Do subjective perceptions shape adaptation to climate change? Evidence from Bangladesh

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Abstract

Mounting evidence that climate is changing requires a better understanding of how individuals adapt, in particular for communities that rely on agricultural activities in developing countries. Combining a survey of rural households in Bangladesh with a meteorological measure of dryness, I study the role of subjective perceptions of climate change on irrigation use. I formalize a theoretical framework of behavioral inattention to examine how farmers' beliefs differentially shape their responsiveness to dryness exposure. I empirically test the implications and document that the effect is stronger for more severe environmental conditions, with heterogeneous responses by growing seasons, types of irrigation and socio-demographic characteristics. I further explore three cognitive mechanisms, exploiting the intensity and the frequency of drought events and comparing self-reported and objective records. In a counterfactual analysis with beliefs based on meteorological conditions, I document that farmers underuse irrigation and incur substantial monetary losses as a result of inaccurate beliefs, generating a belief gap.

Keywords: Adaptation, Agriculture, Beliefs, Climate Change, Droughts, Irrigation

JEL Classification: D83, O13, Q12, Q15, Q51, Q54

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1 Introduction

Human-induced warming has slowed growth of agricultural productivity over the past decades in mid- and low-latitudes and climate-related extremes have affected the productivity of the agricultural sector (IPCC, 2022). The projected changes in climate threaten agricultural productivity and the communities whose economic livelihood depends on it (Ortiz-Bobea et al., 2021). Bangladesh, one of the most vulnerable least developed countries, was ranked 7^{th} on the Global Climate Risk Index 2021 of the countries most affected since 2000 (Eckstein et al., 2021). Current adaptive responses in crop production are estimated to be insufficient to offset the negative effects of climate change (IPCC, 2022). Recent studies advocate for the importance of measuring and quantifying adaptation responses to changing climatic conditions (Auffhammer, 2018; Auffhammer & Schlenker, 2014; Hsiang, 2016). Nevertheless, there is a lack of evidence on the role of cognitive and psychological factors driving adaptive behavioral responses (Grothmann & Patt, 2005). Misconception about climate change and inaccurate assessment of weather events can prevent households from responding to changes in the environment and lead to an insufficient degree of adaptation or maladaptation, with amplified climate damages. Moreover, unobserved differences in beliefs may affect adaptive behavior and omitting them could lead to biased identification of the effect of weather fluctuations on adaptation (Bento et al., 2020).

This paper provides evidence on farmers' heterogeneous adaptive response to dryness exposure in Bangladesh accounting for subjective perceptions of increase in droughts and sheds light on other cognitive mechanisms underpinning their adaptive decisions. Hereinafter, adaptation refers to farmers' use of irrigation. I combine a two-wave rural household survey that contains information on subjective perceptions and on respondents' recall of the intensity and frequency of past drought events with a meteorological local measure of exposure to dryness, using the Standardized Precipitation Evapotranspiration Index (SPEI) from Vicente-Serrano et al. (2010).

To introduce the role of subjective perceptions as opposed to meteorological conditions in the individual decision-making process, I formalize a theoretical framework of behavioral inattention and action (Gabaix, 2019). In this model, I consider a profit-maximizer farmer and relax the perfect information assumption for which agents perfectly observe long-run climate and year-to-year fluctuations and make decisions based on them. Drawing on suggestive evidence of inaccurate beliefs about past climatic conditions in my sample, I introduce a behavioral friction driving the wedge between expected profits for a rational farmer and perceived profits for a behavioral farmer with inaccurate beliefs and characterize the conditions under which beliefs differentially shape farmer responsiveness to dryness exposure. In the empirical analysis, using the share of irrigated cultivated land and the individual subjective perception of an increase in droughts, I exploit *within*-farmer variation over time, accounting for individual- and year-specific unobserved heterogeneity, and estimate the irrigation-belief relationship allowing the response function to vary with long-run dryness exposure.

The baseline results show that farmers' subjective perceptions of increase in droughts differentially shape their responsiveness to dryness exposure in the use of irrigation. The effect is stronger for more severe environmental conditions and is heterogeneous across growing seasons, driving responses only in the monsoon season. For instance, for a farmer exposed to environmental conditions that are one-half standard deviation drier than the historical average, subjective perceptions are associated with an increase by around 28 percentage points in the share of irrigated land. In contrast, I find that, in places that have not been relatively drier in the time period studied, farmers who believe that droughts have increased decrease the share of irrigated land. I rule out potential concerns on reverse causality and on farmers' response through other coping mechanisms behind this result. I also document that the main findings are driven by older farmers and with formal education. These characteristics proxy for the importance of learning about agricultural technologies, effectiveness of adaptive behavioral responses and knowledge of the relationship between dryness and irrigation. The estimates are robust to variations in the definition of long-run exposure and to the use of other measures of irrigation.

The results do not rule out alternative behavioral channels, such as salience and recall errors. I investigate three potential mechanisms through which cognitive factors may affect irrigation decisions. I exploit the intensity and the frequency of droughts comparing self-reported experiences and objective records. First, I examine whether the timing of past droughts shapes irrigation decisions. I use the self-reported year of the most badly affecting drought to test whether more recent shocks have a stronger effect on adaptive decisions. I find that only self-reported one-year lagged drought events have a strong statistically significant effect, providing suggestive evidence on the role of salient events (Gallagher, 2014). Second, I compare the self-reported year with the year of the objectively most severe drought event. Inaccurate farmers who misjudge the year of the most badly affecting drought compared to the objectively recorded timing make potentially sub-optimal irrigation decisions, increasing the share of rainfed land and reducing the share of irrigated land. Third, I examine the role of overestimating the frequency of past drought events, comparing the number of self-reported and objectively recorded droughts and document that the adaptive response depends on the accuracy of recollection: overestimating the number of droughts leads to a higher share of irrigated land.

The main findings document that subjective perceptions shape individual adaptive responses in response to larger dryness conditions, but do not shed light on the welfare consequences. To do so, I compare the baseline estimates with predicted values in the use of irrigation if farmers held accurate beliefs constructed from meteorological records. Using estimates from the literature on the returns to irrigation in Bangladesh (Haque, 1975; Parvin & Rahman, 2009) and in similar geographical contexts (Bhandari, 2001; Jones et al., 2022; Mandal & Singh, 2004; Sekhri, 2014), I compute the monetary loss due to the *belief gap* in the use of irrigation predicted with observed and accurate beliefs. The median monetary loss amounts to \$102 in the monsoon and \$23 in the winter season, respectively around 25% and 4% of the total production value in the two seasons. Farmers are more accurate in the winter dry season and thus incur lower losses. This may be explained by the fact that climatic characteristics in the winter season in Bangladesh already require a higher use of irrigation. The projected increase in the frequency and intensity of droughts and in the variability of rainfall in the monsoon season due to climate change in Bangladesh may exacerbate farmer losses as a result of misperceived climatic changes (Alamgir et al., 2015; Habiba et al., 2011).

The paper relates to various strands of the literature with novel contributions. Most important, it relates to the climate adaptation literature, which has documented little evidence of agricultural adaptation (Auffhammer, 2018; Burke & Emerick, 2016; Moore et al., 2017). There is a growing literature on various adaptive responses to climate change in developing countries, among which crop diversity (Auffhammer & Carleton, 2018), land adjustments (Aragón et al., 2021) and irrigation investment (Taraz, 2017; Taylor, 2021). Although the lack of recognition of climate change is deemed to be one of the drivers of limited adaptation, previous studies have neglected the role of beliefs, assuming perfect information and full rationality. The sole exception is Kala (2017), who studies farmers' learning models in India. Farmers may not adapt because they do not realize that climate is changing and adaptation is needed. To test this hypothesis, the literature has explored farmer responsiveness as a function of characteristics that likely shape their ability to learn about climate change (Burke & Emerick, 2016). To the best of my knowledge, this is the first study that accounts for individual subjective perceptions of climate change on on-farm adaptation, combining stated and revealed preference approaches.

Second, it relates to a branch of the literature that has started investigating the relationship between farmers' perceptions of climate change and adaptation strategies. The articles cover restricted geographical zones and provide results based on cross-sectional surveys.[1] This strand of literature does not unravel perceptions of the different aspects of climatic changes and does not compare subjective perceptions and self-reported experiences with weather data. Some studies disentangle the determinants of perceptions and adaptation strategies in a two-step approach, either without analysing the role of the former on the latter, or implementing a Heckman's selection probit model.[2] Furthermore, all the studies use self-reported adaptation decisions in a dichotomous format, potentially subject to recall bias or "yeah saying" (Choi & Pak, 2005). In this paper, I spell out the role of cognitive factors by comparing subjective perceptions and self-reported experiences of droughts with meteorological measures of dryness and drought occurrence. By examining the effect of subjective perceptions on adaptation, exploiting the intensive margin in the use of irrigation, I quantify the role of beliefs, accounting for time-invariant individual-specific unobserved heterogeneity such as risk attitudes, that may otherwise confound the effect on behavioral responses.

Third, the paper is related to the literature that studies the expectation formation process about climate change and its impacts on various outcomes (Alem & Colmer, 2018; Giné et al., 2015). Previous studies have shown that expectations about climate are inconsistent with the predictions from rational expectations (Cameron, 2005) and that individuals over-adjust their expectations to climate in response to recent, local, and extreme weather events, indicating that more attention should be paid to availability heuristics[3] (Konisky et al., 2016; Lee et al., 2018; Marx et al., 2007). Through expectation formation, agents make decisions requiring forward-looking inference on climate based on past weather fluctuations and climatic conditions (Ji & Cobourn, 2021). This paper contributes to this strand of the literature by testing the role of self-reported drought events on irrigation decisions and the effect of inaccuracy in the reported timing. These mechanisms may cause short-run economic losses due to sub-optimal decisions based on the misjudgment of recent realizations of drought events and disproportionate influence of recent realizations.

[1] Studies are mainly based in Africa (Ado et al., 2019; Debela et al., 2015; Deressa et al., 2011; Elum et al., 2017; Fosu-Mensah et al., 2012; Martey & Kuwornu, 2021; Mertz et al., 2009; Silvestri et al., 2012) and in South-Asia (Aftab et al., 2021; Khanal et al., 2018; Le Dang et al., 2014; Singh et al., 2018; Waibel et al., 2018).

[2] Several surveys ask the adaptation questions only to respondents who report a perceived change in cliamte, assuming that perception is a necessary condition for adaptation. This approach is criticized in Munro (2020, p.1099): "[...] it might be sensible in surveys dealing with perception and adaptation to always ask the adaptation question even when respondents do not report [...] changes in climate". In the survey used here, adaptation is measured from the land management module, which is not conditional on the perception module answers.

[3] The availability bias emerges when "[...]people assess the frequency of a class or the probability of an event by the ease with which instances or occurrences can be brought to mind" (Kahneman & Tversky, 1982).

The remainder of the paper is organized as follows. Section 2 defines the background and the context. Section 3 describes the data used in the empirical analysis. Section 4 defines the conceptual framework and the empirical approach used to test the implications. Section 5 presents and discusses the main results. Section 6 investigates three key mechanisms of the role of cognitive factors. Section 7 quantifies the monetized losses due to inaccurate beliefs and section 8 concludes.

2 Background

Context. Bangladesh has a tropical monsoon climate with considerable variations in rainfall and temperatures across the country and over the year. The growing season extends over the twelve months, and can be divided into three overlapping seasons. These seasons are articulated following the production of three different types of rice, which is the staple and main crop both in terms of cropped area and production in Bangladesh (FAO, 2014; Johnson, 1982). The crop rice calendar determines three different growing seasons with different weather characteristics. During *Kharif 1*, the pre-monsoon season that goes from April to July with variable rainfall and high temperatures, the *Aus* rice is grown. *Kharif 2* is the monsoon season spanning from July to November and it is characterized by heavy rain and floods. About 80% of the total rainfall occurs during this season (FAO, 2014) and *Aman* rice is the major crop. *Boro* rice is cultivated during *Rabi*, the winter dry season from December to April, with low or minimal rainfall and low temperatures (Paul & Rashid, 2016). Hereinafter, growing seasons are defined by the variety of rice that is grown.

Water resources and irrigation. Agriculture has been identified as the primary channel through which the impacts of climate change are transmitted to rural households (Auffhammer & Schlenker, 2014). In Bangladesh, rural households are subject to considerable disparity of water availability between the monsoon and the dry season and across the country. The spatial and temporal heterogeneity is going to be exacerbated by projected climatic changes. For this reason, irrigation is a precondition for enhancing agricultural production and buffering the risk created by climate variability (Bell et al., 2015).

The main sources of irrigation in Bangladesh are surface water and groundwater. The latter has a predominant role since farmers can irrigate on demand rather than wait for their turn to access surface water (Bryan et al., 2018), and, in particular in the winter dry season, during which surface water is practically unavailable (Shahid & Hazarika, 2010). The most widely adopted irrigation technologies in Bangladesh include shallow tube wells (STWs), deep tube wells (DTWs) and low lift pumps (LLPs) (FAO, 2014). The first two use groundwater and operate either with electricity or diesel. The STWs operate with a pumping unit that has a motorized suction mode with centrifugal pumps and are generally 40-60 metres deep and have a relatively small command area (Mondal & Saleh, 2003). The DTWs operate on power force mode with submersible pumps in the wells, have a larger command areas, can reach 100 metres in depth and water is supplied through buried pipes (Zahid & Ahmed, 2006). The LLPs use surface water and have centrifugal pumps mounted on a floating platform drawing water from rivers, creeks and ponds (Majumder & Rahman, 2011).

Previous work shows that adequate irrigation application and operation mode of irrigation wells increases rice yields and productivity in Bangladesh (Bell et al., 2015; Mainuddin et al., 2020). Although irrigation pump-types are not found to significantly impact the average rice yield, except when the groundwater level falls below the suction limit preventing farmers from using the STW (Mainuddin et al., 2021), timely application of adequate irrigation water is extremely important since rice is very sensitive to water deficit (Doorenbos & Kassam, 1979). In 2008, the national irrigation coverage amounted to more than 5 million hectares, with groundwater covering almost 80% of the total irrigated area. In particular, STWs and DTWs comprised more than 78% of total irrigated area (FAO, 2014). There are more than 165000 DTWs in Bangladesh, most often government owned due to high installation costs (Winston et al., 2013). Focusing on STW and DTW groundwater irrigation technologies guarantees a comprehensive coverage of the adaptive responses related to irrigation in Bangladesh.

Irrigation price. There are different water pricing systems in Bangladesh. The most widely implemented include a share of crop as water charge, a land area-based fixed water charge, and a two-part tariff comprising diesel/electricity charge paid by farmer plus a land area-based fixed charge. The main source of power energy for lifting water is electricity, followed by diesel (Zahid & Ahmed, 2006). Many small farmers do not own their pumps and they can either rent from pump owners or buy water from the pump owners to irrigate their crops using a seasonal contract and not paying labor costs (Chowdhury, 2013). Nevertheless, previous research has shown that pump ownership does not have a significant effect on production, and farmers who rent in irrigation water do not perform worse than pump owners, suggesting that informal markets in groundwater irrigation may facilitate access and equity for irrigating farmers in Bangladesh (Bell et al., 2015).

3 Data

This paper explores the role of subjective perceptions in adaptive behavior. Ideally, this would require eliciting subjective probabilistic beliefs (Delavande, 2014) of a comprehensive set of different aspects of climate change previously defined and compared to objective meteorological measures to compute “calibrations”, as the degree they correspond to relative objective frequencies (Lichtenstein et al., 1982). The data should also record individuals’ behavioral responses and measure their welfare consequences over time. Future data collection efforts should head towards this direction. In this paper, I rely on a survey designed by the International Food Policy Research Institute, with information on subjective perceptions at the individual level and I combine it with a unidimensional meteorological measure of dryness using the SPEI. This section describes the construction of the relevant variables for the empirical analysis and presents summary statistics.

3.1 Rural Household Data

Rural household data are obtained from the Bangladesh Climate Change Adaptation Survey (BC-CAS), that consists in a two-wave survey designed by the International Food Policy Research Institute (2014a). Baseline data are collected as part of a study undertaken with 800 agricultural households in 40 randomly selected unions in Bangladesh.[4] The 40 unions are selected to represent proportionally the seven agro-ecological zones in Bangladesh (Barind Tract, *Beel* and *Haor* Basins, Floodplain, Himalayan Piedmont Plain, Modhupur Tract, Northern and Eastern Hills and Tidal Floodplains) as reported in Table A1. For each union, 20 agricultural households were randomly drawn from a single village in each union.

