Carleton, T., & Hsiang, S. (2016). Social and economic impacts of climate. *Science*, *353*(6304).

Carleton, T., Jina, A., Delgado, M., Greenstone, M., Houser, T., Hsiang, S., Hultgren, A., Kopp, R. E., McCusker, K. E., Nath, I., et al. (2022). Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *The Quarterly Journal of Economics*, *137*(4), 2037–2105.

Carlsson, F., Kataria, M., Krupnick, A., Lampi, E., Löfgren, Å., Qin, P., Sterner, T., & Yang, X. (2021). The climate decade: Changing attitudes on three continents. *Journal of Environmental Economics and Management*, *107*, 102426.

Carlton, J. S., Mase, A. S., Knutson, C. L., Lemos, M. C., Haigh, T., Todey, D. P., & Prokopy, L. S. (2016). The effects of extreme drought on climate change beliefs, risk perceptions, and adaptation attitudes. *Climatic Change*, *135*(2), 211–226.

Carroll, N., Frijters, P., & Shields, M. A. (2009). Quantifying the costs of drought: New evidence from life satisfaction data. *Journal of Population Economics*, *22*(2), 445–461.

Chen, J. J., Mueller, V., Jia, Y., & Tseng, S. K.-H. (2017). Validating migration responses to flooding using satellite and vital registration data. *American Economic Review*, *107*(5), 441–45.

Choi, D., Gao, Z., & Jiang, W. (2020). Attention to global warming. *The Review of Financial Studies*, *33*(3), 1112–1145.

Czarnek, G., Kossowska, M., & Szwed, P. (2021). Right-wing ideology reduces the effects of education on climate change beliefs in more developed countries. *Nature Climate Change*, *11*(1), 9–13.

Delaporte, I., & Maurel, M. (2018). Adaptation to climate change in Bangladesh. *Climate Policy*, *18*(1), 49–62.

Deryugina, T. (2013). How do people update? The effects of local weather fluctuations on beliefs about global warming. *Climatic Change*, *118*(2), 397–416.

Deryugina, T., & Hsiang, S. (2017). *The marginal product of climate* (NBER Working Paper No. 24072). National Bureau of Economic Research.

Druckman, J. N., & McGrath, M. C. (2019). The evidence for motivated reasoning in climate change preference formation. *Nature Climate Change*, *9*(2), 111–119.

Faia, E., Fuster, A., Pezone, V., & Zafar, B. (2021). *Biases in information selection and processing: Survey evidence from the pandemic* (NBER Working Paper No. 28484). National Bureau of Economic Research.

Feddersen, J., Metcalfe, R., & Wooden, M. (2016). Subjective wellbeing: Why weather matters. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *179*(1), 203–228.

Forgas, J. P., Goldenberg, L., & Unkelbach, C. (2009). Can bad weather improve your memory? An unobtrusive field study of natural mood effects on real-life memory. *Journal of Experimental Social Psychology*, *45*(1), 254–257.

Fryer, R. G., Harms, P., & Jackson, M. O. (2019). Updating beliefs when evidence is open to interpretation: Implications for bias and polarization. *Journal of the European Economic Association*, *17*(5), 1470–1501.

GADM. (2021). GADM database of Global Administrative Areas, version 3.6. www.gadm.org

Gallagher, J. (2014). Learning about an infrequent event: Evidence from flood insurance take-up in the United States. *American Economic Journal: Applied Economics*, 206–233.

Goebbert, K., Jenkins-Smith, H. C., Klockow, K., Nowlin, M. C., & Silva, C. L. (2012). Weather, climate, and worldviews: The sources and consequences of public perceptions of changes in local weather patterns. *Weather, Climate, and Society*, *4*(2), 132–144.

Gramig, B. M., Barnard, J. M., & Prokopy, L. S. (2013). Farmer beliefs about climate change and carbon sequestration incentives. *Climate Research*, *56*(2), 157–167.

Gray, C. L., & Mueller, V. (2012). Natural disasters and population mobility in Bangladesh. *Proceedings of the National Academy of Sciences*, *109*(16), 6000–6005.

Guiteras, R., Jina, A., & Mobarak, A. M. (2015). Satellites, self-reports, and submersion: Exposure to floods in Bangladesh. *American Economic Review*, *105*(5), 232–36.

Hansen, J., Sato, M., & Ruedy, R. (2012). Perception of climate change. *Proceedings of the National Academy of Sciences*, *109*(37), E2415–E2423.

Hoffmann, R., Muttarak, R., Peisker, J., & Stanig, P. (2022). Climate change experiences raise environmental concerns and promote green voting. *Nature Climate Change*, *12*(2), 148–155.

Howe, P. D., Boudet, H., Leiserowitz, A., & Maibach, E. W. (2014). Mapping the shadow of experience of extreme weather events. *Climatic Change*, *127*(2), 381–389.

Howe, P. D., & 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. *Global Environmental Change*, *23*(6), 1488–1500.

Hsiang, S. (2016). Climate Econometrics. *Annual Review of Resource Economics*, *8*(1), 43–75.

Hsiang, S., & Jina, A. (2014). *The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones* (NBER Working Paper No. 20352). National Bureau of Economic Research.

Hultgren, A., Carleton, T., Delgado, M., Gergel, D. R., Greenstone, M., Houser, T., Hsiang, S., Jina, A., Kopp, R. E., Malevich, S. B., et al. (2022). Estimating global impacts to agriculture from climate change accounting for adaptation. *Available at SSRN https://ssrn.com/abstract=4222020*.

International Food Policy Research Institute. (2014a). Bangladesh Climate Change Adaptation Survey (BCCAS), Round I. https://doi.org/10.7910/DVN/27704

International Food Policy Research Institute. (2014b). Bangladesh Climate Change Adaptation Survey (BCCAS), Round II. https://doi.org/10.7910/DVN/27883

IPCC. (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

Joireman, J., Truelove, H. B., & Duell, B. (2010). Effect of outdoor temperature, heat primes and anchoring on belief in global warming. *Journal of Environmental Psychology*, *30*(4), 358–367.

Kahneman, D., & Tversky, A. (1982). *Judgment under uncertainty: Heuristics and biases*. Cambridge University Press.

Kala, N. (2017). Learning, adaptation, and climate uncertainty: Evidence from Indian agriculture. *MIT Center for Energy and Environmental Policy Research Working Paper*, *23*.

Kaufmann, R. K., Mann, M. L., Gopal, S., Liederman, J. A., Howe, P. D., Pretis, F., Tang, X., & Gilmore, M. (2017). Spatial heterogeneity of climate change as an experiential basis for skepticism. *Proceedings of the National Academy of Sciences*, *114*(1), 67–71.

Keshavarz, M., & Karami, E. (2012). Drought and happiness in rural Iran. *Journal of Soil Science and Environmental Management*, *3*(3), 66–76.

Konisky, D. M., Hughes, L., & Kaylor, C. H. (2016). Extreme weather events and climate change concern. *Climatic Change*, *134*(4), 533–547.

Lang, C. (2014). Do weather fluctuations cause people to seek information about climate change? *Climatic Change*, *125*(3), 291–303.

Lee, T. M., Markowitz, E. M., Howe, P. D., Ko, C.-Y., & Leiserowitz, A. A. (2015). Predictors of public climate change awareness and risk perception around the world. *Nature Climate Change*, *5*(11), 1014–1020.

Lemoine, D. (2021). *Estimating the consequences of climate change from variation in weather* (NBER Working Paper No. 25008). National Bureau of Economic Research.

Lemos, M. C., Eakin, H., Dilling, L., & Worl, J. (2019). Social sciences, weather, and climate change. *Meteorological Monographs*, *59*, 26–1.

Li, Y., Johnson, E. J., & Zaval, L. (2011). Local warming: Daily temperature change influences belief in global warming. *Psychological Science*, *22*(4), 454–459.

Lodge, M., & Taber, C. S. (2013). *The rationalizing voter*. Cambridge University Press.

Maddison, D., & Rehdanz, K. (2011). The impact of climate on life satisfaction. *Ecological Economics*, *70*(12), 2437–2445.

McCright, A. M., Dunlap, R. E., & Xiao, C. (2014). The impacts of temperature anomalies and political orientation on perceived winter warming. *Nature Climate Change*, *4*(12), 1077–1081.

McKee, T. B., Doesken, N. J., Kleist, J., et al. (1993). The relationship of drought frequency and duration to time scales. *Proceedings of the 8th Conference on Applied Climatology*, *17*(22), 179–183.

Mellon, J. (2021). Rain, rain, go away: 176 potential exclusion-restriction violations for studies using weather as an instrumental variable. https://doi.org/10.2139/ssrn.3715610

Mertz, O., Halsnæs, K., Olesen, J. E., & Rasmussen, K. (2009). Adaptation to climate change in developing countries. *Environmental management*, *43*(5), 743–752.