The first wave of the survey was conducted in January 2011, and it covers data from the production year between December 2009 and December 2010. The survey contains information on demographic characteristics, land tenure, crop management, incidence and perception of climatic shocks and has been previously used to examine the impact of climatic shocks on agricultural income and adaptation strategies, although without taking into account subjective perceptions (Delaporte & Maurel, 2018). A follow-up second wave of the survey was conducted in September 2012, and it covers data from the production year between September 2011 and August 2012 (International Food Policy Research Institute, 2014b). A timeline of the survey waves with respect to the three

[4] Unions are the smallest rural administrative and local government unit in Bangladesh. The administrative structure is: Division $\supset$ District (*Zila*) $\supset$ Sub-district (*Upazila*) $\supset$ Union. There are 5,158 unions with an average size of approximately 10–20 km^2.

agricultural growing seasons in Bangladesh is reported in Figure A1.

Descriptive statistics. Table A5 presents key descriptive statistics of the households and their agricultural characteristics by survey wave. There is only one respondent for each household interviewed, who is the head of the household.[5] More than 97% of the households (766 out of 800) were reinterviewed in the second wave. The remaining 34 households could not be interviewed because they migrated (15 households) or nobody was at home at the time of the survey. Since the focus is on self-reported subjective perceptions, the final sample includes only those households who have been surveyed in both waves, did not move between the two waves and whose respondent was the same in both waves. Using this approach, I account for unobserved heterogeneity at the respondent level, allaying concerns about any bias in the coefficients associated with self-reported subjective measures. The resulting final estimation sample is a balanced panel of 714 individuals. The geographical distribution of the households in the final estimation sample across AEZs is reported in Table A2. Table A3 reports the total number of households by union in the final estimation sample. There are no substantial differences in the geographical distribution between the full and the estimation sample, which provides support to the absence of geographic bias when focusing only on the 714 households. To further ascertain the absence of selection bias due to attrition in the second wave, I compare means for major outcomes and control variables in the first wave for attritors and non-attritors. Table A6 displays the differences in means, that are never statistically significant, except for the indicator variable of the head of the household being a farmer.[6]

Agricultural production. Households in the survey mainly rely on production and cultivation of rice. Table A8 provides descriptive statistics on the average share of cultivated land devoted to each crop. The three types of rices, *Aus*, *Aman* and *Boro* make up around 80% of the total cropped area for each household, with *Aman* and *Boro* cultivated in more than 70% of cultivated land. Similar figures are obtained when weighting the crop shares by the total agricultural production of the household, as reported in Table A9.[7] For this reason, in the empirical analysis I distinguish the irrigation decisions made in the monsoon and in the winter growing seasons, respectively *Aman* and *Boro*, as in Carleton (2017), Chakravorty et al. (2022), and Taraz (2017).

[5] A household is defined as a group of people who live together and take food from the same pot. It counts as household member anyone who has lived in the household at least six months, and at least half of the week in each week in those months. People who do not share blood relations with the head of the household (e.g. servants, lodgers or agricultural laborers) are considered members of the household if they "have stayed in the household at least 3 months of the past 6 months and take food from the same pot" (International Food Policy Research Institute, 2014a).

[6] Key results are robust to the exclusion of the variable that is used as control in the main specifications.

[7] This information is available only for the first wave of the survey.

Irrigation status. To study how cultivated land is allocated to irrigation status, I use the survey module on land use. This module provides information on the irrigation status of each plot by growing season, distinguishing by irrigation technique. First, I pool all plots of own operated cultivated land in *Aman* and *Boro* and distinguish between the average share of land irrigated and left rainfed over the agricultural production year. Then, I consider the most largely implemented irrigation types in the survey, which correspond to the most widely adopted in Bangladesh, namely STW and DTW (see Section 2). The share of cultivated land is constructed from the sum of all own operated cultivated plots' surfaces divided by the total own operated cultivated land of a household. Table A10 reports descriptive statistics for the land left rainfed and under irrigation pooled over the production year.

Seasons are characterized by very different climatic conditions, and irrigation use highly differs across them (Bell et al., 2015). There is considerable variation within plot in the data, where around 56% of the plots change irrigation status between the monsoon and non-monsoon seasons. Table A11 displays the summary statistics for all available irrigation methods by growing season. In the *Aman* season, most of the cultivated land is left rainfed (on average more than 75%), and the most largely adopted irrigation technology is STW that covers more than 15% of the cultivated land. In the *Boro* season, households rely much less on surface water: on average, the share of rainfed cultivated land plummets to 26%, the STW covers on average more than 40% of the cultivated land and DTW covers more than 10%. Table A12 reports summary statistics on the five most widely adopted methods used as outcomes in the empirical analysis: rainfed and STW irrigated land in *Aman*, and rainfed, STW and DTW irrigated land in *Boro*.

Subjective perceptions. Most importantly, the survey contains questions on individual subjective perceptions of different aspects of climate change over the previous twenty years: increases in droughts, increases in erratic rainfall and decreases in precipitations. For each question, I construct a dichotomous variable that indicates whether the respondent perceived it. The mean and standard deviation for each subjective perception by survey wave is reported in Table A13. This information contributes to provide a direct measure of subjective perception as a potential determinant of adaptation, which has thus far only been conjectured to be affected by a difficulty in learning about climate change and cognitive factors (Bento et al., 2020; Burke & Emerick, 2016). I advance on this literature by accounting for individual perceptions of climate change when studying adaptive behavioral responses. Since it is not possible to ascertain that changes in perceptions are driven by exogenous shocks, I compare farmers' characteristics that do and do not perceive an increase in droughts in Table A7, Panel A. Significant differences exist between the two groups in receiving advice from extension agents and in perceptions of increases in erratic rainfall and decrease in precipitation. Although differences in levels are not problematic for estimation since I include individual fixed effects in every specification, differences in the subjective perceptions variables persist also in the average changes between waves (Panel B of Table A7). I control for these variables in every specification in the empirical analysis.

Why do people change their perceptions? Despite the relatively short time span between the two waves (less than two years), there is considerable heterogeneity in survey responses across waves in respondents' perceptions. Most notably, around 52% of the respondents did not report a perceived increase in droughts in the first wave and reported it in the second wave, while only around 7% had an opposite reporting pattern. This is even more relevant since only one union in the sample (Chaklarhat) recorded an extreme drought event between the two waves, in which 30% of the respondents changes perceptions and reported a perceived increase in droughts and 60% did not change their perceptions across the two waves. A potential explanation of this result is that individuals have their own definition of droughts. This would not pose a problem to the analysis so long as this is time-invariant, which is plausible given the temporal proximity of the two waves.

Further analysis on the relationship between subjective perceptions and meteorological records is discussed and reported in Section 3.2. Here, I examine whether belief updates come from social or informational channels. First, I compare the variance in perceptions across unions between the two waves to investigate a potential local convergence or divergence phenomenon of beliefs update. The average variance is 0.178 in the first wave and 0.171 in the second wave, providing evidence that there is slight convergence in perceptions within each union, although the difference is not statistically significant at any conventional level. Another possibility is that perceptions can be influenced by the land management strategies designed to adapt to unfavorable conditions (Niles & Mueller, 2016), up to the point that reverse causality may undermine this study. This possibility is explored and ruled out in Section 5.2.

Another potential channel of belief update is the role of social learning (Conley & Udry, 2010). Farmers compare neighbors' productivity to theirs and update their beliefs to align with the input adjustments of those who were successful in the previous period. I test this hypothesis by regressing the differences between the deviations from the union's averages in perceptions over the two waves on the differences between the deviations from the union's averages in the share of irrigated land. Under the assumption that irrigation has positive returns on productivity (Bell et al., 2015), a negative and statistical significant coefficient on the double difference (over time and from union's average) of use of irrigation would provide evidence of the social learning channel for beliefs update. Table B1 displays the coefficients on the double difference of use of irrigation that are never statistically different from zero, ruling out the social learning channel.

Self-reported experience of droughts. Individuals are also asked a series of questions about their memories of weather events in recent years. In particular, they report the number of droughts that adversely affected their properties and productivity in the five years before the first wave and between the first and second wave. Using this question, I construct the variable *self-reported # droughts*, used to compute a measure of accuracy of recollection of droughts, explained below. In the same survey module, individuals are asked to report the year, over the same period of the previous question, in which they were most badly affected by droughts. To maintain symmetry between the two waves, I construct two non-mutually exclusive dichotomous variables, $Drought_{t-1}$ and $Drought_{t-2}$, that take value one if the individual reported the most badly affecting drought event to have occurred respectively one and two years before the irrigation decision recorded in the survey. Table A4 reports the exact wording and formulation of each question in the two waves employed to construct the main variables used in the empirical analysis.

3.2 Dryness and Drought Events Data

Dryness exposure. To compare subjective perceptions and objective exposure measures to dryness, I use a meteorological measure, the Standardized Precipitation Evapotranspiration Index (SPEI) from Vicente-Serrano et al. (2010), which provides information about drought conditions at the global scale, with a 0.5° spatial resolution ($\approx$ 55km at the Equator), at a monthly time resolution.[8] The SPEI is a measure of dryness derived as the difference between precipitation and potential evapotranspiration to obtain a measure of drought based on water balance. It is based on monthly precipitation and potential evapotranspiration from the Climatic Research Unit of the University of East Anglia (CRU TS version 4.03). This index captures deviation in dryness relative to the average observed during the whole 1901-2018 period. 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 conditions, and positive for wet conditions. For instance, a value of

[8] I construct union-level measures overlaying the gridded SPEI database to the map of Bangladesh. The raster is aggregated spatially to the monthly union means. In the computation of the union-level averages, the grid cells' values are weighted by the fraction of surface covered by the union. Figure A2 displays the surveyed unions (in purple) and overlays the raster data of the SPEI database in September 2012.

SPEI equal to -1 can be interpreted as the difference between precipitation and potential evapotranspiration one standard deviation lower than the historical average for a given grid cell. Since the analysis exploits inter-seasonal variation in dryness conditions, I use the SPEI-1, which is based on the accumulating deficit of water balance over one month.

This index presents specific advantages. It provides a unidimensional measure of climatic conditions considering the joint effects of precipitation, potential evapotranspiration and temperature. The SPEI has been used in the conflict (Almer et al., 2017; Harari & La Ferrara, 2018) and agricultural (Albert et al., 2021) literature, and specifically for measuring droughts in Bangladesh (Abdullah & Rahman, 2015; Miah et al., 2017; Mohsenipour et al., 2018). Despite the recurrent and devastating nature of droughts (Mondol et al., 2021; Shahid & Behrawan, 2008; Shahid & Hazarika, 2010), previous research has mainly focused on the effect of floods in Bangladesh (Chen et al., 2017; Gray & Mueller, 2012; Guiteras et al., 2015). This paper exploits a meteorological measure of dryness to compute the exposure and the number of drought events and combine it with subjective self-reported measures to study the most frequent extreme weather event in Bangladesh (Alamgir et al., 2015).

I derive continuous measures of exposure to dryness at the union level over the entire production year and by growing season, using the definition of growing seasons in Sacks et al. (2010) as the time interval between the planting and harvesting dates for the two types of rice (*Aman* and *Boro*). To facilitate the interpretation, all the continuous measures constructed from the SPEI are taken in the additive inverse form, SPEI $\times$ (-1), such that higher values are associated with higher dryness.

I construct two measures of exposure to dryness to account for both the long-run average and the short-term deviation in exposure (Bento et al., 2020; Hsiang & Jina, 2014). I build a long-run exposure to dryness by taking the average of the monthly SPEI realizations over the previous twenty years for the production year and within each growing season. These measures should be interpreted as the 'objective counterfactual' of the subjective perception of increase in droughts in the past twenty years. In an OLS regression of perceptions on long-run average exposure to dryness and short-term deviation, the coefficient on long-run exposure is 16.23 (s.e. = 2.47, p-value$<$0.001). Using seasonal measures, the coefficient on *Aman* long-run dryness is 6.38 (s.e. = 0.91, p-value$<$0.001) and on *Boro* is -1.69 (s.e. = 2.74). Full results are reported in Table B2.

Considering long-run exposure is essential in situations that analyse expectation formation and adaptation decision-making. Agents may adapt to the average exposure, deeming it as the reference point to infer deviations from the average, and their perceptions would be based on it. This would imply that households exposed to more severe droughts and those not frequently exposed might consider droughts of the same magnitude in different ways (Guiteras et al., 2015). To account for this, I also consider short-term deviation as the difference between the average SPEI in the year or growing season preceding the production year and the long-run average SPEI.

Drought events. In order to have a measure of farmers' interpretation of past drought events, I compare the self-reported number of drought events to the objectively recorded drought events. The climatology literature defines a drought event as the period of consecutive time points in which the SPEI index is below certain thresholds (Spinoni et al., 2014). The SPEI values can be categorized in 5 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 available values for each grid cell.

Overestimation. Following this classification, I match all the households in each union with the recorded number of extreme drought events occurred in the five years before the first wave of the survey (between 2006 and 2010) and between the first and the second wave (2011 and 2012). The choice of the time periods is coherent with the questions asked in the BCCAS on the incidence of extreme weather events. I also employ other cutoffs to define the objective number of droughts, including moderate and severe drought events, to test the robustness of the results. Droughts are deemed 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). Following this approach, I create an individual-specific measure of overestimation of the frequency of past drought events:

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

that compares the self-reported number of drought events by individual i in union u in survey wave t and the objective number of drought events in union u over the same time period (where $type \in \{\text{moderate; severe; extreme}\}$). These wave-specific measures of accuracy infer whether respondents overestimate or underestimate the number of drought events that they have experienced. A positive value indicates that individuals overestimated the number of drought events. I also construct an indicator variable, *Overestimation*, that takes value one if Δ is strictly positive. Table A15 displays summary statistics of the measures of exposure to dryness and of the number of drought events recorded using the SPEI. Table A16 provides descriptive statistics of the main regressors used in the empirical analysis combining self-reported information from the BCCAS and meteorological measures. I also conduct a test in balance of the covariates included in the main specification by regressing each of them on long-run dryness conditions. Table A17 shows that dryness does not affect any other characteristics of farmers in the sample such as cultivated land, household size, assets ownership. This suggests that changes in climatic conditions are driving changes in adaptive actions only through changes in individual understanding of these events and beliefs.

4 Methodology

4.1 Theoretical Framework

Climate influences outcomes through two pathways: the actual weather realizations and through beliefs about climate. Hsiang (2016) defines these channels respectively as "direct" and "belief" effect and shows that the marginal effects of climate and weather are locally equivalent for optimal beliefs (Deryugina & Hsiang, 2017). Most of the literature studying adaptation employs empirical tests that only include measures of climatic conditions and weather fluctuations (Aragón et al., 2021; Auffhammer & Carleton, 2018; Taraz, 2017), assuming perfect information and abstracting from any heterogeneity in individual beliefs and understanding of climatic changes (Bento et al., 2020; Burke & Emerick, 2016). In this section, I consider a model of learning and adaptation (Shrader, 2020) and extend it with new insights from a behavioral perspective where individual beliefs do not necessarily coincide with meteorological records.

Consider a farmer who maximizes expected profits producing a univariate output at time t with output price normalized to one and choosing a single input, irrigation use a, with an associated price c.[9] The input enters a production function, $F(a, w)$, twice continuously differentiable and concave, where the other input is weather, w, drawn from a Gaussian distribution $\mathcal{N}(\mu_t, \sigma^2)$. I consider a unidimensional weather measure that embeds all the relevant climatic aspects for the agents (temperature, precipitation, potential evapotranspiration).[10] Following Shrader (2020), the

[9]This setting can be generalized to a farmer using k different irrigation techniques or introduce several inputs, such that $\mathbf{a} = \{a_1, ..., a_k\}$, each of them with an associated price $\mathbf{c} = \{c_1, ..., c_k\}$. For simplicity, I ignore credit constraints.

[10]Nothing prevents from including a vector of weather variables where derivatives would be replaced by Jacobian matrices.

production function is multiplicatively separable in terms of weather and input. At the beginning of each period, a rational farmer chooses the optimal level of input $a^r = \text{argmax}_a \mathbb{E}_{t-1}(\pi_t)$ that maximizes expected profits[11]:

$$\max_a \mathbb{E}(\pi) = \mathbb{E}(w)F(a) - c(a) \tag{2}$$

Because of the presence of costs associated with the use of irrigation (e.g. maintenance and pumping costs, digging channels to reach other plots, renting tubewells, contractual arrangements with equipment owners), the farmer chooses input a before weather in period t is realized and commits to such choice ex-ante, so that current weather does not affect the decision.[12] This canonical setting assumes that private individual beliefs are always equal to or sufficient for the public information about the weather (Kelly et al., 2005; Moore, 2017; Shrader, 2020).

I relax this assumption by considering a simple model of deterministic behavioral inattention and action (Gabaix, 2019). A farmer has been exposed to a sequence of weather realizations over the previous twenty years $\{w_{t-20}, ..., w_{t-1}\}$ and forms beliefs $\mathbb{E}^b(w)$ about the underlying climate distribution from which weather realizations are drawn. Beliefs can either be accurate - and coincide with $\mathbb{E}(w)$ - or be inaccurate.

A behavioral farmer replaces the maximization problem in (2) with an "attention-augmented" production function (Gabaix, 2019) that is characterized by the degree of attention, i.e., the farmer's subjective model of the world. The behavioral farmer selects the input level, a^b, that maximizes expected profit:

$$\max_a \mathbb{E}^s_{t-1}(\pi_t) = \mathbb{E}^s(w)F(a) - c(a) \tag{3}$$

where $\mathbb{E}(w)$ is replaced by the subjectively perceived $\mathbb{E}^s(w)$, which is a convex combination of the expected weather realization using the history of past weather conditions and her beliefs about the climate distribution, parametrized by the weight γ:

$$\mathbb{E}^s(w) := \gamma\mathbb{E}(w) + (1-\gamma)\mathbb{E}^b(w) \tag{4}$$

[11] Subscripts on an expectation operator denote the information set on which the expectation is conditioned (showcased here and then omitted for brevity).

[12] This assumption is empirically tested in Table B3, where I consider the baseline specification and regress the share of irrigated land on contemporaneous seasonal deviations in the SPEI and find a null effect.

The chosen input of the behavioral farmer a^b is affected by the degree of inaccuracy of beliefs with respect to expected weather realizations and by the extent to which she weighs beliefs. In other words, farmers are making a decision based on a combination weighted by γ of what has happened and their interpretation of that. Equation (4) allows for individuals to observe the same weather realizations but have different beliefs, considering realizations drawn from different climate distributions, and thus react differently.

Although the data used in the empirical analysis do not contain information on forward-looking perceptions about changes in droughts, previous studies have shown a strong significant correlation between past- and forward-looking perceptions about the weather and climatic events (Bakkensen et al., 2019). In a non-stationary climate with scientific uncertainty, accurate expectations of next period's weather are not necessarily formed from the average of the past twenty years. Nevertheless, those that believe that droughts have increased take weather realizations as a signal of the future path of weather - which differs from those believing that the climate distribution is fixed.

The behavioral friction in the model drives the wedge between expected profits for a rational farmer and perceived profits for a behavioral farmer with inaccurate beliefs, allowing for agents' subjective state of the world and objective meteorological conditions to differ. When $\gamma = 1$, the farmer behaves as a rational agent and $\mathbb{E}^s(w) = \mathbb{E}(w)$. Subjective perceptions do not differentially shape agents' responsiveness. When $\gamma \in [0, 1)$, beliefs matter for irrigation decisions and the farmer may be losing profit by ignoring information up to the point $\gamma = 0$, where the farmer "does not think about" $\mathbb{E}(w)$ and replaces the subjective model of the world only with her beliefs (Gabaix, 2019).

To fix ideas, take $F(a) = a^\alpha$, where $\alpha \in (0, 1)$ and a linear cost function. Assuming interior solutions for the non-negativity constraint in the input choice, the behavioral farmer maximizes expected profits and chooses a^b:

$$a^b = \left[\frac{\alpha \mathbb{E}^s(w)}{c}\right]^{\frac{1}{1-\alpha}} \tag{5}$$

Using the implicit function theorem, it follows that for a shift to drier conditions (increase in $\mathbb{E}(w)$), the farmer uses more irrigation. The comparative statics with respect to individual beliefs, however, have an ambiguous sign. On the one hand, one could expect the sign to be positive as a perception that droughts have increased should be associated with an increase in the adaptive response of individuals. On the other hand, however, in a setting with no changes in climatic conditions, a farmer who believes droughts have increased may either decide not to use irrigation unless needed or to substitute the irrigation with other adaptive responses. Both options are explored and discussed in the empirical analysis in Section 5. The parameter of interest is the differential role of beliefs for changes in weather conditions. Adaptive decisions taken by farmers depend not only on meteorological changes, but also on changes in their beliefs about climatic conditions. The differential effect of beliefs $\mathbb{E}^b(w)$ on a^b is

$$\frac{\partial^2 a^b}{\partial \mathbb{E}^b(w) \partial \mathbb{E}(w)} \Big[c, \mathbb{E}^b(w), \mathbb{E}(w), \alpha, \gamma\Big] = \frac{\left(\frac{\alpha}{1-\alpha}\right) \cdot \left(\frac{\alpha}{c}\right)^{\frac{1}{1-\alpha}} \cdot (1-\gamma) \cdot \gamma \cdot \left(\mathbb{E}^s(w)\right)^{\frac{2\alpha-1}{1-\alpha}}}{1-\alpha} > 0 \tag{6}$$

The sign in equation (6) is unambiguous: farmers differentially respond to changes in weather conditions depending on their beliefs by increasing their use of irrigation, as long as $\gamma \neq 1$. It follows a testable implication of this model that beliefs matter for the adaptive decision, if Equation (6) is different from zero. The intuition behind this result is that in places where environmental conditions are becoming drier, changes in beliefs are associated with increases in the use of irrigation.

The parameter γ relates to farmer's behavioral preferences (and to some extent heuristics/biases), attention, confidence in own beliefs, information sharing. This causes departure from the neoclassical setting where only expected weather matters and convergence to correct adjusted posterior, from any prior inaccurate belief. Considering comparative statics with γ, I obtain:

$$\frac{\partial a^b}{\partial \gamma} \Big[c, \mathbb{E}^b(w), \mathbb{E}(w), \alpha, \gamma\Big] = \frac{\left(\frac{\alpha}{c}\right)^{\frac{1}{1-\alpha}} \Big(\mathbb{E}(w) - \mathbb{E}^b(w)\Big) \left[\mathbb{E}^s(w)\right]^{\frac{\alpha}{1-\alpha}}}{1-\alpha} \tag{7}$$

The direction of changes in input adjustment is ambiguous as it depends on $\mathbb{E}(w) - \mathbb{E}^b(w)$, i.e. the inaccuracy of beliefs with respect to the average weather realization. If $\mathbb{E}(w) - \mathbb{E}^b(w) > 0$, i.e., environmental conditions have been on average drier than the farmer believes, then $\frac{\partial a^b}{\partial \gamma} > 0$. For inaccurate farmers who are underestimating shifts in climatic distributions, giving more weight to the objective meteorological conditions (increasing γ) would increase the input use. If the farmer is accurate, $\mathbb{E}(w) = \mathbb{E}^b(w)$, then the inattention parameter γ does not affect irrigation decisions.

Why do beliefs about climate matter for short-run behavioral responses? Climate change is imperfectly observed by individuals, resulting in differences between beliefs about climate and its true state. Belief-related adjustment costs arise if the observer would have acted differently in response to the actual climate distribution relative to the climate distribution that they believe

(Moore, 2017). These adjustment costs are the difference in expected profits given the irrigation options that would have been chosen with full information about the climate state ($\mathbb{E}(w) = \mathbb{E}^b(w)$). A necessary and sufficient condition for the existence of belief-related adjustment costs is that beliefs about the climate state are inaccurate (i.e., $\mathbb{E}^b(w) \neq \mathbb{E}(w)$)). This assumption appears to empirically hold in Table A14, where I compare reported subjective perceptions with changes to dryness conditions in a two-way frequency table. I categorize the continuous measure of long-run dryness conditions into a binary variable, whose values correspond to the beliefs that individuals would have had based on meteorological conditions.

Two farmers exposed to the same climatic conditions may put in place different short-run behavioral responses as a result of different beliefs about such climatic conditions. The interpretation of past weather realizations would differ and so would the expectation of weather realizations. Consider a farmer with beliefs that droughts have increased over the past twenty years and another farmer who does not perceive droughts to have increased. The former has interpreted the weather realizations as a shift in the distribution. In contrast, the latter has a different interpretation of the weather realizations that as draws from a fixed climate distribution. This will drive different behavioral responses.[13]

Although beliefs shape heterogeneously the agents' responses for changes in objective weather conditions (Bento et al., 2020), identifying their effect is challenging since they are seldom observed.[14] Previous research has so far assumed that agents are rational and have optimal beliefs and thus will optimally adjust (Deryugina & Hsiang, 2017; Hsiang, 2016). In Section 4.2, I develop an empirical model to quantify the differential role of beliefs for changes in environmental conditions, consistent with Equation (6).

Profit loss due to inaccurate beliefs. A rational farmer and a behavioral farmer with inaccurate beliefs with respect to climatic conditions will make different irrigation decisions. If the farmer is not accurate, optimal irrigation choice is (5). If the farmer has accurate beliefs, the optimal use of irrigation is

$$a^r(\mathbb{E}(w), \alpha, c) = \left[\frac{\alpha \mathbb{E}(w)}{c}\right]^{\frac{1}{1-\alpha}} \tag{8}$$

[13]To draw a parallel to another adaptive response outside of agriculture, consider two individuals exposed to the same meteorological conditions and have observed extremely hot summers. One believes that these are a consequence of a shift in the climate distribution, and the other does not. In this setting, the former will ex-ante commit to invest in coping mechanisms for the next summer, e.g. air conditioning, whereas the latter will not.

[14]Bento et al. (2020) accounts for beliefs by splitting the sample into terciles of high, median and low beliefs of county residents and interacting it with climatic trends and temperature shocks, finding that high-belief counties have a larger behavioral response.

The expected profit loss due to inaccurate beliefs is

$$\mathbb{E}(\pi(a^r)) - \mathbb{E}(\pi(a^b) = \left[\mathbb{E}(w)^{\frac{1}{1-\alpha}} - \mathbb{E}^s(w)^{\frac{1}{1-\alpha}}\right] \cdot \left[\alpha^{\frac{\alpha}{1-\alpha}} - \alpha^{\frac{1}{1-\alpha}}\right] \cdot c^{-\frac{\alpha}{1-\alpha}} \tag{9}$$

In Section 7, I provide a back-of-the-envelope calculation of the monetary loss due to inaccurate beliefs combining estimates from the literature with the results obtained in the empirical analysis.

4.2 From Theory to Empirics

Following the theoretical framework, the empirical approach explores the differential role of subjective perceptions on irrigation, accounting for exposure to dryness. The baseline econometric specification is:

$$a_{it}^{(k)} = \beta_1 b_{it} + \beta_2 b_{it} \times \overline{w}_u + \beta_3 \tilde{w}_{ut-1} + X_{it}'\gamma + \lambda_i + \mu_t + \varepsilon_{it} \tag{10}$$

where $a_{it}^{(k)}$ is the share of irrigated land for individual i in year t. I initially pool the average share of irrigated land under any irrigation method across the *Aman* and *Boro* seasons, and consider the most widely adopted irrigation techniques k ($\in$ {STW, DTW}). In Section 5.2, I explore the effect for season-specific irrigation decisions for rainfed, STW- and DTW-irrigated cultivated land using season-specific measures of exposure to dryness.

I estimate the perception-adaptation relationship allowing the response function to vary with long-run exposure to dryness $\overline{w}_u$. The main explanatory variables are b_{it}, a dummy variable indicating whether the individual perceived an increase in droughts over the previous twenty years, $\overline{w}_u$ is the average long-run excess dryness over the twenty years before the first wave of the survey relative to historical average and $\tilde{w}_{ut-1}$ is the one-year lagged deviation.

The main coefficient of interest in Equation (10) is β_2, that accounts for heterogeneous short-run behavioral responses to exposure to dryness accounting for individual beliefs. The estimation of this coefficient represents a testable hypothesis of a behavioral farmer who responds differently to weather conditions depending on individual beliefs, against the null hypothesis that beliefs do not matter for adaptive responsiveness. An estimated coefficient that is not statistically different from zero would suggest that the second-order cross partial derivative in Equation (6) is equal to zero, which is the case if and only if $\gamma = 1$, i.e. and adaptation is only a function of objective environmental conditions, as previously assumed by the literature (Shrader, 2020).

Many factors may compromise the identification of the β's coefficients in Equation (10). Those factors can be grouped into three potential sources of endogeneity, respectively reverse causality, unobserved heterogeneity and measurement error. Below, I discuss my primary identification strategy and discuss each of these potential sources of bias.

Equation (10) includes a vector λ of individual fixed effects, accounting for 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 risk preferences (Hsiang, 2016). I also include a vector μ of year fixed effects, which control for unobserved shocks common to all individuals in a given year. Therefore, identification comes from within-individual variation, conditional on the year fixed effects and other observable controls.[15] Any remaining heterogeneity biasing the estimates must vary systematically over time across individuals and not be accounted for in Equation (10). Any threats to identification applies to the coefficients β_1 and β_2. The β_3 coefficient on short-run deviations $\tilde{w}_{ut-1}$ can be interpreted causally as within-union realizations of weather are plausibly exogenous (Carleton & Hsiang, 2016; Carleton et al., 2022).

A potential concern may be reverse causality. Farmers who do not perceive changes in droughts and did not increase the irrigated land may suffer greater damages to their agricultural production as a result of changes in weather conditions. Consequently, they may self-report a perceived increase in droughts as a result of larger damages. Reverse causality may also occur if increasing the use of irrigation or a relatively high baseline use of irrigation prevents individuals from updating beliefs and change perceptions about droughts. In both cases, the estimated coefficient associated with perceptions would be negative. I empirically test for reverse causality in Section 5.2.

Equation (10) includes an interaction between the potentially endogenous variable b_{it} with plausibly exogenous cross-sectional variation in excess dryness conditions, $\overline{w}_u$. I exploit cross-sectional variation in long-run dryness conditions between unions to estimate the differential responsiveness to perceptions. The term can thus be interpreted as exogenous, once the main effect of the endogenous variable is accounted for (Angrist & Krueger, 1999; Bun & Harrison, 2019; Nizalova & Murtazashvili, 2016).[16] Since there exists no experimental or quasi-experimental variation in climate within a location (Carleton & Greenstone, 2021), I use a time-invariant measure of long-run exposure to dryness computed over the twenty-year before the first wave. The estimated model does not include uninteracted term for long-run dryness, $\overline{w}_u$, because collinear with the fixed effects,

[15]Union fixed effects are superfluous in this setting since all individuals in the estimation sample never change place of residence.

[16]For an empirical application with exogenous weather variables interacted with potentially endogenous fractions of area insured, see Annan and Schlenker (2015).

which shuts down the possibility to influence irrigation decisions regardless of individual subjective perceptions. In a robustness test, I explore the possibility of using a time-varying version of long-run dryness.

In the case of unobserved heterogeneity, the combined use of individual and year fixed effects should eliminate most unobserved heterogeneity between individual-year observations. Therefore, the identifying assumption is that any remaining unobserved heterogeneity does not significantly bias the estimates of β_1 and β_2. Since I cannot completely rule out the possibility that there is unobserved heterogeneity in the data that varies systematically across individuals and over time, I also include in the specification time-varying individual specific covariates that may contemporaneously change as a result of climatic changes and affect irrigation. Although most of the variables are balanced between farmers who perceived and who did not perceive an increase in droughts (Table A7) and although meteorological dryness does not affect any other characteristics of farmers (Table A17), I include a set of covariates X'_{it} that accounts for whether the respondent is a farmer as primary occupation, if the respondent receives extension advice, if the household has access to electricity, ownership status of STW or DTW pumps, shares of soil type of cultivated land and total hectares of land holdings as a measure of wealth of the household, subjective perceptions of erratic rainfall and decrease in precipitation.

Lastly, in the case of measurement error, it may be that perceptions of increases in droughts are overreported. Although systematic measurement error is a threat to the identification of β_1, the estimated relationship between the perceptions and use of irrigation would suffer from attenuation bias, biasing the estimates toward zero.

Given the spatial resolution of the data, I take spatial correlation into account for the estimation of standard errors. Using clustered standard errors at the union level would underestimate the standard errors, since in five cases the boundaries of more than one sampled union fall within the same grid cell of the meteorological data and unions' borders lay across different grid cells (Figure A2). Therefore, I estimate standard errors allowing for both cross-sectional spatial correlation and location-specific serial correlation. I impose a two-year constraint, compatible with the temporal distance between the two survey waves, on the temporal decay for the Newey-West/Bartlett kernel that weights serial correlation across time periods. In the spatial dimension, I retain a radius of 200 km with a Bartlett (triangular) kernel: close to the average distance between union centroids and around four-times the spatial resolution of the SPEI to allow for correlated shocks across grid cells.

The estimates are robust when changing either the spatial or temporal cutoff, or both.[17] Inference is also largely unchanged when standard errors are clustered at the grid cell-level.[18,19]

5 Results

This section presents and discusses the key findings from estimating Equation (10). First, I consider the average share of irrigated cultivated land and then I decompose the share of cultivated land irrigated between the most adopted irrigation techniques (STWs and DTWs) averaged over the two growing seasons. In Section 5.2, I investigate season-specific irrigation decisions distinguishing between irrigated land in *Aman* and in *Boro* separately and using season-specific exposure measures. In Section 5.3, I explore heterogeneity along socio-demographic characteristics.