Mohsenipour, M., Shahid, S., Chung, E.-s., & Wang, X.-j. (2018). Changing pattern of droughts during cropping seasons of Bangladesh. *Water resources management*, *32*(5), 1555–1568.

Moore, F. C., Obradovich, N., Lehner, F., & Baylis, P. (2019). Rapidly declining remarkability of temperature anomalies may obscure public perception of climate change. *Proceedings of the National Academy of Sciences*, *116*(11), 4905–4910.

Myers, T. A., Maibach, E. W., Roser-Renouf, C., Akerlof, K., & Leiserowitz, A. A. (2013). The relationship between personal experience and belief in the reality of global warming. *Nature Climate Change*, *3*(4), 343–347.

Oreskes, N. (2004). The scientific consensus on climate change. *Science*, *306*(5702), 1686–1686.

Osberghaus, D., & Fugger, C. (2022). Natural disasters and climate change beliefs: The role of distance and prior beliefs. *Global Environmental Change*, *74*, 102515.

Palm, R., Lewis, G. B., & Feng, B. (2017). What causes people to change their opinion about climate change? *Annals of the American Association of Geographers*, *107*(4), 883–896.

Paulo, A., Rosa, R., & Pereira, L. (2012). Climate trends and behaviour of drought indices based on precipitation and evapotranspiration in Portugal. *Natural Hazards and Earth System Sciences*, *12*(5), 1481–1491.

Poortinga, W., Whitmarsh, L., Steg, L., Böhm, G., & Fisher, S. (2019). Climate change perceptions and their individual-level determinants: A cross-European analysis. *Global Environmental Change*, *55*, 25–35.

Rabin, M., & Schrag, J. L. (1999). First impressions matter: A model of confirmatory bias. *The Quarterly Journal of Economics*, *114*(1), 37–82.

Rejesus, R. M., Mutuc-Hensley, M., Mitchell, P. D., Coble, K. H., & Knight, T. O. (2013). US agricultural producer perceptions of climate change. *Journal of Agricultural and Applied Economics*, *45*(4), 701–718.

Rode, A., Carleton, T., Delgado, M., Greenstone, M., Houser, T., Hsiang, S., Hultgren, A., Jina, A., Kopp, R. E., McCusker, K. E., et al. (2021). Estimating a social cost of carbon for global energy consumption. *Nature*, *598*(7880), 308–314.

Rzepa, A., & Ray, J. (2020). World risk poll reveals global threat from climate change (Gallup Blog, Ed.) [News.Gallup.com [Online; posted 6-October-2020; Accessed on 1-March-2023]].

Sekulova, F., & van den Bergh, J. C. (2013). Climate change, income and happiness: An empirical study for Barcelona. *Global Environmental Change*, *23*(6), 1467–1475.

Shahid, S. (2011). Spatial assessment of drought hazard, vulnerability and risk in Bangladesh. In Neves, F.D., and Sanz, J.D. (Ed.), *Droughts: New Research* (pp. 215–241). Nova Science Pub Inc.: New York, NY, USA.

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. *Journal of Risk Research*, *19*(6), 722–742.

Spinoni, J., Naumann, G., Carrao, H., Barbosa, P., & Vogt, J. (2014). World drought frequency, duration, and severity for 1951–2010. *International Journal of Climatology*, *34*(8), 2792–2804.

Stahlmann-Brown, P., & Walsh, P. (2022). Soil moisture and expectations regarding future climate: Evidence from panel data. *Climatic Change*, *171*(1), 1–20.

Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. In D. W. K. Andrews & J. H. Stock (Eds.), *Identification and inference for econometric models: Essays in Honor of Thomas Rothenberg* (pp. 80–108). Cambridge University Press.

Vicente-Serrano, S. M., Beguerıa, S., & López-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: The Standardized Precipitation Evapotranspiration Index. *Journal of Climate*, *23*(7), 1696–1718.

Weber, E. U. (1997). Perception and expectation of climate change: Precondition for economic and technological adaptation. In Bazerman M., Messick D., Tenbrunsel A., and Wade-Benzoni K. (Ed.), *Psychological perspectives to environmental and ethical issues in management* (pp. 314–341). San Francisco, CA: Jossey-Bass.

Weber, E. U. (2010). What shapes perceptions of climate change? *Wiley Interdisciplinary Reviews: Climate Change*, *1*(3), 332–342.

Zanocco, C., Boudet, H., Nilson, R., Satein, H., Whitley, H., & Flora, J. (2018). Place, proximity, and perceived harm: Extreme weather events and views about climate change. *Climatic Change*, *149*(3), 349–365.

Zappalà, G. (2022). Adapting to climate change accounting for individual beliefs. *Working Paper*.

Zargar, A., Sadiq, R., Naser, B., & Khan, F. I. (2011). A review of drought indices. *Environmental Reviews*, *19*, 333–349.

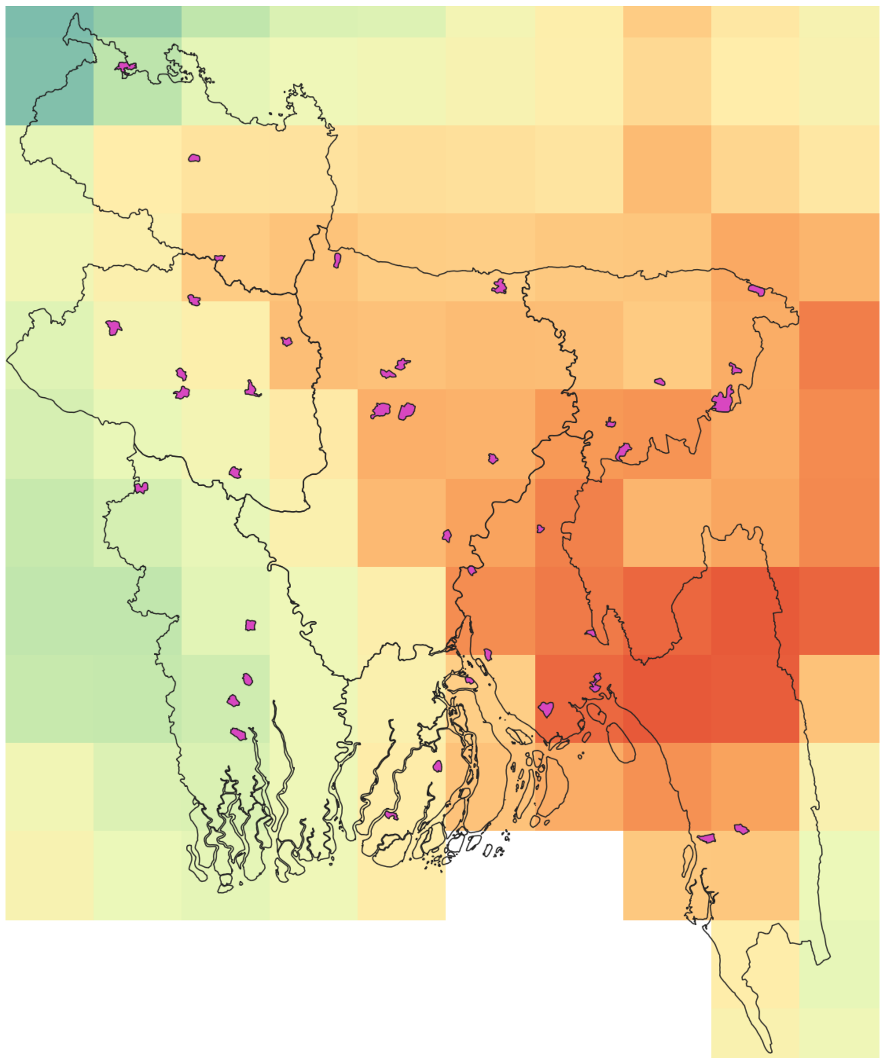
Zaval, L., Keenan, E. A., Johnson, E. J., & Weber, E. U. (2014). How warm days increase belief in global warming. *Nature Climate Change*, *4*(2), 143–147.

Zhao, J., & Luo, Y. (2021). A framework to address cognitive biases of climate change. *Neuron*, *109*(22), 3548–3551.