5.1 Subjective Perceptions and Irrigation Status

I first estimate a version of Equation (10) in which I consider measures of exposures to dryness and irrigation decisions over the two main growing seasons.[20] Table 1 displays the estimates of the coefficients on subjective perceptions and the interaction with long-run exposure to dryness. In column (1), I report the partial correlation between the share of irrigated land and perceptions of increase in droughts purged by individual and year fixed effects. The estimate is negative and not statistically significant. Including controls (column 2), the estimate is smaller and statistically significant. When I also include the interaction term (column 3), perceptions are still negatively associated with the share of irrigated cultivated land, with the effect smaller in size. This coefficient represents the correlation between perceptions and irrigation for a farmer who has been exposed to dryness conditions that do not different from the historical average, normalized to zero. This case never occurs in the data, where in all unions in the sample (except for Khalilnagar, Laskar and

[17]Tables C1 and C2 display the baseline results when changing the spatial cutoff to 100, 400 or 800 km and the temporal autocorrelation cutoff to 5, 10 and 999 years.

[18]Baseline results clustering standard errors at the grid cell-level are displayed in Tables C3 and C4. Seemingly Unrelated Regressions (SUR) (Zellner, 1962) does not suit the setting since each equation contains exactly the same set of regressors (Kruskal, 1960). The correction using bootstrap iteration, which would provide robust estimates of standard errors to heteroskedasticity and cluster-correlation structures (Freedman & Peters, 1984), is not feasible due to the small size of the estimation sample.

[19]The estimation of Driscoll and Kraay standard errors, adjusted for heteroskedasticity and autocorrelation and robust to general forms of spatial and temporal dependence, is based on large T asymptotics (Driscoll & Kraay, 1998). With T fixed and N large, as it is the case here, there is not sufficient information in the time dimension relative to the cross-section dimension for this approach to work (Hoechle, 2007; Vogelsang, 2012)

[20]Results are robust, and estimates more precise, when including the irrigation and meteorological records in *Aus*.

Rudaghara) the environment was drier than the historical average in the twenty years before the first wave. There are four potential interpretations behind thing finding. First, irrigation is a costly action, and farmers, although they believe in a change in the climate distribution, reduce the use of irrigation in non-dry periods. Second, the result may be explained by a depletion of groundwater supplies. Although it cannot be fully ruled out, behavioral responses as a result of short-run changes in beliefs between the two waves are unlikely to be explained by groundwater resources depletion which occurs over a longer time horizon (Scanlon et al., 2012; Taraz, 2017). Third, it may lend support to the hypothesis of substitution between irrigation and other coping mechanisms, whose opportunity cost may be now lower for a perceived change in dryness conditions. Finally, it may raise concerns around reverse causality between behavioral responses and perceptions. The two last hypotheses are widely discussed and empirically tested below.

For a farmer exposed to non-zero long-run dryness, the marginal effect of subjective perceptions includes the interaction term, around ten-fold larger than the uninteracted coefficient. The F-stat on the hypothesis that the sum of the coefficients is not statistically different from zero is above the conventional thresholds.[21] The magnitude of the effect of subjective perceptions depends on the long-run exposure to dryness. Under a long-run exposure one standard deviation drier than the historical average, the effect of subjective perceptions is associated with an increase by around 65 percentage points (p.p.) in the share of irrigated land. This effect, which may seem extremely large in magnitude, is computed for a twenty-year average exposure much larger than the mean in the sample (0.07). The effect of subjective perceptions of increases in drought on the share of irrigated cultivated land is positive for households exposed to at least a long-term average one-tenth of SD drier than the historical average, roughly the seventieth percentile across unions.

The key finding is that two individuals exposed to the same conditions of dryness, but differing in subjective perceptions, will choose different levels of input use, *ceteris paribus*. In particular, beliefs that differ from meteorological records and with non-zero weight in farmers' decision-making process may prevent them from making the optimal decision, and potentially result in *maladaptation*. People's responsiveness to a change in climate depends on their underlying beliefs, questioning previous assumptions on rational agents and internalized information set to form beliefs on climatic conditions (Deryugina & Hsiang, 2017). There are two potential sources that explain the heterogeneity in beliefs for given climatic conditions. On the one hand, people may have different definitions of droughts and behaviorally respond in an internally consistent way to this perception regardless

[21] p-value < 0.05.

of meteorological conditions. On the other hand, heterogeneity may be in farmers' perceptions for a given definition of drought. Since the empirical approach exploits within-farmer variation in perceptions over two years, it is unlikely, although not impossible, that individuals change their definitions of droughts. Moreover, the negative sign associated with the uninteracted term seem to rule out the hypothesis of an internal consistent behavior of farmer for an individual-specific definition of droughts. The use of meteorological data is to be interpreted as a characterization of the environment that agents have been exposed to rather than the generating source of beliefs that farmers ought to have, from a positive standpoint.

Columns (4) and (5) display the estimates of Equation (10) for the share of cultivated land under the most widely adopted irrigation techniques across growing seasons, respectively STW and DTW. The estimates show that irrigation decisions are driven by changes in the use of STWs, that account for around 60% of the total irrigated land. Subjective perceptions do not have a statistically significant effect on the average annual share of cultivated land irrigated with DTW (column 3). DTWs are mainly used in the *Boro* dry season when stored water in shallow aquifers may not meet farmers' needs, whereas the average share of land equipped with this technology is negligible in the monsoon season. In this period of the year, precipitation is abundant and replenishes shallow aquifers so that farmers may prefer using STW when irrigating the land.

Table 1: Subjective perceptions and irrigation status.

Dependent variable: Share of cultivated land	Irrigated			STW	DTW
	(1)	(2)	(3)	(4)	(5)
Perc. Increase in Drought (β_1)	-0.0231	-0.0340**	-0.0470***	-0.0340*	0.00386
	(0.0141)	(0.0145)	(0.0146)	(0.0178)	(0.0117)
Perc. Increase in Drought $\times$ Long-run dryness (β_2)			0.649**	0.725**	-0.377
			(0.291)	(0.359)	(0.238)
Controls		X	X	X	X
Fixed Effects	X	X	X	X	X
p-value ($\beta_1 + \beta_2$)			0.0159	0.0491	0.1131
Mean Outcome	0.489	0.489	0.489	0.299	0.068
SD Outcome	0.327	0.327	0.327	0.354	0.191
N	1428	1428	1428	1428	1428
adj. R^2	0.566	0.688	0.699	0.689	0.601

Notes: The outcome variable is the average share of cultivated land across the two main growing seasons under any irrigation status (columns 1-3), irrigated with STW (column 4) and with DTW (column 5). Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. *Controls*: seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects*: Individual, Year. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Sub-sample analysis. In Table B4, I provide results for the average perception-adaptation relationship using alternative samples. In columns (1) and (2), I address the fact that changes in irrigation may be explained by investment besides use, which could have been limited by financial constraints. Although informal markets in groundwater irrigation in Bangladesh are equitable and accessible (Bell et al., 2015), farmers who perceived an increase in drought may not respond differently under drier conditions because of liquidity constraints. To rule out this channel, I exclude those farmers who did not irrigate any plot in the first wave and thus may have had to invest in irrigation in the second wave (column 1) and find similar estimates than the baseline results, with the interaction term that is larger in magnitude. The results are similar also when excluding farmers who may have not irrigated in any of the two waves because of other constraints than changes in perceptions or weather conditions (column 2).

I also estimate the baseline specification excluding farmers that did not harvest *Aman* or *Boro* rice in the first wave (column 3). Although I cannot entirely rule out the potential adaptive margin of changes in crop choice, this channel would underestimate the perception-adaptation relationship, assuming that farmers exposed to drier conditions and perceiving an increase in drought would grow more drought-tolerant crops that need less irrigation. I also test that the effect does not depend on ownership of the irrigation system, excluding the small share of farmers that own either STW or DTW pumps (column 4). Results are very close in magnitude to the baseline estimates, providing suggestive evidence that ownership does not play a role and informal markets for irrigation are easily accessible and efficient in Bangladesh (Bell et al., 2015). Finally, I also exclude farmers in the sole union (Piprul) in which no extreme drought event over the previous twenty years was recorded (column 5). The absence of such events does not rule out the occurrence of milder drought events or periods of relative drier conditions which may be used as climatic conditions for farmers to form their beliefs about droughts.

Other adaptive margins. The main finding suggests that farmers adjust their use of irrigation as a result of their perception of increases in droughts if they have been exposed historically to drier conditions. The negative coefficient of the uninteracted term of perceptions may suggest that farmers respond to their beliefs through other coping mechanisms that have become relatively cheaper compared to adjusting input use in agricultural production. For this reason, I study other adaptive margins previously documented in the literature, in particular sales and consumption of livestock[22] (Rosenzweig & Wolpin, 1993) and working in non-agricultural activities or changing use

[22] The definition of livestock adopted here includes cattle, chicken, pigs, and sheep.

of labor both hired or self-employed in agricultural activities (Aragón et al., 2021; Colmer, 2018).

In Table B5, I report the estimates from the baseline specification with other coping mechanisms as outcome variables. The first set of outcomes focuses on livestock as a buffer and I find no evidence that farmers' beliefs differentially change farmers' sale or consumption behavior as a response to the long-run dryness conditions. Similar results hold when focusing on a binary indicator of the head of the household having an off-farm job[23] and when looking at the number of agricultural workers, crop farmers or members of the households self-employed in agricultural activities. These result seem to rule out the hypothesis that farmers use more than one adaptation strategy and only adjust their use of irrigation in response to dryness conditions.

5.2 Unbundling the effect by growing season

Since prior work has shown the differential effect of climatic conditions in the wet and dry seasons on irrigation and other adaptation strategies (Auffhammer & Carleton, 2018; Guiteras, 2009; Taraz, 2017), I test for heterogeneity across the two main growing seasons, *Aman* and *Boro*, using Equation (10). The results are reported in Table 2. In columns (1) and (2), I report the results in the *Aman* monsoon season, respectively for the share of rainfed cultivated land and the share of cultivated land irrigated with STW. In columns (3)-(5), I consider the share of rainfed, STW irrigated and DTW irrigated land in the *Boro* growing season. The use of DTW irrigation in the monsoon season is negligible (average share of land irrigated with DTW is 0.01), explaining the asymmetry in the outcomes of interest across the two main growing seasons.

Similarly to the previous findings, in the *Aman* season in column (1), perceptions of an increase in droughts have a positive and statistically significant effect on the share of rainfed cultivated land, but the marginal effect of subjective perceptions is moderated by the coefficient of the interaction term between perceptions and long-run exposure. Likewise, in column (2), subjective perceptions of increase in droughts has a negative and statistically significant effect on the share of irrigated land with STW. The coefficient of the interaction term is positive, statistically significant and around ten times larger than the uninteracted term. During the *Aman* season, for a long-run dryness one standard deviation drier than the historical average, the effect of subjective perceptions is associated with a decrease by around 46 p.p. in the share of rainfed land and an increase in the share of land under STW irrigation by around 39 p.p..

[23]The definition of off-farm occupation includes business/trading, richshaw/van puller, tailor, potter, cobbler, handcrafts, small and cottage industry, mechanic, plumber, doctor, engineer, lawyer, religious.

Interestingly, subjective perceptions are never statistically different from zero when considering irrigation decisions in the *Boro* growing season (columns 3 to 5). These findings uncover substantial and meaningful heterogeneity across growing seasons behind the results in Table 1. Without excessive speculation over these results, the *Boro* season is known to be dry and irrigation is already often implemented (the average share of cultivated land left rainfed is around 50 p.p. lower than in the *Aman* season and the average total share of irrigated land is more than 50 percent). For this reason, changes in perceptions may play a minor role in the adaptive decision. The lack of information on growing season-specific beliefs hinders further investigation of this result, which is left for future research.

Table 2: Subjective perceptions and irrigation by growing season.

Growing Season:	Aman		Boro		
Dependent variable: Share of cultivated land	Rainfed	STW	Rainfed	STW	DTW
	(1)	(2)	(3)	(4)	(5)
Perc. Increase in Drought (β_1)	0.0871**	-0.0498*	0.0229	-0.0234	0.0188
	(0.0361)	(0.0246)	(0.0233)	(0.0298)	(0.0287)
Perc. Increase in Drought × Long-run dryness (β_2)	-0.545*	0.437*	0.275	0.0254	-0.296
	(0.279)	(0.233)	(0.338)	(0.391)	(0.290)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
p-value ($\beta_1 + \beta_2$)	0.0232	0.0207	0.4227	0.2576	0.1332
Mean Outcome	0.763	0.163	0.260	0.435	0.112
SD Outcome	0.405	0.348	0.411	0.470	0.300
N	1428	1428	1428	1428	1428
adj. R^2	0.560	0.572	0.750	0.669	0.583

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: $^{*}p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls*: Seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects*: Individual, Year.

Time-varying long-run dryness. I test for the robustness of the annual and seasonal results using a different source of variation, constructing a time-varying measure of long-run dryness as the average monthly SPEI in the twenty years preceding the survey wave. I exploit plausibly random wave-to-wave fluctuations in the SPEI realizations within union and include both the uninteracted term and its interaction with subjective perceptions. This variation captures short-run changes in long-run averages, which are the objective weather fluctuations that farmers are exposed to over the same time period in which perceptions change between the two waves. Tables C5 and C6 report the results with the coefficients on subjective perceptions and the interaction terms close in magnitude to the main results both for annual and seasonal estimates.

Outcome variable. I also test that the results are robust to the use of a different outcome variable for the irrigation status. This alternative outcome measures the total hectares of cultivated land under each irrigation status by growing season. Results are reported in Table C7. The interaction term between subjective perceptions and long-run exposure is negative and statistically significant on the cultivated land left rainfed in both *Aman* and *Boro* seasons (columns 1 and 3). Consistent with the baseline results, the effect of the interaction term on the surface of land under STW irrigation in *Aman* is positive, although not precisely estimated. Since the distribution of the share of cultivated land under each irrigation status has two mass points at zero and one as displayed in Figure A4, I also consider a dichotomous version of the outcome variable that takes value one if the share of cultivated land rainfed or under each irrigation status considered is strictly positive, and zero otherwise. I estimate a linear probability model using the newly constructed outcome variable, with the estimates that are more precise, probing their robustness (Table C8).

Reverse causality. Past irrigation decisions may determine the future perceptions of droughts, since leaving more land rainfed may increase the probability of experiencing drought damages. By attributing the cause of the damage to increases in droughts, individuals may be more likely to report having perceived an increase in these weather events as a result of their past actions. Symmetrically, irrigating a larger share of cultivated land would decrease drought damages and lower the probability of reporting a perception that droughts have increased. To allay the concerns on the presence of reverse causality in the estimations, I regress the perception of increases in droughts recorded in the second wave of the survey and the change in perceptions between the two waves on the share of irrigated cultivated land in the first wave of the survey, in a cross-sectional setting. Reassuringly, I find that the estimates of the irrigation statuses are never statistically significant and very close to zero in magnitude (Table C9).

5.3 Unbundling the effect by socio-demographic characteristics

The results displayed in Tables 1 and 2 show the farmers' responsiveness on average differs by subjective perceptions over the agricultural production year and by growing season. The estimates can be heterogeneous across different characteristics of the respondents. To explore this, I analyse of sub-samples based on individual characteristics. In particular, I split the sample between individuals below and above the median age, respectively 18-44 and 45+. I also split the respondents around the median number of years of education between those with no formal education and those with at least one year.

Starting from annual-level analysis, only in the sub-sample of individuals above the median age the coefficients associated with subjective perceptions and with the interaction term are statistically significant (p-value<0.001). The interaction term is not statistically significant in the sub-sample of individuals below the median age (Table B7). This result provides suggestive evidence that there is a learning channel through which older individuals would undertake adaptation strategies aligned with their subjective perceptions depending on the degree of exposure to objective conditions. A similar result holds also when exploring the STW irrigation technique in columns (3) and (4), with the interaction term much larger in magnitude in the sample of farmers above the median age.

The sub-sample analysis by years of education yields similar findings. Higher education attainment may explain learning about agricultural technologies, effectiveness of the adaptation strategies and knowledge of the relationship between dryness and irrigation use (Feder et al., 1985). Unfortunately, this information is not directly observed. The heterogeneous effect in the educated and non-educated farmers of beliefs and exposure to dryness provides some evidence that educational attainment affects subsequent adaptation. Table B8 displays the estimates on subjective perceptions and long-run exposure using the sub-samples of individuals with no formal education and with at least one year of education. Subjective perceptions maintain a negative coefficient on the share of irrigated land and a positive one on the share of rainfed land, with the marginal effect moderated by the interaction term with long-run exposure that is respectively positive and negative. Here, subjective perceptions are not statistically significant in any specification in the sub-sample of individuals with no formal education. Overall, these findings may be indicative of the importance of formal education among farmers. In the sample of individuals with at least one year of formal education, the marginal effect of subjective perceptions on irrigated land is positive for a lower average level of long-run exposure to dryness.