A Appendix

A.1 Figures

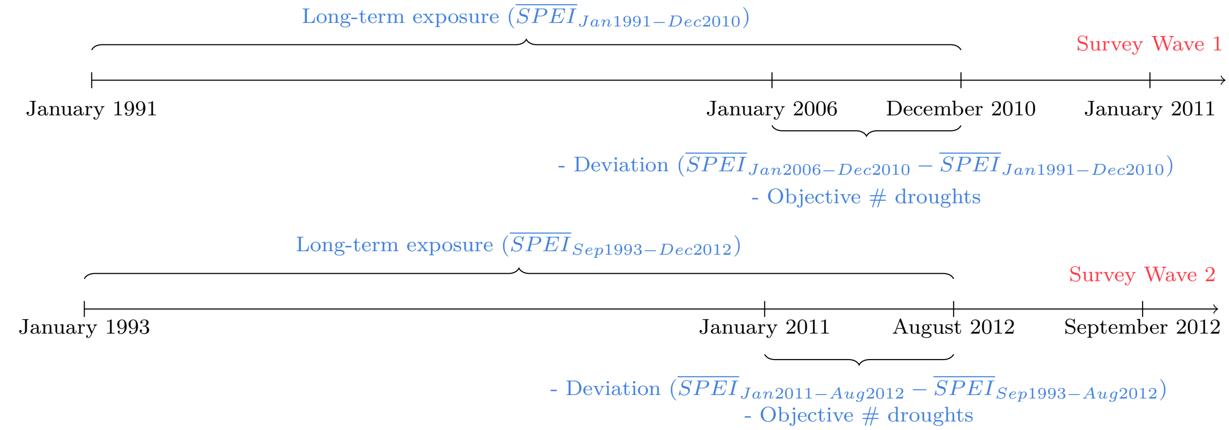
Figure A1: Bangladesh map with surveyed unions and SPEI grid cell data



Notes: The map plots the administrative boundaries of the 40 surveyed unions in purple and the regional boundaries of Bangladesh. The administrative layer (from GADM (2021)) is overlaid to the raster SPEI gridded data from Vicente-Serrano et al. (2010) with 0.5 degree resolution (≈ 55 km at the Equator) with September 2012 values, where colors range from red to blue, respectively from a drier to a wetter environment. In five cases, there are two unions within the same grid cell, thus sharing the same SPEI values. The five cases are Adabaria and Arpangashia; Char Darbesh and Char Jabbar; Dakatia and Kakrajan; Kushmail and Naogaon. In one case, there are three unions within the same grid cell: Kalilnagar, Laskar and Rudaghara. The remaining 28 unions are uniquely matched with SPEI grid cells.

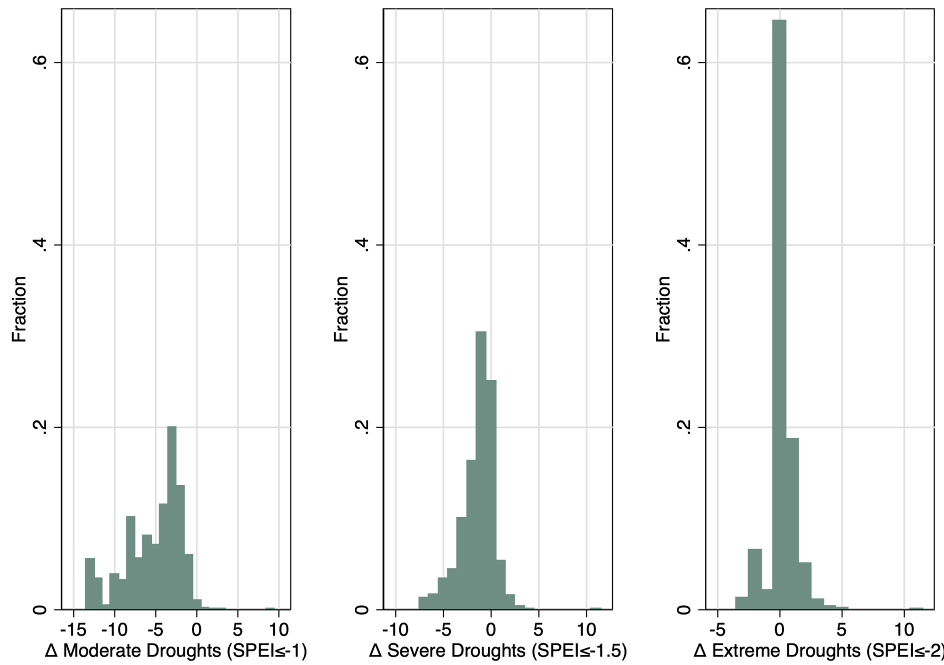
.

Figure A2: Timeline of BCCAS survey waves and dryness and drought events variables



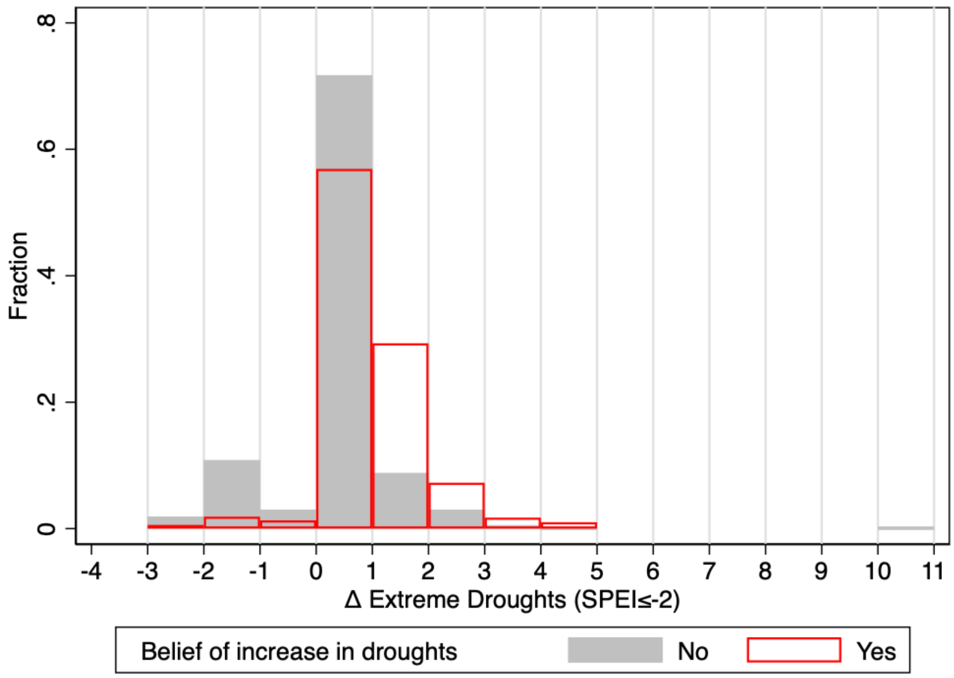
Notes: The timelines display the time horizon of the variables of exposure to dryness for each survey wave, respectively conducted in January 2011 and September 2012. Long-term exposure is the average monthly SPEI ($\times(-1)$) over the twenty years preceding each survey wave. Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and long-term exposure ($\times(-1)$). The number of objective droughts (Objective # droughts) is computed over the same time horizon covered by *self-reported # droughts* in each survey wave, and it records the number of (non-consecutive) SPEI monthly realizations below a certain cut-off (-1 for moderate, -1.5 for severe, -2 for extreme).

Figure A3: Frequency distribution of Δ for moderate, severe and extreme droughts



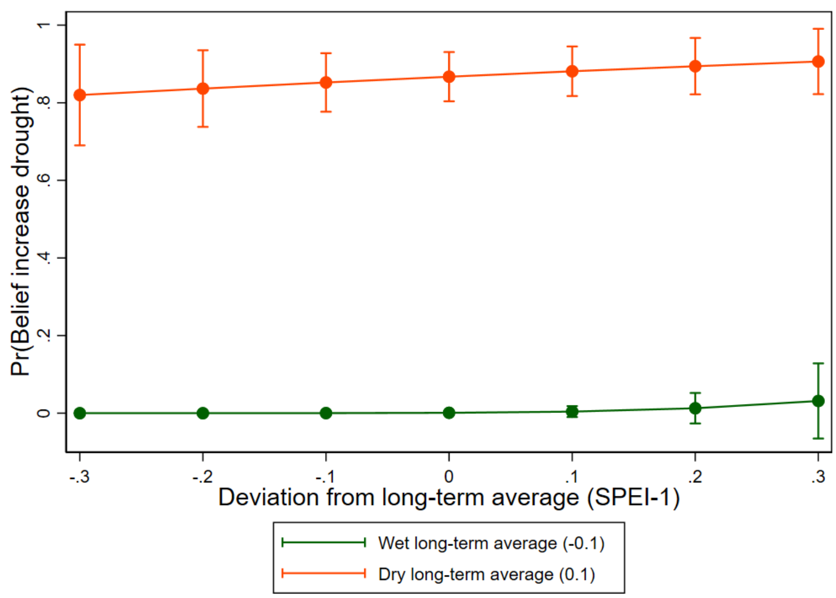
Notes: Author's computation using SPEI, BCCAS and cut-offs from McKee et al. (1993) and Paulo et al. (2012). I use the cut-offs for moderate (SPEI $\leq$ -1), severe (SPEI $\leq$ -1.5) and extreme drought events (SPEI $\leq$ -2) to compute the number of objective drought events in a given union and subtract it from the number of self-reported drought events in the BCCAS over the same time period as in Equation (1). When using moderate or severe drought events as 'objective counterfactual' of the self-reported number of droughts, there is systematic underestimation of the frequency of droughts among individuals.