I replicate the same analysis for the irrigation decisions in *Aman*. Table B9 shows the results of the sub-sample analysis by age and education. On the one hand, there is no substantial heterogeneity by age with the estimates that are qualitatively similar both in the sample below and above the median age. On the other hand, the learning channel through educational attainment persists also in the growing season results, providing further evidence on the importance of formal education among farmers.

6 Cognitive mechanisms

The baseline results show that individual heterogeneity in beliefs explains different short-run behavioral responses for similar exposure conditions. These findings are consistent with a model of behavioral inattention and action with individual learning about climate. This underlines the importance of accounting for both the average level of exposure and most importantly individual knowledge about it. There are other potential channels, however, that may explain short-run behavioral responses. Single weather events can also be interpreted differently depending on average exposure and knowledge of it. In this section, I address three potential cognitive mechanisms consistent with the baseline results that may play a role in individual behavioral responses.

Agents adopt cognitive heuristics when assessing future uncertain events, exhibiting availability bias (Gallagher, 2014), recall errors (Guiteras et al., 2015) or motivated reasoning (Druckman & McGrath, 2019; Zappalà, 2022). I exploit the intensity and frequency of drought events, comparing self-reported and meteorological records. In Section 6.1, I investigate whether the timing of self-reported drought events affects the irrigation decisions. Overweighting recent weather realizations could result in potentially sub-optimal irrigation decisions, when evaluated ex-post because of imperfect foresight (Ji & Cobourn, 2021). In Section 6.2, I test if recall errors in the timing of droughts leads to potentially sub-optimal irrigation decisions. The third mechanism in Section 6.3 explores whether the respondents' recollection of the frequency of droughts matters for irrigation.

6.1 Salience

This section investigates whether the timing of past drought events shapes individual behavioral responses. The literature on cognitive heuristics and expectation formation has introduced the "recency bias" in models of agents' learning (Kala, 2017). This heuristic describes the phenomenon according to which individuals assign higher probabilities to events that have happened recently, compared to remembering something occurred a long time ago and react to them (Camerer & Loewenstein, 2011; Kahneman & Tversky, 1973; Kunreuther & Slovic, 1978; Slovic et al., 1974).

This phenomenon has been documented using different empirical evidence, in particular with respect to flood risks (Bakkensen et al., 2019; Gallagher, 2014), climate change through temperature anomalies (Deryugina, 2013; Li et al., 2011), short-term weather fluctuations (Ji & Cobourn, 2021), and financial markets (Malmendier & Nagel, 2011). I test this phenomenon with drought events. Experiencing a particularly harmful drought may lead agents to overreact and make adaptive decisions, without necessarily changing their long-lasting underlying beliefs on the frequency of these events. I consider the self-reported year of the most harmful drought and use the two non-mutually exclusive event time indicators described in Section 3.1. The estimating equation is

$$a_{it}^{(k)} = \sum_{\tau=1}^{2} \zeta_\tau \text{Drought}_{it-\tau} + \beta_1 b_{it} + \beta_2 b_{it} \times \overline{w}_u + \beta_3 \tilde{w}_{ut} + X_{it}'\boldsymbol{\gamma} + \lambda_i + \mu_t + \varepsilon_{it} \tag{11}$$

with the same setup as the baseline Equation (10), including subjective perceptions of an increase in droughts (b_{it}), long-run exposure ($\overline{w}_u$) and seasonal deviations ($\tilde{w}_{ut}$).

Table 3 displays the results. The coefficient associated with the self-reported measure of the most harmful drought occurred the year before the irrigation decision is negative and statistically significant for the share of rainfed cultivated land (column 1) and positive for the share of cultivated land under STW irrigation status (column 2) in the *Aman* season. These results are consistent with the hypothesis of overreaction in the adaptive decisions to salient drought events when accounting for the season-specific deviations, long-run exposure to dryness and subjective perceptions.

Similar results are obtained for *Boro*. One-year lagged drought has a positive and statistically significant effect on the share of cultivated land under DTW irrigation status (column 5). Interestingly, $Drought_{it-1}$ has a negative and statistically significant effect on the share of cultivated land irrigated with STW (column 4). This result is specific to the winter dry season. Groundwater droughts occur during this season when groundwater recharge or discharge deviate from normal, and the groundwater heads in an aquifer fall below a critical level over a certain period of time resulting in several adverse effects. During the peak water demand in the months of March and April, groundwater level can fall below the suction limit making difficult for the farmers to pump water using the STW (Mainuddin et al., 2021; Shahid & Hazarika, 2010). This type of droughts usually affects shallow aquifers and it is caused by low precipitation in combination with high evapotranspiration, which lead to low groundwater recharge of underground aquifers (Adhikary et al., 2013). Unfortunately, the survey does not disentangle which type of droughts (whether meteorological or groundwater) is reported by the respondent, but the occurrence of a groundwater drought affecting the water recharge of shallow aquifers may explain the negative effect of one-year lagged droughts on the share of cultivated land under STW irrigation.

The behavioral response to being hit by a drought does not last more than one year. The coefficient on $Drought_{it-2}$ is never statistically different from zero in any of the estimated equations, strengthening the hypothesis that agents respond by changing adaptive behavior in the year after they experienced the most harmful drought, without adjusting permanently.

I examine what happens with an objective measure of drought events obtained from the SPEI. I construct two different measures, respectively whether an extreme drought event occurred during the previous growing season and whether this event was the most harmful (i.e. the lowest value of SPEI) over the same time interval covered by the survey questions.[24]

Results provide evidence on the effect of salient drought events driving reaction in irrigation in the following year (Table C10). A household in a union hit by an extreme drought event in the previous year increases the share of land under DTW irrigation by 6.1 p.p. (column 3) and decreases the share of rainfed land by 9.4 p.p. (column 1) during *Boro*, *ceteris paribus*. As previously found, the occurrence of a drought event in the *Boro* season negatively drives the allocation of land irrigated using STWs. When considering the most harmful drought events, results are qualitatively similar and the estimates larger in magnitude.

Table 3: Self-reported timing of the most harmful drought and irrigation status

Growing Season:	Aman		Boro		
Dependent variable: Share of cultivated land	Rainfed	STW	Rainfed	STW	DTW
	(1)	(2)	(3)	(4)	(5)
Drought$_{t-1}$ (ζ_1)	-0.0804**	0.0507*	0.0174	-0.0829**	0.0462
	(0.0355)	(0.0273)	(0.0250)	(0.0328)	(0.0282)
Drought$_{t-2}$ (ζ_2)	0.0284	-0.100	-0.0318	-0.00403	0.0243
	(0.0955)	(0.0681)	(0.0945)	(0.152)	(0.0285)
Perc. Increase in Drought (β_1)	0.0960***	-0.0563***	0.0284	-0.0134	0.00398
	(0.0275)	(0.0187)	(0.0174)	(0.0238)	(0.0175)
Perc. Increase in Drought × Long-run dryness (β_2)	-0.666***	0.536***	0.253	0.114	-0.346
	(0.251)	(0.206)	(0.263)	(0.312)	(0.211)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
Mean Outcome	0.763	0.163	0.260	0.435	0.112
SD Outcome	0.405	0.348	0.411	0.470	0.300
N	1428	1428	1428	1428	1428
adj. R^2	0.562	0.574	0.749	0.671	0.584

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: $^{*}p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls*: seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects*: Individual, Year.

[24] Since all the drought events recorded have occurred during the *Boro* season, I run the regressions only considering the outcomes and weather variables in this growing season.

6.2 Recall error

The use of self-reported measures not accounting for meteorological records might cast some doubts due to recall errors and reference dependence (Guiteras et al., 2015). A subjective measure of salient events may not shed light on the mechanisms underlying overreaction to such events. Results in the previous section show that behavioral responses are qualitatively similar using self-reported and meteorological records for drought events, but do not compare the two.

This section proposes an empirical test of recall error, by comparing the self-reported and objectively recorded years of the most extreme drought event. I expand Equation (10) with an indicator variable that takes value one if individuals do not self-report the most harmful drought event in $t-1$ when the minimum SPEI was recorded, and zero otherwise. This setting tests the hypothesis that being inaccurate about previous year's drought events leads farmers to reduce irrigated cultivated land and increase rainfed land.

Recall errors appear to affect farmers' behavioral responses in a potentially sub-optimal manner (Table 4). Being inaccurate is associated with a 8.5 p.p. increase in the share of rainfed cultivated land in the *Aman* season (column 1) and with a 5.4 p.p. decrease in the share of cultivated land under STW irrigation (column 2). In the *Boro* season, being inaccurate is associated with a 6.3 p.p. decrease in the share of cultivated land under DTW irrigation (column 5), a 4.4 p.p. decrease in the share of rainfed cultivated land (column 3), and a 11.3 p.p. increase in the share of land under STW irrigation (column 4). The rationale behind the sign of these coefficients can be explained by the occurrence of a groundwater drought rather than a meteorological drought in the winter season that prevents shallow aquifers to be recharged. Under these conditions, increasing the share of irrigated land with STWs and reducing the use of DTWs would be potentially sub-optimal.

6.3 Overestimation

The previous sections provide evidence of salience and recall errors using the timing and intensity of droughts. I now explore whether their frequency drives adaptive behavior (Spinoni et al., 2014). I test how the accuracy in the recollection of the number of droughts may drive irrigation decisions. I use the measure of overestimation Δ, described in Equation (1), that considers the distance between the self-reported and the meteorological number of extreme drought events. Due to its left-skewed distribution for objective extreme drought events (Figure A3), I limit the analysis to the subsample of individuals who are either accurate (Δ=0) or overestimate the number of drought events (Δ>0).

Table 4: Recall error in the timing of harmful droughts and irrigation status

Growing Season:	Aman		Boro		
Dependent variable: Share of cultivated land	Rainfed	STW	Rainfed	STW	DTW
	(1)	(2)	(3)	(4)	(5)
Inaccuracy	0.0847**	-0.0535**	-0.0439*	0.113***	-0.0618*
	(0.0421)	(0.0239)	(0.0231)	(0.0399)	(0.0340)
Perc. Increase in Drought	0.101***	-0.0588***	0.0155	-0.0111	-0.00605
	(0.0283)	(0.0200)	(0.0171)	(0.0249)	(0.0172)
Perc. Increase in Drought × Long-run dryness	-0.670***	0.555**	0.00692	0.558	-0.639**
	(0.249)	(0.224)	(0.328)	(0.404)	(0.290)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
Mean Outcome	0.760	0.166	0.256	0.441	0.113
SD Outcome	0.406	0.351	0.409	0.470	0.301
N	1392	1392	1392	1392	1392
adj. R^2	0.562	0.573	0.751	0.673	0.587

Notes: The sample includes individuals whose self-reported year of the most harmful drought coincides with the meteorological recorded the year before the irrigation decision is taken and those that did not self-report a drought event objectively recorded. I exclude the sample of individuals who self-reported a drought event when it did not occur. The outcome variable is the share of land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: $^{*}p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls*: seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects*: Individual, Year.

I expand the baseline specification in Equation (10) with either a binary variable, *Overestimation*, distinguishing accurate farmers from those who overestimate droughts, or the count variable Δ, measuring the extent of overestimation. Overestimating the number of drought events should lead to an increase in the share of irrigated land and a decrease in the share of rainfed cultivated land.

The estimates reported in Table 5 provide evidence that overestimating the frequency of drought events drive irrigation decisions in the expected direction. In Panel A, I report the coefficient associated with the indicator variable for overestimating droughts. Overestimating droughts is associated with a 6 p.p. decrease in the share of rainfed cultivated land (column 1) and with a 4.3 p.p. increase in the share of cultivated land under STW irrigation (column 2) in the *Aman* season. Similarly to previous findings, in the *Boro* season, the experience of drought events has a negative effect on the share of cultivated land under STW irrigation (column 4) and a positive effect on the share of cultivated land under DTW irrigation (column 5). Individuals may reduce land irrigated with STWs since droughts in the winter dry season also affect water recharge of shallow aquifers and rely on water extraction from deep aquifers using DTWs.

I also exploit the extent to which farmers overestimate droughts using the Δ measure. The results in Panel B lends further support to the argument that accuracy of recollecting drought events drives irrigation decisions, although imprecisely estimated in *Aman*. During *Boro*, an increase in the difference between self-reported and objective droughts by one event reduces the share of cultivated land irrigated with STW by 2.6 p.p. (column 5) and increases the share of land irrigated with DTW by 3.2 p.p. (column 6). This result suggests that farmers tend to substitute land left rainfed and irrigated with the STW with irrigation using the DTW, lending further support to the hypothesis of occurrence of groundwater drought events.

I test for the robustness of the results by altering the cutoffs and altering the construction of Δ and including moderate ($-1.5 < \text{SPEI} \leq -1$) or severe ($-2 < \text{SPEI} \leq -1.5$) droughts. The results are qualitatively similar with the estimates smaller in magnitude (Table C11). By relaxing the cutoff for recording a drought, the number of objective drought events increases, and Δ would be smaller by construction, potentially biasing these estimates downwards.

Finally, to further test that results are not driven by the arbitrary measure of objective drought events, I use another dataset that provides a measure of drought events, the EM-DAT database (EM-DAT, 2022) collected by the Centre for Research on the Epidemiology of Disasters (CRED). This dataset contains information on the occurrence and effects of natural disasters (see Section A.6.4). Previous studies have already discussed the limits of EM-DAT as measures of extreme

Table 5: Overestimating drought frequency and irrigation status

Growing Season:	Aman		Boro		
Dependent variable: Share of cultivated land	Rainfed	STW	Rainfed	STW	DTW
	(1)	(2)	(3)	(4)	(5)
Panel A: Binary variable					
Overestimation	-0.0599**	0.0429**	0.0167	-0.0938***	0.0639**
	(0.0259)	(0.0190)	(0.0178)	(0.0312)	(0.0282)
Panel B: Count variable					
Δ Droughts	-0.0269	0.0148	-0.000543	-0.0265**	0.0317***
	(0.0170)	(0.0136)	(0.00741)	(0.0134)	(0.0103)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
Mean Outcome	0.748	0.171	0.236	0.445	0.124
SD Outcome	0.413	0.355	0.396	0.471	0.312
N	1286	1286	1286	1286	1286
adj. R^2	0.590	0.627	0.693	0.661	0.596

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: $^{*}p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$. *Controls*: Seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects*: Individual, Year.

events (Cavallo et al., 2013; Felbermayr & Gröschl, 2014; Noy, 2009). For this reason, results should be interpreted with caution (Table C12).

7 Welfare loss due to inaccurate beliefs

In this section, I use the season-specific baseline results to monetize the loss in profits generated by holding inaccurate beliefs using estimates of returns to irrigation. To quantify the loss due to inaccurate beliefs, given seasonal heterogeneity in the use of irrigation, I consider the predicted hectares of cultivated land under STW irrigation in the two growing seasons studied as a function of observed beliefs (columns 2 and 4 in Table C7) and compare it with predicted hectares as a function of accurate beliefs. I define accurate beliefs b^* as a dichotomous variable that takes value one if the seasonal long-run exposure to dryness is strictly above zero (indicating a drier environment than historical averages), and zero otherwise.[25] Table A14 shows the two-way frequency distribution between observed and accurate beliefs over the year and in the two growing seasons, where around 54% of the respondents has accurate beliefs over the years, 44% in Aman and around 68% in Boro. These results seem to indicate that dryness conditions during the winter season most closely match belief formations about droughts. I compute the difference in irrigation use at the individual level over time if the individual held beliefs based on meteorological records.

$$\Delta\widehat{a}_i^{season} = \sum_{t=1}^{2}\left[\widehat{a}_{it}^{season}(b^*, w, X) - \widehat{a}_{it}^{season}(b, w, X)\right] \tag{12}$$

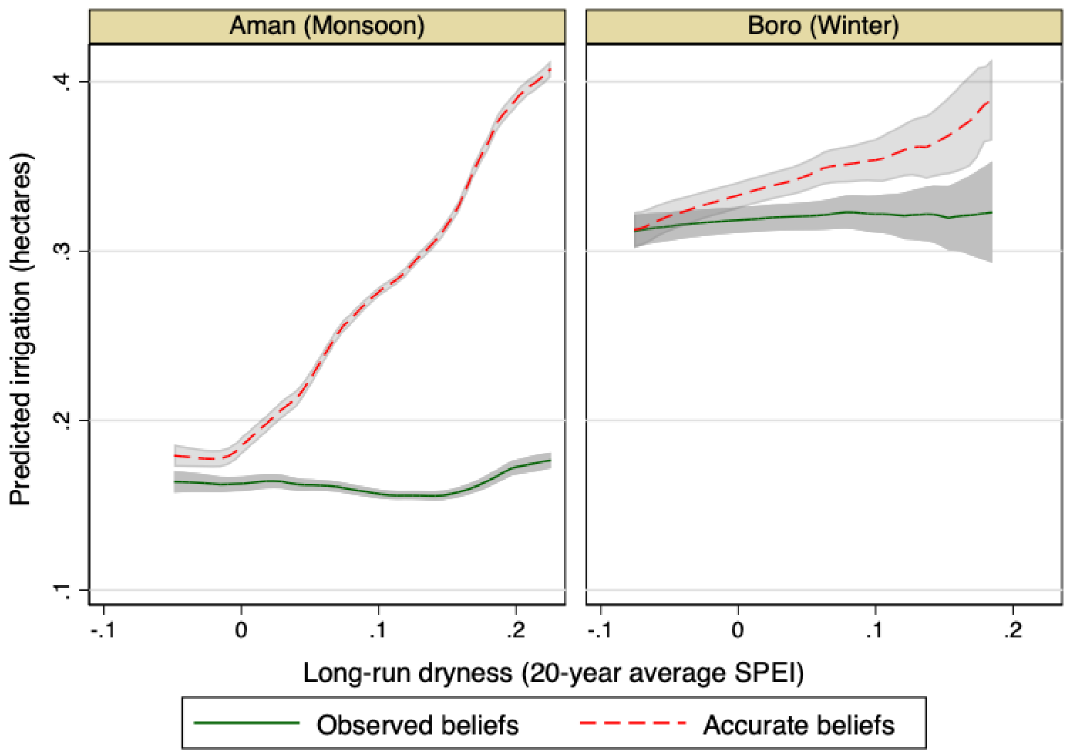
where $season \in \{Aman; Boro\}$. Δa^{Aman} is centered at -0.086 ha (SD = 0.047, interquartile range is [-0.097, -0.08]) and Δa^{Boro} is centered at -0.014 ha (SD = 0.015, IQR is [-0.025, -0.007]). These results indicate that farmers are irrigating less land than what they would have irrigated, if they had beliefs based on meteorological records, particularly in the monsoon season.

To confirm this, Figure 1 shows the semiparametric relationship between irrigation and long-run dryness, plotting a local smooth regression line of the hectares of land irrigated in each growing season predicted using accurate and observed beliefs on long-run exposure to dryness. The figure shows that irrigation is underutilized, in particular in the *Aman* monsoon season, with the *belief gap* that widens for drier conditions. During *Boro*, there are no statistically significant differences in the

[25] I refer to beliefs constructed from meteorological records as "accurate" without any normative implication on how beliefs ought to be formed. I adopt this approach to harmonize the social and environmental and translate farmer perceptions into hydrometeorological physically based metrics matching the wording and time-horizon of the survey questions.

predicted use of irrigation for accurate and observed beliefs under wet conditions. Nevertheless, a *belief gap* emerges as conditions become drier. Below, I monetize the difference in the use of irrigation stemming from the *belief gap* measures using estimates of returns to irrigation in similar contexts in the literature.

Figure 1: Semiparametric relationship between irrigation and long-run dryness for observed and accurate beliefs



Notes: Each line shows a local linear regression (Epanechnikov kernel) of hectares of land irrigated with STW predicted from estimating Equation (10) and long-run exposure to dryness. The green solid line uses observed self-reported farmer beliefs b. The red, dashed line uses accurate beliefs b^*, where accurate beliefs are equal to one if seasonal long-run dryness exposure if strictly above zero, and zero otherwise. Shaded areas give the 95% confidence intervals. The figure shows that the *belief gap* in the use of irrigation widens for drier conditions.

There is growing evidence on the returns to irrigation that uses quasi-experimental variation in groundwater irrigation in South Asia, exploiting variation in slope characteristics of river basins (Duflo & Pande, 2007), aquifer characteristics (Sekhri, 2014), or well-failures (Jacoby, 2017), and spatial discontinuities in Rwanda (Jones et al., 2022). Irrigation has substantially contributed to increases in agricultural productivity in Bangladesh (Ahmed & Sampath, 1992; Haque, 1975; Hossain et al., 2005) and has been shown as a determining factor in agricultural success (Bell et al., 2015). To the best of my knowledge, there is no systematic estimate of the returns to tube wells irrigation on agricultural outcomes in Bangladesh. I provide an estimate of the monetary loss due to inaccurate beliefs using different estimates that consider settings plausibly similar to the one adopted in my analysis. Table B6 summarizes the estimates found in the literature reporting the geographical and temporal context, the crop production and the irrigation technology considered.

First and foremost, I use the estimates by Haque (1975) on the analysis of small scale irrigation systems in Bangladesh, that provides quantitative estimates of the effect of using STW irrigation compared to non irrigated farms by growing seasons. Using Equation (12), the median loss due to inaccurate beliefs is 214.16kg in Aman rice production and 49.07kg in Boro rice production. To monetize the value loss due to inaccurate beliefs, I use the most recent price at which the government procures Aman and Boro rice, equal to 40 Taka/kg[26] (DailySun, 2021; TheBusinessStandard, 2022). The median monetized value loss in Aman due to inaccurate beliefs is \$102.80 (IQR is [\$95.63, \$115.98]) and \$23.55 in Boro (IQR is [\$12.11, \$42.06]). To understand the magnitude of this loss, the median household production in the first wave of the survey was 800kg of Aman rice and 1260kg of Boro rice. The median monetized loss of holding inaccurate beliefs is around 26.7% of the total production value of Aman rice and 4% of total production of Boro.

A similar value for the monetized loss in the *Boro* season is obtained using the estimate by Parvin and Rahman (2009). These studies share the geographical context, the crop produced and the irrigation technology considered in my setting. Estimates obtained from returns to irrigation quantified in other geographical contexts in South-East Asia and with other crops produced have lower magnitude but remain comparable between them (Bhandari, 2001; Mandal & Singh, 2004). These differences underline some potential caveats to my welfare calculations. First, I always assume that rice productivity has remained constant over time, in spite of evidence showing increasing long-term production trends for both *Aman* and *Boro* (Al Mamun et al., 2021; Parvin & Rahman, 2009). Second, the differential effect of irrigation on yields is not conditional on increases in dryness and drought events, suggesting that the estimates likely represent a lower bound (Mohsenipour et al., 2018). Other estimates from recent studies of returns to irrigation that identify plausibly causal estimates provide monetized losses smaller in magnitude, however, they present substantially different geographical settings, crops produced and irrigation technology(Jones et al., 2022; Sekhri, 2014).[27]

[26] In 2022 USD, 1 Taka $\approx$ 0.012 \$.

[27] Other estimates on the returns to irrigation are provided by Duflo and Pande (2007) and Fishman (2018). Duflo

8 Discussion and Conclusion

Scientific estimates have shown that climate change may have severe impacts on agricultural-related activities (IPCC, 2022). Droughts have been described as "one of the world's most widespread climate disasters affecting agricultural production" (Geng et al., 2016). The profits of farmers depend on the weather and the agricultural decisions they make in response. In particular, their adaptive responses hinge upon their ability to understand and predict the weather conditions they face. For this reason, it is critical to understand farmers' adaptive behavior and their decision-making process. The literature has investigated many possible "adaptation gaps" (Carleton & Hsiang, 2016), for instance, weak incentives to adapt (Annan & Schlenker, 2015), limited access to credit (Burgess et al., 2014), limited information about benefits (Hornbeck, 2012) and access to technologies (Olmstead & Rhode, 2011). The climate literature has recently advanced on the quantification of climate impact on a series of outcomes and actions accounting for adaptation (e.g., Carleton et al., 2022) but has so far assumed perfect information, neglecting the role of inaccurate beliefs about climate change and limited rationality (Deryugina & Hsiang, 2017).

In this paper, I develop a theoretical framework allowing for individual understanding of climate change and long-run climatic conditions to differ. This framework adapts a behavioral inattention model à la Gabaix (2019) to the context of climate change beliefs and introduces a behavioral friction in standard farmer profit-maximization problem. The model's implications show under which circumstances beliefs affect the decision-making process and how they differentially shape farmers' responsiveness to dryness exposure. I take this model to individual farmer beliefs and irrigation data combined with a meteorological measure of dryness in Bangladesh.

In a fixed-effect panel analysis, I find, consistent with the conceptual framework, that as long as individual subjective perceptions do not coincide with objective climatic conditions, they shape adaptation to climate change and heterogeneously drive farmers' behavioral responses to dryness. In particular, farmers who believe that droughts have increased are significantly more likely to increase irrigated land after a period of dryness. The effect is stronger for more severe environmental conditions and is heterogeneous across growing seasons, driving decisions only in the monsoon season. I additionally show the role of cognitive mechanisms exploiting the timing and the frequency

and Pande (2007) estimates the effect of dam irrigation on agricultural output in Indian districts, finding similar estimates as Jones et al. (2022), whereas Fishman (2018) shows that irrigated locations experience lower damages from increasing precipitation variability in India. Nevertheless, estimates from the two studies cannot be utilized for this exercise, respectively due to lack of information on summary statistics of the sample used and since the direct effect of irrigation is not reported in the estimates.

of drought events. I document that only self-reported one-year lagged drought events have a strong statistically significant effect on use of irrigation and recall error can lead to potentially sub-optimal decisions, increasing the share of land left rainfed. On the contrary, overestimating the frequency of past drought events leads to a behavioral response increasing irrigated land.

In a counterfactual analysis, I use the baseline empirical estimates to quantify the monetary loss due to inaccurate beliefs. I compare the predicted use of irrigation as a function of observed beliefs and beliefs based on meteorological records and find that farmers' systematically underuse irrigation compared to the benchmark case if they had beliefs constructed from meteorological records. This result provides evidence on the existence of a *belief gap*, that widens for drier climatic conditions. Using estimates of returns to irrigation from the literature, I find that the median monetized loss due to inaccurate beliefs is around \$102 in the monsoon and \$23 in the winter season, respectively around 25% and 4% of the total production value in the two seasons. With the estimated changes in climatic conditions, the monetary losses are projected to exacerbate particularly during the monsoon season in light of more erratic and less frequent precipitations.

While the foregoing suggests that heterogeneous beliefs differentially shape the responsiveness to dryness conditions, the study has some limitations. First and foremost, in spite of the suite of robustness checks conducted, there remains a possibility that my findings might be spurious. Nevertheless, to the best of my knowledge, this is the first paper that allows for heterogeneous responses to changes in climate allowing for incomplete rationality of decision-makers. Second, it is difficult to determine the exact pathway through which these effects work since self-reported measures of drought and subjective perceptions are not measured within each growing season, during which environmental conditions in Bangladesh have been shown to differ substantially. The availability of more precise and season-specific information on subjective perceptions would help to better understand the mechanisms behind the behavioral responses of rural households and shed light on the cognitive factors at stake. This is a promising avenue for future research.

Although past work has highlighted the limits of self-reported data in understanding the impacts of extreme events (Guiteras et al., 2015), it is crucial to understand how people's perception and experience of new exposures in a changing climate characterize differential behavioral responses. The combined used of meteorological records and individual stated preferences can help uncover these mechanisms.

By addressing questions of perceptions and adaptation strategies, these findings have important implications for the debate on public awareness and adaptation to climate change in developing countries, providing empirical evidence to inform environmental and agricultural policy. These results can help identify the most vulnerable rural households and inform adaptation policies targeting regions with high degree of exposure to dryness with informational campaigns and providing effective and timely drought communication.

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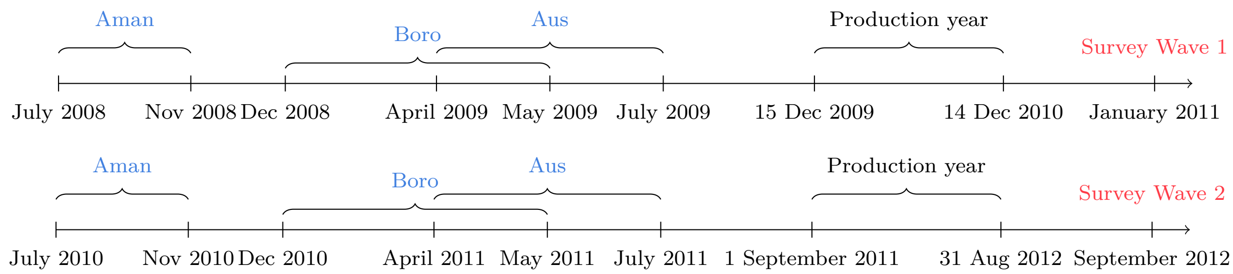
A Appendix