Figure A4: Frequency distribution of overestimation for extreme droughts by belief of increase in droughts



Notes: Author's computation using SPEI, BCCAS and cut-offs from McKee et al. (1993) and Paulo et al. (2012). I use the cut-off for extreme drought events (SPEI $\leq$ -2) to compute the number of objective drought events in a given union and subtract it from the number of self-reported drought events in the BCCAS over the same time period, as explained in Equation (1). The grey bars show the frequency distribution of the measure Δ for individuals who did not hold a belief that droughts have increased over the past twenty years, the red-border bars display the frequency distribution of the measure Δ for individuals who reported that droughts have increased over the past twenty years.

Figure A5: Interaction between long-term drought exposure and deviations relative to lifetime



Notes: The figure shows the predicted marginal effects of deviations from long-term average exposure at different values of long-term average exposure, respectively -0.1 (in green) and 0.1 (in red). Positive values indicate drier conditions than the individuals' lifetime exposure and negative values wetter conditions. The estimates are obtained from a logit regression that determines the probability of reporting a belief of increase in droughts as a function of long-term average exposure, the short-term deviation from the average and their interaction using the SPEI-1 rescaled to each individual's specific lifetime exposure and year- and individual-specific fixed effects.

.

A.2 Data

Table A1: Unions and number of households in the *BCCAS* sample

Division	District	Upazila	Union	Number of households
Barisal	Barguna	Amtali	Arpangashia	15
Barisal	Barisal	Mehendiganj	Gobindapur	14
Barisal	Patuakhali	Bauphal	Adabaria	15
Chittagong	Chandpur	Matlab Uttar	Sadullapur	19
Chittagong	Chittagong	Banshkhali	Chambal	19
Chittagong	Chittagong	Lohagara	Charamba	19
Chittagong	Comilla	Chauddagram	Jagannath Dighi	19
Chittagong	Comilla	Muradnagar	Purba Purbadhair	17
Chittagong	Feni	Sonagazi	Char Darbesh	18
Chittagong	Lakshmipur	Roypur	Char Mohana	18
Chittagong	Noakhali	Subarnachar	Char Jabbar	20
Dhaka	Jamalpur	Bakshiganj	Battajore	15
Dhaka	Mymensingh	Bhaluka	Dakatia	18
Dhaka	Mymensingh	Fulbaria	Kushmail	20
Dhaka	Mymensingh	Fulbaria	Naogaon	17
Dhaka	Narayanganj	Narayanganj Sadar	Siddirganj Paurashava	17
Dhaka	Narsingdi	Manohardi	Gotashia	19
Dhaka	Netrakona	Kalmakanda	Nazirpur	17
Dhaka	Tangail	Sakhipur	Kakrajan	20
Khulna	Khulna	Dumuria	Rudaghara	17

Division	District	Upazila	Union	Number of households
Khulna	Jessore	Bagher Para	Jamdia	20
Khulna	Meherpur	Gangni	Kazipur	17
Khulna	Khulna	Paikgachha	Laskar	17
Khulna	Satkhira	Tala	Khalilnagar	19
Rajshahi	Bogra	Sariakandi	Kamalpur	17
Rajshahi	Joypurhat	Khetlal	Mamudpur	18
Rajshahi	Naogaon	Atrai	Panchupur	18
Rajshahi	Naogaon	Niamatpur	Bhabicha	15
Rajshahi	Natore	Natore Sadar	Piprul	19
Rajshahi	Pabna	Pabna Sadar	Gayeshpur	16
Rajshahi	Sirajganj	Tarash	Deshigram	18
Rangpur	Dinajpur	Ghoraghat	Ghoraghat	20
Rangpur	Panchagarh	Panchagarh Sadar	Chaklarhat	20
Rangpur	Rangpur	Taraganj	Ekarchali	20
Sylhet	Habiganj	Chunarughat	Deorgachh	20
Sylhet	Habiganj	Habiganj Sadar	Nizampur	18
Sylhet	Maulvibazar	Juri	Paschim Juri	17
Sylhet	Maulvibazar	Kulaura	Karmadha	18
Sylhet	Maulvibazar	Maulvi Bazar Sadar	Kamalpur	18
Sylhet	Sylhet	Kanaighat	Paschim Lakshmip Rasad	16

Table A2: Survey variables' definition and construction

VARIABLE	SURVEY QUESTION CODE	WAVE	SURVEY QUESTION	SOURCE
Belief of increase in droughts (0/1)	L.11	1	Have you noticed any changes in climate over the last 20 years? If yes, please specify what changes you have noticed (1 if "Longer periods of droughts" and 0 otherwise)	BCCAS Household Questionnaire
Belief of increase in droughts (0/1)	Q.04-Q.07	2	Have you noticed any long term changes in rainfall variability over the last 20 years? If yes, what changes have you noticed? (1 if "Longer periods of droughts" and 0 otherwise) Have you noticed any changes in climate over the last 20 years? If yes, please specify what changes you have noticed (1 if "Longer periods of droughts" and 0 otherwise)	BCCAS Household Questionnaire
self-reported # droughts	L.03	1	In the last five years, have the HH's properties and productivity been affected by droughts? How many times did it occur in last 5 years?	BCCAS Household Questionnaire
self-reported # droughts	L.03	2	Since the last survey interview have the HH's properties and productivity been affected by droughts? How many times did it occur in these two years?	BCCAS Household Questionnaire
Information on soil and water conservation and crop protection	M.06	1 & 2	"Does the information you receive from extension agents meet your needs? What type of information is provided?" (1 if "Information on soil and water conservation" or "Information on crop protection", 0 otherwsise)	BCCAS Household Questionnaire
Information on soil and water conservation, crop protection and new crop varieties	M.06	1 & 2	"Does the information you receive from extension agents meet your needs? What type of information is provided?" (1 if "Information on soil and water conservation" or "Information on crop protection" or "Information on new crop varieties", 0 otherwsise)	BCCAS Household Questionnaire
Information on soil and water conservation, crop protection, new crop varieties and crop utilization	M.06	1 & 2	"Does the information you receive from extension agents meet your needs? What type of information is provided?" (1 if "Information on soil and water conservation" or "Information on crop protection" or "Information on new crop varieties" or "Information on crop utilization", 0 otherwsise)	BCCAS Household Questionnaire
Information from TV/Radio/Newsletter	M.08	1 & 2	"Do you receive information from sources besides the extension worker? If yes, what are those sources?" (1 if "Radio", "Television" or "Newsletter", and 0 otherwise)	BCCAS Household Questionnaire
Krishi Bank	C.01 (Question ID 11)	1 & 2	"Do you have a Bangladesh Krishi Bank in this village?" (Yes/No)	BCCAS Community Questionnaire
Commercial Bank	C.01 (Question ID 12)	1 & 2	"Do you have a Commercial bank in this village?" (Yes/No)	BCCAS Community Questionnaire
Grameen Bank	C.01 (Question ID 13)	1 & 2	"Do you have a Grameen Bank in this village?" (Yes/No)	BCCAS Community Questionnaire
Agriculture extension officer	C.01 (Question ID 20)	1 & 2	"Do you have an agriculture extension officer/Block supervisor in this village?" (Yes/No)	BCCAS Community Questionnaire
Access to electricity	C.01 (Question ID 21)	1 & 2	"Do you have access to electricity in this village?" (Yes/No)	BCCAS Community Questionnaire
Shop for pesticides and/or fertilizer	C.01 (Question ID 19)	1 & 2	"Do you have a Shop for pesticides and/or fertilizer in this village?" (Yes/No)	BCCAS Community Questionnaire

Notes: The variable self-reported # droughts is used to compute the variable Δ, subtracting the objective # droughts, being the recorded number of (non-consecutive) monthly realizations of the SPEI below a certain cut-off (-1 for moderate, -1.5 for severe and -2 for extreme events) over the same time period as the survey question, as explained in Equation (1).