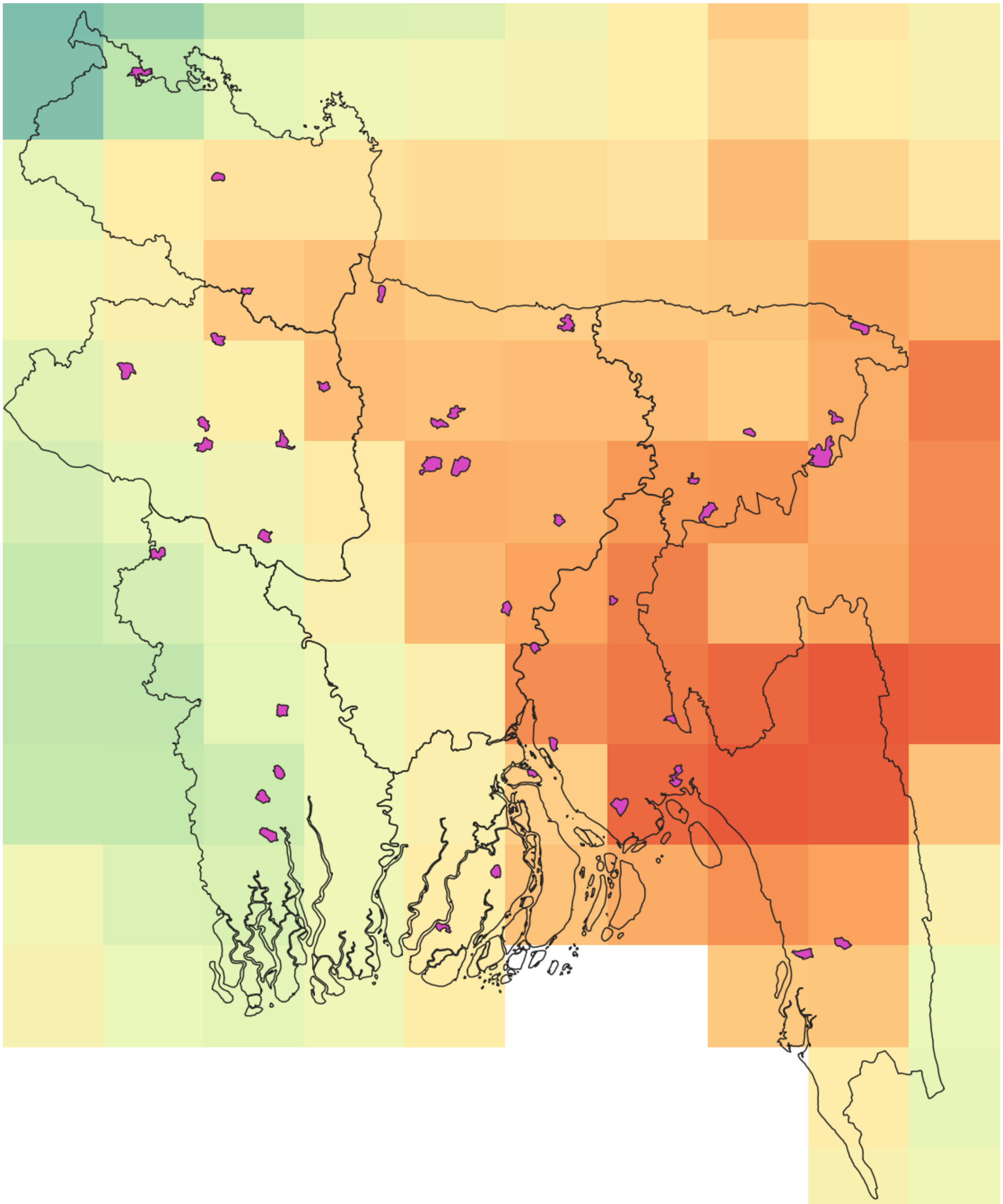
A.1 Figures

Figure A1: Timeline of BCCAS survey waves and growing seasons in Bangladesh



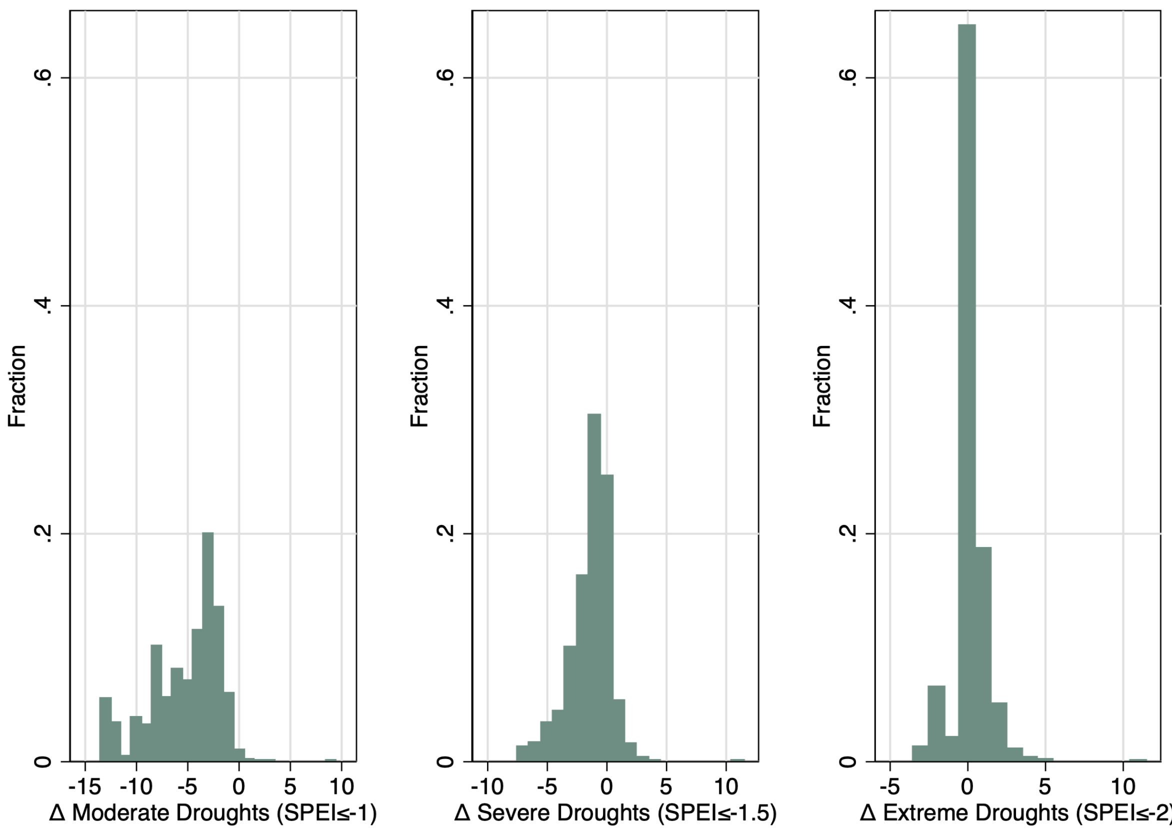
Notes: Each timeline shows the relative time interval of the growing seasons for each survey wave based on Sacks et al. (2010) and the period to which the information on irrigation decisions refer in the BCCAS (International Food Policy Research Institute, 2014a, 2014b). Since the SPEI data has a monthly time resolution, I define each growing season to start on the first of the month of the average planting date and to end on the last of the month of the average harvest date as in Missirian and Schlenker (2017). The exact dates of each growing season in Sacks et al. (2010) are: *Aus*: 14$^{\text{th}}$ April - 25$^{\text{th}}$ July, *Aman*: 5$^{\text{th}}$ July - 28$^{\text{th}}$ November, *Boro*: 19$^{\text{th}}$ December - 8$^{\text{th}}$ May.

Figure A2: Map of Bangladesh with surveyed unions and SPEI gridded data



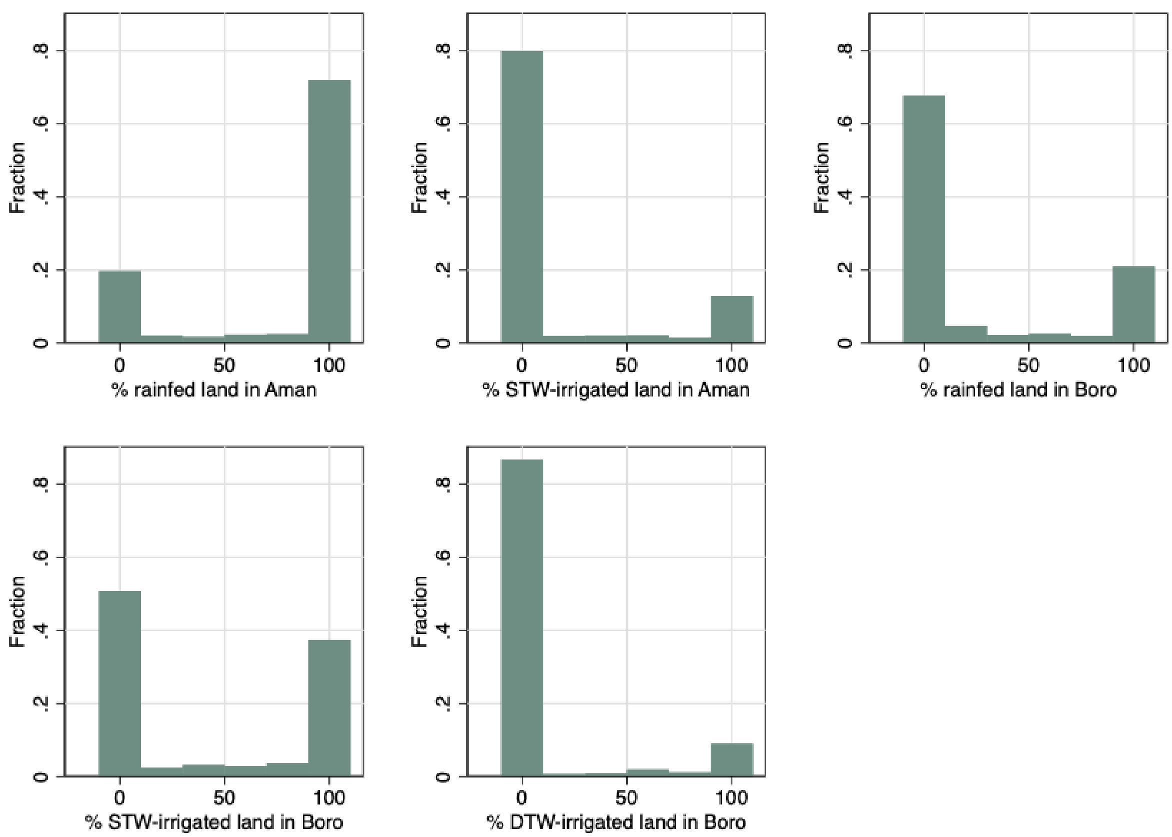
Notes: Map of Bangladesh with regional boundaries. The map plots the administrative boundaries of the 40 surveyed unions in purple. The administrative layer (from GADM (2021)) is overlaid to the raster SPEI gridded data from Vicente-Serrano et al. (2010) with 0.5 degree resolution (≈ 55 km at the Equator) with September 2012 values, where colors range from red to blue, with red being negative values and blue being positive, 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 cell values.

Figure A3: Frequency distribution of Δ using moderate, severe and extreme drought cut-offs



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) in the main text. 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 the share of cultivated land rainfed and irrigated in *Aman* and *Boro* seasons



Notes: The sample includes the 1428 observations across the two waves for the 714 individuals interviewed. Each graph plots the binned frequency distribution (using 5 bins) of the share of cultivated land that is left rainfed, irrigated with STW and with DTW in *Aman* and *Boro* growing seasons.

A.2 Data Appendix

Table A1: Number of unions and households drawn by agroecological zone covered in the survey

Agroecological zone	Unions	Households
Barind Tract	4	80
Beel and Haor Basin	5	100
Floodplain	10	200
Himalayan Piedmont Plain	5	100
Modhupur Tract	4	80
Northern and Eastern Hills	5	100
Tidal Floodplain	7	140
Total	40	800

Table A2: Number of unions and households per AEZ covered in the estimation sample

Agroecological zone	Union	Households
Barind Tract	4	71
Beel and Haor Basin	5	89
Floodplain	10	181
Himalayan Piedmont Plain	5	89
Modhupur Tract	4	75
Northern and Eastern Hills	5	92
Tidal Floodplain	7	117
Total	40	714

Table A3: 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 A4: BCCAS main variables' definition and construction

VARIABLE	SURVEY QUESTION CODE	WAVE	SURVEY QUESTION
Perc. Increase in Drought (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)
Perc. Increase in Drought (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)
Drought$_{t-1}$ (0/1)	L.02	1	In the last five years, have the HH's properties and productivity been affected by droughts? In which years most badly affected? (1 if "2009", 0 otherwise)
Drought$_{t-1}$ (0/1)	L.02	2	Since the last survey interview have the HH's properties and productivity been affected by droughts? In which years most badly affected? (1 if "2011", 0 otherwise)
Drought$_{t-2}$ (0/1)	L.02	1	In the last five years, have the HH's properties and productivity been affected by droughts? In which years most badly affected? (1 if "2008", 0 otherwise)
Drought$_{t-2}$ (0/1)	L.02	2	Since the last survey interview have the HH's properties and productivity been affected by droughts? In which years most badly affected? (1 if "2010", 0 otherwise)
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 these two years?
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?

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 the main text in Equation (1).

A.3 Descriptive Statistics

Table A5: Summary statistics of BCCAS estimation sample by survey wave

	Mean		SD	
	2011	2012	2011	2012
A. Respondent characteristics				
Age	46	47.9	13.5	13.5
Male	0.945	0.945	0.227	0.227
Literacy	0.483	0.462	0.5	0.499
Completed years of education by head of household	3.49	3.49	4.19	4.21
Farmer	0.718	0.644	0.45	0.479
B. Household characteristics				
Household size	5.05	5.46	2.21	2.46
Number of agricultural workers in household	0.113	0.105	0.396	0.384
At least 1 HH member is self-employed in HH farming activities	0.745	0.71	0.436	0.454
Receives information from extension agents	0.176	0.359	0.381	0.48
Household with electricity	0.47	0.56	0.50	0.49
C. Agricultural characteristics				
Total land holdings (in hectares)	0.68	0.793	1.3	1.3
Total cultivated land (in hectares)	0.56	0.69	1.2	1.27
Share of clay cultivated land	0.039	0.0293	0.183	0.158
Share of loam cultivated land	0.252	0.171	0.422	0.358
Share of sandy cultivated land	0.0283	0.0219	0.15	0.131
Share of clay-loam cultivated land	0.468	0.505	0.486	0.481
Share of sandy-loam cultivated land	0.213	0.272	0.395	0.425
Ownership of Shallow Tube Wells (STWs)	0.102	0.103	0.303	0.305
Ownership of Deep Tube Wells (DTWs)	0.013	0.014	0.112	0.112
Observations	714	714		

Notes: The sample includes the 714 individuals interviewed in both survey waves in January 2011 and September 2012. Shares of soil type are weighted by the total size of the cultivated plots as reported by the household.

Table A6: T-tests for differences in means for attritors versus non-attritors

	Non Attritors (N=714)		Attritors (N=86)		Difference	
	Mean	SD	Mean	SD	Mean	p-value
Head of household is a farmer	0.718	0.016	0.617	0.052	0.102	(0.0491)
Household with electricity	0.469	0.018	0.406	0.053	0.062	(0.275)
Receives information from extension agents	0.176	0.014	0.139	0.0375	0.037	(0.392)
Perc. Increase in Drought	0.252	0.016	0.290	0.049	-0.038	(0.439)
Δ Droughts	0.102	0.047	0.314	0.143	-0.211	(0.144)
Drought$_{t-1}$	0.038	0.007	0.034	0.019	0.002	(0.228)
Drought$_{t-2}$	0.014	0.004	0	0	0.014	(0.424)
Total area land holdings in hectares	0.680	0.048	0.505	0.045	0.175	(0.216)
Share of clay cultivated land	0.038	0.006	0.024	0.014	0.014	(0.479)
Share of loam cultivated land	0.248	0.015	0.187	0.041	0.241	(0.201)
Share of sandy cultivated land	0.027	0.005	0.054	0.023	-0.026	(0.142)
Share of clay-loam cultivated land	0.462	0.018	0.526	0.053	-0.064	(0.247)
Share of sandy-loam cultivated land	0.210	0.014	0.183	0.041	0.026	(0.557)
Ownership of Shallow Tube Wells (STWs)	0.154	0.013	0.117	0.035	0.037	(0.819)
Ownership of Deep Tube Wells (DTWs)	0.052	0.008	0.035	0.020	0.017	(0.124)
Share of irrigated cultivated land	0.511	0.012	0.501	0.039	0.010	(0.536)
Share of STW irrigated land	0.317	0.013	0.288	0.038	0.029	(0.464)
Share of DTW irrigated land	0.056	0.006	0.058	0.019	-0.002	(0.641)
Share of rainfed cultivated land in Aman	0.741	0.015	0.706	0.048	0.034	(0.956)
Share of STW irrigated land in Aman	0.178	0.013	0.162	0.037	0.016	(0.802)
Share of rainfed cultivated land in Boro	0.281	0.015	0.295	0.048	-0.013	(0.306)
Share of STW irrigated land in Boro	0.457	0.017	0.413	0.051	0.043	(0.319)
Share of DTW irrigated land in Boro	0.089	0.009	0.082	0.028	0.006	(0.505)

Notes: The table compares the differences in means between the final estimation sample of non-attritors (N=714) and the sample of attritors that have not been interviewed in the second wave because they migrated, they were not at home at the time of the survey or the respondent changed from the first wave. Shares of soil type and irrigated land are weighted by the total size of the cultivated land as reported by the household.

Table A7: Balance test. Farmer characteristics by perceptions of increase in drought.

	Perception increase in drought		
	No	Yes	p-value
Panel A: Farmer characteristics			
Farmer	0.703	0.657	0.061
Receives information from extension agents	0.206	0.334	<0.001
Household with electricity	0.497	0.537	0.127
Ownership of Shallow Tube Wells (STWs)	0.100	0.106	0.718
Ownership of Deep Tube Wells (DTWs)	0.009	0.017	0.191
Perception increase in erratic rainfall	0.391	0.762	<0.001
Perception decrease in precipitations	0.352	0.767	<0.001
Land holdings (in hectares)	0.688	0.789	0.144
Share of clay cultivated land	0.034	0.033	0.884
Share of loam cultivated land	0.197	0.220	0.261
Share of sandy cultivated land	0.029	0.020	0.196
Share of clay-loam cultivated land	0.476	0.482	0.800
Share of sandy-loam cultivated land	0.252	0.224	0.190
Number of individuals	739	689	
Panel B: Wave 1 - Wave 2 changes in farmer characteristics			
Farmer	-0.058	-0.080	0.566
Receives information from extension agents	0.180	0.183	0.960
Household with electricity	0.131	0.078	0.0875
Ownership of Shallow Tube Wells (STWs)	-0.01	0.006	0.221
Ownership of Deep Tube Wells (DTWs)	-0.005	0.004	0.344
Perception increase in erratic rainfall	0.458	0.644	<0.001
Perception decrease in precipitations	0.507	0.717	<0.001
Land holdings (in hectares)	0.136	0.103	0.278
Share of clay cultivated land	-0.003	-0.012	0.525
Share of loam cultivated land	-0.120	-0.064	0.033
Share of sandy cultivated land	-0.007	-0.006	0.926
Share of clay-loam cultivated land	0.038	0.032	0.869
Share of sandy-loam cultivated land	0.098	0.040	0.048
Number of individuals	205	509	

Notes: The table compares the differences in means between the group of respondents who did and did not perceive an increase in droughts, across the two waves in Panel A, and in the second wave in Panel B comparing changes in farmer characteristics between the two waves. p-value column shows the p-values of the hypotheses that the mean outcomes of the groups by perceptions of increase in droughts are equal.

Table A8: Summary statistics of area-weighted agricultural plot utilization

	N	Mean	SD	Min	Max
Aus	714	0.09	0.17	0.00	0.86
Aman	714	0.37	0.27	0.00	1.00
Boro	714	0.34	0.32	0.00	1.00
Potato	714	0.01	0.05	0.00	0.58
Wheat	714	0.01	0.05	0.00	0.58
Jute	714	0.02	0.08	0.00	0.77
Chili	714	0.01	0.05	0.00	0.50
Eggplant	714	0.01	0.07	0.00	1.00
Other	714	0.14	0.15	0.00	1.00
Observations	714				

Notes: Proportion of cultivated crop over total agricultural plot utilization weighted by planted area. Data refer only to survey wave 1, since the module is absent in survey wave 2.

Table A9: Summary statistics of production-weighted rice types

	N	Mean	SD	Min	Max
Aus	714	0.07	0.14	0.00	1.00
Aman	714	0.31	0.27	0.00	1.00
Boro	714	0.35	0.33	0.00	1.00
Local Aus	714	0.01	0.07	0.00	0.86
Local Improved Variety (LIV) Aus	714	0.01	0.05	0.00	0.50
High Yield Variety (HYV) Aus	714	0.05	0.12	0.00	1.00
HYV Transplanted Aus	714	0.01	0.07	0.00	1.00
Local Aman	714	0.05	0.15	0.00	1.00
LIV Transplanted Aman	714	0.01	0.09	0.00	1.00
HYV Transplanted Aman	714	0.24	0.26	0.00	1.00
Hybrid Aman	714	0.01	0.08	0.00	1.00
HYV Boro	714	0.27	0.32	0.00	1.00
Hybrid Boro	714	0.06	0.20	0.00	1.00
Observations	714				

Notes: Share of rice production weighted by the total agricultural production of the household. Three different types of rice depending on the growing season: aus, aman and boro. Data refer only to survey wave 1, since the module is absent in survey wave 2.