A.3 Tables

A.3.1 Descriptive Statistics

Table A3: T-tests for differences in means for attritors versus non-attritors

	Non Attritors (N=714)		Attritors (N=96)		Difference	
	Mean	SD	Mean	SD	Mean	t-test
Panel A. Subjective measures						
Belief of increase in droughts	0.252	0.016	0.290	0.049	-0.038	(-0.77)
Δ Drought (Moderate)	-7.834	0.109	-7.360	0.338	-0.474	(-1.41)
Δ Drought (Severe)	-2.127	0.072	-1.953	0.200	-0.174	(-0.79)
Δ Drought (Extreme)	-0.125	0.041	0.023	0.140	-0.148	(-1.14)
Panel B. Objective exposure measures						
LT Exposure	0.070	0.001	0.061	0.004	0.009	(2.08)
Deviation	0.041	0.001	0.040	0.003	0.001	(0.26)
Panel C. Objective number of droughts						
# Moderate Droughts (SPEI≤ -1)	8.110	0.106	7.779	0.321	0.331	(1.01)
# Severe Droughts (SPEI≤ -1.5)	2.403	0.071	2.372	0.190	0.031	(0.14)
# Extreme Droughts (SPEI≤ -2)	0.400	0.031	0.395	0.086	0.005	(0.05)

Notes: The sample compares the means in the estimation sample of the 714 individuals interviewed in both survey waves in January 2011 and September 2012 and the 96 individuals who have not been reinterviewed in the second wave (because they migrated, they were not at home in the moment of the survey or the respondent changed from wave 1). The variable Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below a certain cut-off (-1 for moderate, -1.5 for severe and -2 for extreme events) over the same time period. LT Exposure is the average SPEI over the previous twenty years ($\times$ (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). Panel A shows the summary statistics for subjective variables that use information from the BCCAS. Panel B and C report values computed using the SPEI. The values in Panels B and C differ from those in Panel A in Table A5 since they are computed at the individual level and not at the grid cell level. The average LT Exposure is the only variable statistically different at the 5% level in the estimation sample of non-attritors from the sample of attritors. However, this result should not raise concern on the validity of the findings since the difference is negligible, less than one percent of SD, and the sample of non attritors has an average LT Exposure higher than the one of the sample of attritors.

Table A4: Summary statistics of subjective measures

	N	Mean	SD	Min	Max
Panel A. Survey Wave 1 (2011)					
Belief of increase in droughts	714	0.25	0.43	0	1
Δ Drought (Moderate)	714	-7.83	2.92	-13	0
Δ Drought (Severe)	714	-2.13	1.94	-7	3
Δ Drought (Extreme)	714	-0.12	1.11	-3	4
Panel B. Survey Wave 2 (2012)					
Belief of increase in droughts	714	0.71	0.45	0	1
Δ Drought (Moderate)	714	-2.74	1.35	-6	9
Δ Drought (Severe)	714	-0.59	1.08	-3	11
Δ Drought (Extreme)	714	0.45	0.84	-1	11
Panel C. Changes					
Belief of increase in droughts	714	0.46	0.62	-1	1
Δ Drought (Moderate)	714	5.09	2.95	-3	14
Δ Drought (Severe)	714	1.53	2.02	-4	12
Δ Drought (Extreme)	714	0.57	1.35	-4	11
Panel D. Total					
Belief of increase in droughts	1428	0.48	0.50	0	1
Δ Drought (Moderate)	1428	-5.29	3.41	-13	9
Δ Drought (Severe)	1428	-1.36	1.75	-7	11
Δ Drought (Extreme)	1428	0.16	1.03	-3	11

Notes: The sample includes the 714 individuals interviewed in both survey waves in January 2011 and September 2012. The variable Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below a certain cut-off (-1 for moderate, -1.5 for severe and -2 for extreme events) over the same time period. Panel A shows the summary statistics for survey wave 1 conducted in January 2011, Panel B for survey wave 2 conducted in September 2012, Panel C reports changes for each of the variables across the two survey waves and Panel D displays the values across the two waves.

Table A5: Summary statistics of objective measures

	N	Mean	SD	Min	Max
Panel A. Survey Wave 1 (2011)					
A. Exposure measures					
LT Exposure	34	0.07	0.04	-0.01	0.15
Deviation	34	0.04	0.03	-0.03	0.15
LT Exposure x Deviation	34	0.01	0.01	-0.01	0.02
B. Objective number of droughts					
# Moderate Droughts (SPEI≤ -1)	34	8.20	3.02	3	13
# Severe Droughts (SPEI≤ -1.5)	34	2.44	2.02	0	7
# Extreme Droughts (SPEI≤ -2)	34	0.47	0.89	0	3
Panel B. Survey Wave 2 (2012)					
A. Exposure measures					
LT Exposure	34	0.10	0.04	0.03	0.15
Deviation	34	-0.09	0.11	-0.44	0.06
LT Exposure x Deviation	34	0.01	0.01	-0.07	0.01
B. Objective number of droughts					
# Moderate Droughts (SPEI≤ -1)	34	3.23	1.10	1	6
# Severe Droughts (SPEI≤ -1.5)	34	1.15	0.74	0	3
# Extreme Droughts (SPEI≤ -2)	34	0.03	0.17	0	1
Panel C. Changes					
A. Exposure measures					
LT Exposure	34	0.03	0.01	-0.01	0.05
Deviation	34	-0.13	0.12	-0.57	0.04
LT Exposure x Deviation	34	-0.01	0.02	-0.09	0.01
B. Objective number of droughts					
# Moderate Droughts (SPEI≤ -1)	34	-4.97	2.68	-10	0
# Severe Droughts (SPEI≤ -1.5)	34	-1.29	1.64	-5	2
# Extreme Droughts (SPEI≤ -2)	34	-0.44	0.82	-2	0
Panel D. Total					
A. Exposure measures					
LT Exposure	68	0.09	0.04	-0.01	0.16
Deviation	68	-0.02	0.10	-0.43	0.15
LT Exposure x Deviation	68	0.01	0.01	-0.07	0.02
B. Objective number of droughts					
# Moderate Droughts (SPEI≤ -1)	68	5.72	3.37	1	13
# Severe Droughts (SPEI≤ -1.5)	68	1.79	1.64	0	7
# Extreme Droughts (SPEI≤ -2)	68	0.25	0.67	0	3

Notes: Statistics computed at the grid-cell level. LT Exposure is the average SPEI over the previous twenty years ($\times$ (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). The number of drought events is computed using the classification of drought events in the literature (McKee et al., 1993; Paulo et al., 2012): moderate/severe/extreme droughts include all (non-consecutive) monthly realizations in the previous five years for survey wave 1 and between January 2011 and September 2012 for survey wave 2 in which the SPEI ≤ -1/-1.5/2. Panel A shows the summary statistics for survey wave 1 conducted in January 2011, Panel B for survey wave 2 conducted in September 2012, Panel C reports changes for each of the variables across the two survey waves and Panel D displays the values across the two waves.

A.3.2 Robustness Checks

Table A6: Drought exposure effect on information seeking variables and union-level adaptive margins

	Information on soil and water conservation				Presence of a bank					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	and crop protection	crop protection and new crop varieties	crop protection, new crop varieties and crop utilization	Info from TV/Radio/Newsletter	Krishi	Commercial	Grameen	Extension office	Electricity access	Pesticides/fertilizer shop
LT Exposure	-2.893	-1.701	-0.246	3.675	-1.602	-2.456	-1.441	8.489	8.120	16.27*
	(2.436)	(2.123)	(2.156)	(2.304)	(3.735)	(2.542)	(2.711)	(10.85)	(5.847)	(8.092)
Deviation	0.0719	0.131	0.0159	-0.120	0.215	0.292	0.302	0.381	-0.391	-0.490
	(0.258)	(0.211)	(0.216)	(0.175)	(0.364)	(0.292)	(0.307)	(1.015)	(0.608)	(0.705)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428	1428	1428	1428	1428

Notes: The table reports the OLS estimates of a regression of adaptive margins and variables on information seeking behavior by individuals on the long-run exposure to dryness and short-term deviations. LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). All regressions control for individual and year fixed effects. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Objective exposure, beliefs and average number of droughts.

	Belief of Increase in Droughts					
	(1)	(2)	(3)	(4)	(5)	(6)
LT Exposure	13.13***	14.52***	11.74***	11.11***	13.85***	13.86***
	(1.855)	(3.101)	(1.955)	(2.300)	(2.140)	(2.262)
# Drought Events	-0.0306	0.0159	-0.205***	-0.253*	0.0704	0.0564
	(0.0356)	(0.114)	(0.0583)	(0.144)	(0.186)	(0.866)
LT Exposure × # Drought Events		-0.465		0.516		0.153
		(0.958)		(1.285)		(8.969)
Drought type	Moderate		Severe		Extreme	
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428
adj. R^2	0.278	0.277	0.286	0.285	0.277	0.276

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual believes that droughts have increased in the past twenty years. All regressions control for individual and year fixed effects. LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)), # Drought Events is the average number of drought events recorded in the five years before the first wave and between the two survey wave. Columns 1-2 include at least moderate droughts (SPEI<-1), columns 3-4 include at least severe droughts (SPEI<-1.5) and columns 5-6 include only extreme droughts (SPEI<-2). Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Objective exposure, beliefs and probability of overestimation. Logit estimates.

	Belief of Increase in Droughts				Probability of Overestimation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LT Exposure	84.79***		84.54***	82.14***	50.10***		49.40***	48.30***
	(6.736)		(7.640)	(8.581)	(5.724)		(7.480)	(7.910)
Deviation		-9.277***	-0.0596	-2.111		-7.322***	-0.212	-1.784
		(2.101)	(0.781)	(3.321)		(2.121)	(1.458)	(4.112)
LT Exposure × Deviation				14.91				12.62
				(23.31)				(29.87)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	846	846	846	846	540	540	540	540

Notes: The table displays the coefficients obtained by the estimation of Equation (4) using Logit. The sample includes in columns (1)-(4) (resp., columns 5-8) the 423 individuals (resp., 270) for which there is variation in the outcome once conditioning on individual and year fixed effects. The dependent variable is a dummy equal to 1 if the individual believes that droughts have increased in the past twenty years (columns 1-4), a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 5-8). All regressions control for individual and year fixed effects. The measure Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). Bootstrapped standard errors with 500 replications in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Objective exposure and extent of overestimation. Poisson estimates.

	Extent of Overestimation			
	(1)	(2)	(3)	(4)
LT Exposure	16.16***		14.88***	13.62***
	(3.442)		(5.002)	(4.999)
Deviation		-2.458**	-0.512	-3.083
		(1.197)	(1.212)	(3.804)
LT Exposure × Deviation				22.41
				(29.38)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	534	534	534	534

Notes: The table displays the coefficients obtained by the estimation of Equation (4) using Poisson estimation method, where the dependent variable is the variable Δ excluding the 142 individuals with negative values (i.e., who underestimated the number of droughts). The sample also excludes 752 observations because of only one observation over time and because of no variation in the outcome once conditioning on individual and year fixed effects. The measure Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). Bootstrapped standard errors with 500 replications in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Objective exposure and overestimation of drought events using moderate objective droughts.

	Probability of Overestimation				Extent of Overestimation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LT Exposure	0.467*		0.539	0.610	131.9**		204.9***	181.7***
	(0.273)		(0.440)	(0.472)	(49.82)		(43.05)	(43.30)
Deviation		0.0147	-0.00960	-0.0564		-0.554	-9.789***	5.435
		(0.0218)	(0.0336)	(0.0736)		(2.770)	(1.920)	(6.161)
LT Exposure × Deviation				0.317				-103.2**
				(0.331)				(40.64)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428	1428	1428
adj. R^2	0.003	0.001	0.002	0.001	0.716	0.642	0.760	0.777

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-4) and the measure of overestimation Δ (columns 5-8). All regressions control for individual and year fixed effects. The measure Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of moderate drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -1 for moderate events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Objective exposure and overestimation of drought events using severe objective droughts.

	Probability of Overestimation				Extent of Overestimation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LT Exposure	6.510***		4.302	3.673	87.93**		101.0***	92.47**
	(1.947)		(2.721)	(2.812)	(32.83)		(33.46)	(35.31)
Deviation		0.490***	0.296	0.709*		2.798	-1.756	3.865
		(0.162)	(0.223)	(0.416)		(1.988)	(1.558)	(4.519)
LT Exposure × Deviation				-2.797				-38.10
				(2.070)				(30.81)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428	1428	1428
adj. R^2	0.015	0.013	0.021	0.021	0.491	0.387	0.496	0.504

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-4) and the measure of overestimation Δ (columns 5-8). All regressions control for individual and year fixed effects. The measure Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of severe drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -1.5 for severe events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: Objective exposure, beliefs and overestimation of drought events using other SPEI time scales

		Overestimation			Overestimation			Overestimation	
	Belief	Probability	Extent	Belief	Probability	Extent	Belief	Probability	Extent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LT Exposure	9.661***	8.793***	37.65*	6.168***	5.781***	15.98**	3.078***	3.302***	6.173***
	(1.907)	(2.781)	(20.17)	(1.196)	(1.526)	(7.062)	(0.602)	(0.607)	(2.210)
Deviation	-0.119	-0.458	-1.665	0.00369	-0.652**	-2.427*	-0.109	-0.333***	-1.012*
	(0.257)	(0.309)	(2.046)	(0.146)	(0.259)	(1.268)	(0.0926)	(0.0950)	(0.500)
LT Exposure × Deviation	0.109	1.244	5.315	0.00950	1.260*	4.073	0.108	0.337	-0.979
	(0.682)	(1.057)	(8.317)	(0.359)	(0.631)	(3.364)	(0.325)	(0.251)	(1.839)
SPEI Temporal Scale		4 months			6 months			12 months	
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428	1428	1428	1428
adj. R^2	0.290	0.185	0.492	0.287	0.184	0.337	0.274	0.194	0.221

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual believes that droughts have increased in the past twenty years (columns 1-4-7), a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 2-5-8) and the measure of overestimation Δ (columns 3-6-9). All regressions control for individual and year fixed effects. The measures of dryness and drought events are constructed using different time scales over which water deficits accumulate, respectively 4 months (columns 1 to 3), 6 months (columns 4 to 6) and 12 months (columns 7 to 9). The measure Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Lifetime exposure, beliefs and overestimation of drought events using different SPEI time scales

		Overestimation			Overestimation			Overestimation			Overestimation	
	Belief	Probability	Extent	Belief	Probability	Extent	Belief	Probability	Extent	Belief	Probability	Extent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LT Exposure	8.384**	9.538***	33.98**	6.041***	6.897***	28.53**	5.047***	6.419***	19.84***	3.145***	3.825***	7.217***
	(3.091)	(1.952)	(14.18)	(1.712)	(1.709)	(11.93)	(1.139)	(1.245)	(5.408)	(0.625)	(0.595)	(2.399)
Deviation	1.151***	0.561**	1.459*	0.682***	0.371**	2.727***	0.489***	-0.0875	-0.538	0.0853	-0.133*	-1.045***
	(0.234)	(0.222)	(0.846)	(0.133)	(0.153)	(0.836)	(0.102)	(0.149)	(0.744)	(0.0607)	(0.0712)	(0.352)
LT Exposure × Deviation	-10.73***	-6.587**	-47.34**	-3.732***	-2.018*	-16.75**	-2.246***	-0.509	-3.971	-0.555**	-0.181	-1.460
	(2.743)	(2.840)	(18.82)	(0.886)	(1.028)	(7.033)	(0.527)	(0.556)	(3.254)	(0.254)	(0.259)	(1.495)
SPEI Temporal Scale		1 month			4 months			6 months			12 months	
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
N	1428	1428	1428	1428	1428	1428	1428	1428				
adj. R^2	0.274	0.157	0.249	0.281	0.178	0.491	0.282	0.182	0.347	0.273	0.197	0.242

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual believes that droughts have increased in the past twenty years (columns 1-4-7), a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 2-5-8) and the measure of overestimation Δ (columns 3-6-9). All regressions control for individual and year fixed effects. The measures of dryness and drought events are constructed using different time scales over which water deficits accumulate, respectively 1 month (columns 1 to 3), 4 months (columns 4 to 6), 6 months (columns 7 to 9) and 12 months (columns 10 to 12). The monthly realizations of SPEI have been rescaled to the lifetime exposure for each individual. The measure Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: Objective exposure, beliefs and overestimation of drought events using SPEI interpolated values

	Belief	Overestimation Probability	Overestimation Extent	Belief	Overestimation Probability	Overestimation Extent	Belief	Overestimation Probability	Overestimation Extent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LT Exposure	16.93***	12.49***	61.98***	16.49***	13.97***	62.95**	17.18***	13.87***	73.97***
	(3.943)	(3.775)	(21.02)	(4.049)	(4.164)	(24.83)	(4.331)	(4.617)	(21.75)
Deviation	-0.505	-0.828	-3.361	-0.295	-1.184	-4.857*	-0.314	-1.215	-5.948**
	(0.765)	(0.702)	(2.458)	(0.875)	(0.838)	(2.721)	(0.951)	(0.935)	(2.543)
LT Exposure × Deviation	3.319	4.608	2.919	2.230	6.748	12.60	2.509	7.296	19.55
	(4.062)	(3.511)	(15.72)	(4.930)	(4.626)	(17.43)	(5.497)	(5.222)	(15.65)
Distance cut-off		40 km			80 km			120 km	
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428	1428	1428	1428
adj. R^2	0.279	0.146	0.257	0.278	0.149	0.224	0.277	0.146	0.229

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual believes that droughts have increased in the past twenty years (columns 1-4-7), a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 2-5-8) and the measure of overestimation Δ (columns 3-6-9). All regressions control for individual and year fixed effects. The measures of dryness and drought events are constructed by interpolating the gridded SPEI values using the inverse squared distance between each grid and the union centroids, considering all data points within the radius of 40 km (columns 1 to 3), 80 km (columns 4 to 6) and 120 km (columns 7 to 9). The measure Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: Objective exposure, beliefs and overestimation. Subsample of individuals with $\Delta \geq 0$

	Probability of Overestimation		Extent of Overestimation	
	Severe Drought	Extreme Drought	Severe Drought	Extreme Drought
	(1)	(2)	(3)	(4)
LT Exposure	6.393	14.73***	14.20	14.02
	(17.46)	(4.536)	(30.50)	(9.089)
Deviation	-1.731	-0.856	-1.514	-0.919
	(1.656)	(0.531)	(2.756)	(1.332)
LT Exposure × Deviation	9.119	4.355*	6.907	4.964
	(7.517)	(2.480)	(11.97)	(6.725)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	102	1166	102	1166
adj. R^2	0.057	0.143	0.032	0.067

Notes: The sample includes the 51 (resp., 583) individuals surveyed in both survey waves who were either accurate ($\Delta = 0$) or overestimated ($\Delta > 0$) the number of drought events. Because of the distribution of the measure Δ for moderate droughts (see Figure A3), this can only be done when constructing the measure Δ with the objective number of severe (SPEI≤ -1.5) or extreme (SPEI≤ -2) drought events. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-2) and the measure of overestimation Δ (columns 3-4). All regressions control for individual and year fixed effects. LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A16: Directional motivated reasoning. Subsample with same number of recorded droughts.

	OLS		2SLS	
	(1)	(2)	(3)	(4)
	Probability	Extent	Probability	Extent
Belief	0.190***	0.270**	0.950**	1.029
	(0.0528)	(0.101)	(0.359)	(0.610)
Deviation	0.232	0.163	-0.295	-0.364
	(0.198)	(0.376)	(0.377)	(0.633)
F-stat			13.986	13.986
	FIRST STAGE: *Belief of Increase in Droughts*			
LT Exposure			18.40***	18.40***
			(4.92)	(4.92)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1142	1142	1142	1142

Notes: The sample includes the 571 individuals surveyed in both survey waves in unions where no extreme drought event (SPEI≤-2) was recorded both in the five years before the first wave and between the two waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-3) and the measure of overestimation Δ (columns 2-4). The measure Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period (in this case always equal to zero by construction). The table reports the OLS estimates of Equation (5) in columns (1) and (2) and the 2SLS estimates in columns (3) and (4) in Panel A. Panel B reports the first stage associated with 2SLS regressions, controlling for Deviation. The main regressor of interest is Belief, which is instrumented with the LT Exposure in columns (3) and (4). All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A17: Directional motivated reasoning. 2SLS Results using SPEI-4, SPEI-6 and SPEI-12.

	Overestimation					
	(1) Probability	(2) Extent	(3) Probability	(4) Extent	(5) Probability	(6) Extent
Belief	0.904***	3.872*	1.005***	2.811***	1.100***	1.860**
	(0.318)	(2.174)	(0.343)	(1.022)	(0.347)	(0.705)
Deviation	-0.0609	0.0320	-0.338**	-1.406**	-0.157**	-1.112***
	(0.173)	(1.010)	(0.149)	(0.585)	(0.0676)	(0.249)
F-stat	26.156	26.156	27.928	27.928	27.216	27.216
SPEI Temporal Scale	4 months		6 months		12 months	
	FIRST STAGE: *Belief of Increase in Droughts*					
LT Exposure	9.655***	9.655***	6.171***	6.171***	3.119***	3.119***
	(1.888)	(1.888)	(1.168)	(1.168)	(0.598)	(0.598)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-3-5) and the measure of overestimation Δ (columns 2-4-6). The measures of dryness and drought events are constructed using different time scales over which water deficits accumulate, respectively 4 months (columns 1-2), 6 months (columns 3-4) and 12 months (columns 5-6). The measure Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The table reports the OLS estimates of Equation (5) in columns (1) and (2) and the 2SLS estimates in columns (3) and (4) in Panel A. Panel B reports the first stage associated with 2SLS regressions, controlling for Deviation. The main regressor of interest is Belief, which is instrumented with the LT Exposure in columns (3) and (4). All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A18: Directional motivated reasoning. 2SLS estimates using relative life exposure with SPEI-1, SPEI-4, SPEI-6 and SPEI-12.

	Overestimation							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Probability	Extent	Probability	Extent	Probability	Extent	Probability	Extent
Belief	0.966***	4.082**	1.289**	4.354***	1.529***	4.596***	1.199***	2.037***
	(0.347)	(1.655)	(0.501)	(1.387)	(0.472)	(1.443)	(0.362)	(0.594)
Deviation	-0.430	-3.182*	-0.282	0.139	-0.544**	-1.823**	-0.141*	-0.622***
	(0.405)	(1.589)	(0.325)	(0.845)	(0.230)	(0.745)	(0.0781)	(0.176)
F-stat	9.447	9.447	11.358	11.358	18.278	18.278	27.150	27.150
SPEI Temporal Scale	1 month		4 months		6 months		12 months	
	FIRST STAGE: *Belief of Increase in Droughts*							
LT Exposure	9.908***	9.908***	6.012***	6.012***	5.043***	5.043***	3.183***	3.183***
	(3.224)	(3.224)	(1.784)	(1.784)	(1.180)	(1.180)	(0.611)	(0.611)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428	1428	1428

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-3-5-7) and the measure of overestimation Δ (columns 2-4-6-8). The measures of dryness and drought events are constructed using different time scales over which water deficits accumulate, respectively 1 month (columns 1-2), 4 months (columns 3-4), 6 months (columns 5-6) and 12 months (columns 7-8). The monthly realizations of SPEI have been rescaled to the lifetime exposure for each individual. The measure Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The table reports the OLS estimates of Equation (5) in columns (1) and (2) and the 2SLS estimates in columns (3) and (4) in Panel A. Panel B reports the first stage associated with 2SLS regressions, controlling for Deviation. The main regressor of interest is Belief, which is instrumented with the LT Exposure in columns (3) and (4). All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A19: Directional motivated reasoning. 2SLS Results using SPEI interpolated values

	Overestimation					
	(1)	(2)	(3)	(4)	(5)	(6)
	Probability	Extent	Probability	Extent	Probability	Extent
Belief	0.700***	3.824**	0.761***	3.745**	0.710***	4.145**
	(0.223)	(1.509)	(0.237)	(1.679)	(0.230)	(1.583)
Deviation	-0.134	-2.887**	-0.205	-3.119**	-0.170	-3.281**
	(0.334)	(1.367)	(0.345)	(1.453)	(0.350)	(1.531)
F-stat	20.538	20.538	18.482	18.482	17.403	17.403
Distance cut-off	40 km		80 km		120 km	
	FIRST STAGE: *Belief of Increase in Droughts*					
LT Exposure	15.99***	15.99***	15.86***	15.86***	16.42***	16.42***
	(3.529)	(3.529)	(3.690)	(3.690)	(3.935)	(3.935)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-3-5) and the measure of overestimation Δ (columns 2-4-6). The measures of dryness and drought events are constructed by interpolating the gridded SPEI values using the inverse squared distance between each grid and the union centroids, considering all data points within the radius of 40 km (columns 1-2), 80 km (columns 3-4) and 120 km (columns 5-6). The measure Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The table reports the OLS estimates of Equation (5) in columns (1) and (2) and the 2SLS estimates in columns (3) and (4) in Panel A. Panel B reports the first stage associated with 2SLS regressions, controlling for Deviation. The main regressor of interest is Belief, which is instrumented with the LT Exposure in columns (3) and (4). All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A20: Directional motivated reasoning using different cut-offs of objective drought events

	Probability of Overestimation		Extent of Overestimation	
	Moderate Drought	Severe Drought	Moderate Drought	Severe Drought
	(1)	(2)	(3)	(4)
Panel A: OLS				
Belief	-0.00538	0.0491*	0.818***	0.602***
	(0.00321)	(0.0287)	(0.264)	(0.173)
Deviation	0.0186	0.454***	-1.150	2.359
	(0.0224)	(0.165)	(2.703)	(1.954)
Panel B: 2SLS				
Belief	0.0369	0.295	14.03***	6.919***
	(0.0335)	(0.179)	(3.727)	(2.408)
Deviation	-0.0122	0.275	-10.79***	-2.248
	(0.0380)	(0.237)	(3.783)	(2.065)
F-stat	21.736	21.736	21.736	21.736
Panel C: First Stage. Dependent Variable is *Belief of Increase in Droughts*				
LT Exposure	14.60***	14.60***	14.60***	14.60***
	(3.131)	(3.131)	(3.131)	(3.131)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-2) and the measure of overestimation Δ (columns 3-4). The measure Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of droughts recorded using the (non-consecutive) monthly realizations of the SPEI below -1 (resp., -1.5) for moderate (resp., severe) drought events over the same time period. The table reports the OLS estimates of Equation (5) in Panel A and the 2SLS estimates in Panel B. Panel C reports the first stage associated with 2SLS regressions, controlling for Deviation. The main regressor of interest is Belief, which is instrumented with the LT Exposure in the 2SLS specifications. All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A21: Directional motivated reasoning. Subsample of individuals with $\Delta \geq 0$.

	Probability of Overestimation		Extent of Overestimation	
	Severe Drought	Extreme Drought	Severe Drought	Extreme Drought
	(1)	(2)	(3)	(4)
Panel A: OLS				
Belief	-0.00898	0.179***	0.0784	0.258**
	(0.115)	(0.0527)	(0.136)	(0.0996)
Deviation	-0.00702	0.236	0.110	0.172
	(0.212)	(0.195)	(0.357)	(0.371)
Panel B: 2SLS				
Belief	0.105	0.845**	0.979	0.788
	(1.571)	(0.377)	(2.310)	(0.627)
Deviation	-0.0984	-0.225	-0.614	-0.195
	(1.203)	(0.385)	(1.740)	(0.652)
F-stat	0.539	11.536	0.539	11.536
Panel C: First Stage. Dependent Variable is *Belief of Increase in Droughts*				
LT Exposure	10.40	15.83***	10.40	15.83***
	(14.17)	(4.662)	(14.17)	(4.662)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	102	1166	102	1166

Notes: The sample includes the 51 (resp., 583) individuals surveyed in both survey waves who were either accurate ($\Delta = 0$) or overestimated ($\Delta > 0$) the number of drought events. Because of the distribution of the measure Δ for moderate droughts (see Figure A3), this can only be done when constructing the measure Δ with the objective number of severe (SPEI≤ -1.5) or extreme (SPEI≤ -2) drought events. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-2) and the measure of overestimation Δ (columns 3-4). The table reports the OLS estimates of Equation (5) in Panel A and the 2SLS estimates in Panel B. Panel C reports the first stage associated with 2SLS regressions, controlling for Deviation. The main regressor of interest is Belief, which is instrumented with the LT Exposure in the 2SLS specifications. All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A22: Directional motivated reasoning. History of transient shocks

	OLS				2SLS			
	Probability		Extent		Probability		Extent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Belief	0.160***	0.165***	0.298***	0.302***	0.775***	1.418**	2.764**	4.253**
	(0.0496)	(0.0510)	(0.104)	(0.103)	(0.253)	(0.530)	(1.295)	(1.668)
Deviation$_{t-1}$	0.309***	0.486*	2.072***	1.895**	0.0561	0.473	1.057*	1.853*
	(0.0918)	(0.255)	(0.373)	(0.827)	(0.140)	(0.296)	(0.611)	(0.981)
Deviation$_{t-2}$	-0.264	-0.105	-3.365***	-2.961***	-0.449*	-0.540	-4.108***	-4.332***
	(0.276)	(0.330)	(0.644)	(0.626)	(0.244)	(0.380)	(0.982)	(1.207)
Deviation$_{t-3}$		-0.0216		-0.383		1.343		3.916
		(0.506)		(2.467)		(0.992)		(3.336)
Deviation$_{t-4}$		-0.573		-1.931**		-1.081*		-3.531**
		(0.380)		(0.773)		(0.606)		(1.511)
Deviation$_{t-5}$		1.258*		0.855		1.116		0.407
		(0.743)		(2.062)		(1.184)		(3.660)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat					14.832	10.307	14.832	10.307
N	1428	1428	1428	1428	1428	1428	1428	1428

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-2 and 5-6) and the measure of overestimation Δ (columns 3-4 and 7-8). The measure Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The table reports the OLS estimates of Equation (5) in columns (1)-(4) and the 2SLS estimates in columns (5)-(8). LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)). Deviation$_{t-\tau}$ is the difference between the average monthly SPEI in $t-\tau$ years before each survey wave and LT Exposure ($\times(-1)$). The main regressor of interest is Belief, which is instrumented with the LT Exposure in columns (5)-(8). All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A23: Directional motivated reasoning. Variations in adaptation strategies. 2SLS estimates.

	Probability of Overestimation							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Belief	0.778***	0.776***	0.746***	0.750***	0.840***	0.756***	0.833***	0.842***
	(0.234)	(0.232)	(0.228)	(0.238)	(0.250)	(0.231)	(0.252)	(0.269)
Deviation	-0.190	-0.185	-0.124	-0.142	-0.189	-0.182	-0.227	-0.136
	(0.342)	(0.342)	(0.334)	(0.347)	(0.349)	(0.327)	(0.340)	(0.357)
Krishi Bank	-0.104							-0.00869
	(0.149)							(0.169)
Commercial Bank		-0.0949*						0.548***
		(0.0515)						(0.169)
Grameen Bank			-0.323**					-0.600***
			(0.149)					(0.102)
Any Bank				-0.212				
				(0.126)				
Agriculture extension officer					-0.0640			-0.107*
					(0.0562)			(0.0628)
Access to electricity						0.0788		0.0597
						(0.0994)		(0.0963)
Shop for pesticides and/or fertilizer							-0.0309	0.0209
							(0.0948)	(0.118)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	22.010	22.145	22.858	22.447	22.244	20.688	20.309	20.677
N	1428	1428	1428	1428	1428	1428	1428	1428

Notes: The table reports the 2SLS estimates of Equation (5) using as dependent variable a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$. The sample includes the 714 individuals surveyed in both survey waves. The measure Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The main regressor of interest is Belief, which is instrumented with the LT Exposure. Each regression controls for a specific margin of adaptation (see Table A2 for the definition of each variable). Any Bank is a dummy variable equal to 1 if at least one of Krishi Bank, Commercial Bank or Grameen Bank is equal to one. All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A24: Directional motivated reasoning. Variations in adaptation strategies. 2SLS estimates.

	Extent of Overestimation							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Belief	3.947**	3.927**	3.918**	3.907**	4.076**	4.013**	4.381***	4.271**
	(1.503)	(1.504)	(1.474)	(1.473)	(1.545)	(1.594)	(1.582)	(1.590)
Deviation	-2.891**	-2.853*	-2.785*	-2.797*	-2.995**	-2.984*	-3.140**	-3.010*
	(1.410)	(1.406)	(1.373)	(1.392)	(1.447)	(1.476)	(1.464)	(1.525)
Krishi Bank	-0.548							-0.498
	(0.534)							(0.640)
Commercial Bank		-0.537***						1.041*
		(0.192)						(0.578)
Grameen Bank			-0.824***					-1.106***
			(0.209)					(0.249)
Any Bank				-0.642**				
				(0.271)				
Agriculture extension officer					-0.0398			0.0473
					(0.257)			(0.264)
Access to electricity						0.0679		0.132
						(0.487)		(0.495)
Shop for pesticides and/or fertilizer							-0.288	-0.308
							(0.410)	(0.494)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	22.010	22.145	22.858	22.447	22.244	20.688	20.309	20.677
N	1428	1428	1428	1428	1428	1428	1428	1428

Notes: The table reports the 2SLS estimates of Equation (5) using as dependent variable the measure Δ. The sample includes the 714 individuals surveyed in both survey waves. Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The main regressor of interest is Belief, which is instrumented with the LT Exposure. Each regression controls for a specific margin of adaptation (see Table A2 for the definition of each variable). Any Bank is a dummy variable equal to 1 if at least one of Krishi Bank, Commercial Bank or Grameen Bank is equal to one. All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A25: Directional motivated reasoning. Information channel. 2SLS Estimates.

	Probability				Extent			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Belief	0.816***	0.810***	0.798***	0.809***	4.062**	4.064**	4.050**	4.110**
	(0.236)	(0.236)	(0.232)	(0.240)	(1.535)	(1.546)	(1.543)	(1.604)
Deviation	-0.221	-0.227	-0.216	-0.218	-3.016**	-3.027**	-3.013**	-3.036**
	(0.339)	(0.337)	(0.333)	(0.337)	(1.420)	(1.425)	(1.420)	(1.440)
Information on soil and water conservation								
and crop protection	0.102*				0.0702			
	(0.0528)				(0.201)			
crop protection and new crop varieties		0.108*				0.123		
		(0.0549)				(0.188)		
crop protection, new crop varieties and crop utilization			0.118**				0.0996	
			(0.0567)				(0.201)	
Information from TV/Radio/Newsletter				-0.0456				-0.246
				(0.0704)				(0.303)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	21.864	21.785	21.908	21.501	21.864	21.785	21.908	21.501
N	1428	1428	1428	1428	1428	1428	1428	1428

Notes: The table reports the 2SLS estimates of Equation (5) using as dependent variable a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-4) and the measure Δ (columns 5-9). The sample includes the 714 individuals surveyed in both survey waves. Δ is constructed as explained in Equation (1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The main regressor of interest is Belief, which is instrumented with the LT Exposure. Each regression controls for a proxy of information (see Table A2 for the definition of each variable). All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.