Table A10: Summary statistics on shares of cultivated land by irrigation status

	N	Mean	SD	Min	Max
Panel A. Survey Wave 1 (2011)					
Share of irrigated cultivated land	714	0.49	0.34	0.00	1.00
Share of STW irrigated cultivated land	714	0.32	0.36	0.00	1.00
Share of DTW irrigated cultivated land	714	0.06	0.17	0.00	1.00
Panel B. Survey Wave 2 (2012)					
Share of irrigated cultivated land	714	0.49	0.31	0.00	1.00
Share of STW irrigated cultivated land	714	0.28	0.37	0.00	1.00
Share of DTW irrigated cultivated land	714	0.08	0.21	0.00	1.00
Panel C. Changes					
Share of irrigated cultivated land	714	-0.01	0.26	-1.00	1.00
Share of STW irrigated cultivated land	714	-0.04	0.29	-1.00	1.00
Share of DTW irrigated cultivated land	714	0.02	0.17	-1.00	1.00
Panel D. Total					
Share of irrigated cultivated land	1428	0.49	0.33	0.00	1.00
Share of STW irrigated cultivated land	1428	0.30	0.35	0.00	1.00
Share of DTW irrigated cultivated land	1428	0.07	0.19	0.00	1.00
Observations	1428				

Notes: Share of cultivated land under each irrigation status across *Aman* and *Boro*, weighted by the size of the cultivated land reported by the households in the survey. The percentage is constructed by using Module C "Roster of land and water bodies owned or under operation" and considering only the plots of cultivated / arable land type and own operated. The module asks to report the irrigation status of each plot for each growing season. STW: Shallow Tube Well; DTW: Deep Tube Well. 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 A11: Summary statistics on shares of cultivated land by irrigation status by growing season

	N	Mean	SD	Min	Max
Aus					
Share of rainfed cultivated land	1428	0.79	0.39	0.00	1.00
Share of traditional method irrigated cultivated land	1428	0.01	0.01	0.00	0.35
Share of LLP irrigated cultivated land	1428	0.02	0.14	0.00	1.00
Share of STW irrigated cultivated land	1428	0.13	0.32	0.00	1.00
Share of DTW irrigated cultivated land	1428	0.01	0.10	0.00	1.00
Share of irrigated cultivated land using other methods	1428	0.03	0.15	0.00	1.00
Aman					
Share of rainfed cultivated land	1428	0.76	0.40	0.00	1.00
Share of traditional method irrigated cultivated land	1428	0.01	0.04	0.00	1.00
Share of treadle pump irrigated cultivated land	1428	0.01	0.01	0.00	0.46
Share of LLP irrigated cultivated land	1428	0.02	0.12	0.00	1.00
Share of STW irrigated cultivated land	1428	0.16	0.35	0.00	1.00
Share of DTW irrigated cultivated land	1428	0.02	0.14	0.00	1.00
Share of irrigated cultivated land using other methods	1428	0.01	0.10	0.00	1.00
Boro					
Share of rainfed cultivated land	1428	0.26	0.41	0.00	1.00
Share of traditional method irrigated cultivated land	1428	0.01	0.08	0.00	1.00
Share of rower pump irrigated cultivated land	1428	0.01	0.03	0.00	1.00
Share of LLP irrigated cultivated land	1428	0.10	0.28	0.00	1.00
Share of STW irrigated cultivated land	1428	0.43	0.47	0.00	1.00
Share of DTW irrigated cultivated land	1428	0.11	0.30	0.00	1.00
Share of irrigated cultivated land using other methods	1428	0.07	0.24	0.00	1.00
Observations	1428				

Notes: Share of cultivated land under each irrigation status during each growing season weighted by the size of the cultivated land reported by the households in the survey. The percentage is constructed by using Module C "Roster of land and water bodies owned or under operation" and considering only the plots of cultivated / arable land type and own operated. The module asks to report the irrigation status of each plot for each growing season. LLP: Low Lift Pump; STW: Shallow Tube Well; DTW: Deep Tube Well. *Aus* refers to the pre-monsoon growing season, *Aman* refers to the monsoon growing season, *Boro* refers to the winter growing season.

Table A12: Summary statistics on share of cultivated land under main irrigation statuses by growing season

	N	Mean	SD	Min	Max
Panel A. Survey Wave 1 (2011)					
Aman					
Share of rainfed cultivated land	714	0.74	0.42	0	1
Share of STW irrigated cultivated land	714	0.18	0.36	0	1
Boro					
Share of rainfed cultivated land	714	0.28	0.42	0	1
Share of STW irrigated cultivated land	714	0.46	0.47	0	1
Share of DTW irrigated cultivated land	714	0.09	0.27	0	1
Panel B. Survey Wave 2 (2012)					
Aman					
Share of rainfed cultivated land	714	0.78	0.39	0	1
Share of STW irrigated cultivated land	714	0.15	0.33	0	1
Boro					
Share of rainfed cultivated land	714	0.24	0.40	0	1
Share of STW irrigated cultivated land	714	0.41	0.47	0	1
Share of DTW irrigated cultivated land	714	0.13	0.33	0	1
Panel C. Changes					
Aman					
Share of rainfed cultivated land	714	0.04	0.39	-1	1
Share of STW irrigated cultivated land	714	-0.03	0.33	-1	1
Boro					
Share of rainfed cultivated land	714	-0.04	0.29	-1	1
Share of STW irrigated cultivated land	714	-0.04	0.39	-1	1
Share of DTW irrigated cultivated land	714	0.04	0.27	-1	1
Panel D. Total					
Aman					
Share of rainfed cultivated land	1428	0.78	0.39	0	1
Share of STW irrigated cultivated land	1428	0.15	0.33	0	1
Boro					
Share of rainfed cultivated land	1428	0.24	0.40	0	1
Share of STW irrigated cultivated land	1428	0.41	0.47	0	1
Share of DTW irrigated cultivated land	1428	0.13	0.33	0	1

Notes: Share of cultivated land under each irrigation status during each growing season weighted by the size of the cultivated land reported by the households in the survey. The percentage is constructed by using Module C "Roster of land and water bodies owned or under operation" and considering only the plots of cultivated / arable land type and own operated. The module asks to report the irrigation status of each plot for each growing season. LLP: Low Lift Pump; STW: Shallow Tube Well; DTW: Deep Tube Well. *Aus* refers to the pre-monsoon growing season, *Aman* refers to the monsoon growing season, *Boro* refers to the winter growing season. 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 A13: Summary statistics on subjective perceptions of climate change

	N	Mean	SD
Panel A. Survey Wave 1 (2011)			
Perc. Increase in Drought	714	0.25	0.43
Perc. Increase in Erratic Rainfall	714	0.27	0.44
Perc. Decrease in Precipitations	714	0.22	0.41
Panel B. Survey Wave 2 (2012)			
Perc. Increase in Drought	714	0.71	0.45
Perc. Increase in Erratic Rainfall	714	0.86	0.34
Perc. Decrease in Precipitations	714	0.88	0.32
Panel C. Changes			
Perc. Increase in Drought	714	0.46	0.62
Perc. Increase in Erratic Rainfall	714	0.59	0.59
Perc. Decrease in Precipitations	714	0.66	0.53
Panel D. Total			
Perc. Increase in Drought	1428	0.48	0.49
Perc. Increase in Erratic Rainfall	1428	0.57	0.50
Perc. Decrease in Precipitations	1428	0.55	0.50
Observations	1428		

Notes: 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 A14: Two-way frequency table observed and accurate beliefs

	Accurate beliefs		Accurate beliefs in Aman		Accurate beliefs in Boro	
Perc. Increase Drought	No (0)	Yes (1)	No (0)	Yes (1)	No (0)	Yes (1)
No (0)	194	545	74	665	459	280
	13.59%	38.17%	5.18%	46.57%	32.14%	19.61%
Yes (1)	117	572	136	553	179	510
	8.19%	40.06%	9.52%	38.73%	12.54%	35.71%

Notes: The table shows the two-way frequency and relative percentages for Perc. Increase Drought (b) in rows and Accurate beliefs (b^*) over the year, in Aman and in Boro, in columns. Accurate belief (b^*) is equal to one if (seasonal) long-run exposure if strictly above zero (i.e., environment relatively drier than historical averages), and zero otherwise.

Table A15: Summary statistics of objective measures using SPEI at the grid cell-level

	N	Mean	SD	Min	Max
Panel A. Survey Wave 1 (2011)					
A. Exposure Measures					
Long-run dryness	34	0.07	0.04	-0.01	0.15
Deviation	34	0.04	0.04	-0.03	0.15
Aman Long-run dryness	34	0.09	0.06	-0.05	0.20
Boro Long-run dryness	34	-0.01	0.04	-0.08	0.10
Aman Deviation	34	0.27	0.14	-0.10	0.48
Boro Deviation	34	0.42	0.11	0.23	0.68
B. Number of Drought Events					
# Moderate Droughts	34	8.20	3.02	3	13
# Severe Droughts	34	2.44	2.01	0	7
# Extreme Droughts	34	0.47	0.89	0	3
Panel B. Survey Wave 2 (2012)					
A. Exposure Measures					
Long-run dryness	34	0.11	0.04	0.03	0.16
Deviation	34	-0.06	0.10	-0.38	0.05
Aman Long-run dryness	34	0.09	0.07	-0.04	0.22
Boro Long-run dryness	34	0.04	0.05	-0.02	0.18
Aman Deviation	34	0.22	0.21	-0.61	0.51
Boro Deviation	34	-0.09	0.14	-0.41	0.24
B. Number of Drought Events					
# Moderate Droughts	34	3.18	1.09	1	6
# Severe Droughts	34	1.09	0.71	0	3
# Extreme Droughts	34	0.03	0.17	0	1
Panel C. Changes					
A. Exposure Measures					
Long-run dryness	34	0.03	0.01	0.01	0.05
Deviation	34	-0.10	0.12	-0.52	0.03
Aman Long-run dryness	34	0.01	0.02	-0.05	0.04
Boro Long-run dryness	34	0.05	0.01	0.02	0.08
Aman Deviation	34	-0.05	0.28	-1.09	0.32
Boro Deviation	34	-0.51	0.21	-0.99	-0.20
B. Number of Drought Events					
# Moderate Droughts	34	-5.03	2.78	-10	0
# Severe Droughts	34	-1.35	1.72	-5	2
# Extreme Droughts	34	-0.44	0.82	-2	0
Panel D. Total					
A. Exposure Measures					
Long-run dryness	68	0.09	0.04	-0.01	0.16
Deviation	68	-0.01	0.09	-0.38	0.15
Aman Long-run dryness	68	0.09	0.06	-0.05	0.22
Boro Long-run dryness	68	0.01	0.05	-0.08	0.18
Aman Deviation	68	0.25	0.18	-0.61	0.50
Boro Deviation	68	0.16	0.29	-0.41	0.68
B. Number of Drought Events					
# Moderate Droughts	68	5.69	3.39	1	13
# Severe Droughts	68	1.76	1.65	0	7
# Extreme Droughts	68	0.25	0.68	0	3

Notes: The sample includes the 34 grid cells that uniquely match the 40 sampled unions as explained in Figure A2. Long-run dryness is the average SPEI over the previous twenty years ($\times$ (0)), Deviation is the deviation between the average SPEI in the year before the first wave and Long-run dryness ($\times(-1)$). 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 (resp. severe and extreme) droughts include all (non-consecutive) monthly realizations between January 2006 and December 2010 for survey wave 1 and between January 2011 and September 2012 for survey wave 2 in which the SPEI ≤ -1 (resp. -1.5 and -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.

Table A16: Summary statistics of main regressors using SPEI and BCCAS

	N	Mean	SD	Min	Max
Panel A. Survey Wave 1 (2011)					
Drought$_{t-1}$	714	0.04	0.19	0	1
Drought$_{t-2}$	714	0.01	0.12	0	1
Inaccuracy	714	0.98	0.14	0	1
Overestimation (Moderate)	714	0.00	0.00	0	0
Overestimation (Severe)	714	0.03	0.18	0	1
Overestimation (Extreme)	714	0.15	0.35	0	1
Δ Droughts (Moderate)	714	-7.83	2.92	-13	0
Δ Droughts (Severe)	714	-2.13	1.94	-7	3
Δ Droughts (Extreme)	714	-0.12	1.11	-3	4
Panel B. Survey Wave 2 (2012)					
Drought$_{t-1}$	714	0.24	0.42	0	1
Drought$_{t-2}$	714	0.01	0.05	0	1
Inaccuracy	714	0.80	0.40	0	1
Overestimation (Moderate)	714	0.01	0.09	0	1
Overestimation (Severe)	714	0.11	0.32	0	1
Overestimation (Extreme)	714	0.36	0.48	0	1
Δ Droughts (Moderate)	714	-2.74	1.35	-6	9
Δ Droughts (Severe)	714	-0.59	1.08	-3	11
Δ Droughts (Extreme)	714	0.45	0.84	-1	11
Panel C. Total					
Drought$_{t-1}$	1428	0.14	0.34	0	1
Drought$_{t-2}$	1428	0.01	0.09	0	1
Inaccuracy	1428	0.89	0.31	0	1
Overestimation (Moderate)	1428	0.00	0.06	0	1
Overestimation (Severe)	1428	0.07	0.26	0	1
Overestimation (Extreme)	1428	0.25	0.44	0	1
Δ Droughts (Moderate)	1428	-5.29	3.41	-13	9
Δ Droughts (Severe)	1428	-1.36	1.75	-7	11
Δ Droughts (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. Inaccuracy is a dummy variable that takes value one if individuals do not report to have been hit by the most harmful drought the year preceding the survey ($Drought_{t-1} = 0$) and the minimum SPEI monthly realization was recorded in the same year. The variable Δ is constructed as explained in Equation (1) in the main text, 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. Overestimation is a dummy variable that takes value one if Δ is strictly positive. 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 displays the values across the two waves.

Table A17: Balance in covariates. Long-run dryness on farmer's characteristics.

	Long-run dryness	
Covariate	Estimate	Standard errors
Farmer	0.621	(2.094)
Receives information from extension agents	-0.729	(1.699)
Household size	-2.519	(2.953)
Household with electricity	-0.731	(1.481)
Ownership of Shallow Tube Wells (STWs)	0.195	(0.564)
Ownership of Deep Tube Wells (DTWs)	-0.906	(0.579)
Perception increase in erratic rainfall	11.18	(3.393)
Perception decrease in precipitations	5.392	(2.631)
Land holdings (in hectares)	-0.660	(1.305)
Share of clay cultivated land	-1.001	(0.706)
Share of loam cultivated land	1.014	(1.531)
Share of sandy cultivated land	-0.408	(0.444)
Share of clay-loam cultivated land	-1.137	(1.742)
Share of sandy-loam cultivated land	2.474	(1.542)

Notes: The panel presents point estimates and standard errors for 14 regressions of a covariate (listed at the left) on long-run dryness. I use a time-varying measure of long-run dryness to account for changes between the two waves. All estimates are based on OLS regressions with individual and year fixed effects. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation.

A.4 Additional Tables

Table B1: Social learning channel of belief update

Outcome variable:	$\Delta\Delta$Perc. Increase Drought					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\Delta$ Irrigation	0.138	-0.0326	-0.0576			
	(0.110)	(0.0591)	(0.0707)			
Δ_{t-1} Irrigation				0.00295	-0.163	-0.130
				(0.136)	(0.0996)	(0.0965)
Season	Annual	*Aman*	*Boro*	Annual	*Aman*	*Boro*
N	714	714	714	714	714	714

Notes: Each column refers to an OLS specification where the sample is a cross-section of 714 rural households' respondents. The outcome variable is the difference between the deviation from the union's average in perceptions of increases in drought over the two survey waves (formally, $\text{perception}_{it} - \overline{\text{perception}}_{ut} - (\text{perception}_{it-1} - \overline{\text{perception}}_{ut-1})$. The main regressors of interest are the differences in deviations from the union's average in the share of irrigated cultivated land. All regressions control for main occupation of the respondent is farmer, the household receives extension advice, access to electricity, hectares of total land holdings, weighted share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam by hectares; union 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 B2: Perceptions and long-run exposure to dryness

Outcome variable:	Perc. Increase Drought		
	(1)	(2)	(3)
Long-run dryness	16.23***	6.383***	-1.691
	(2.475)	(0.914)	(2.740)
Deviation	-0.431*	-0.0193	0.192
	(0.222)	(0.0761)	(0.163)
Season	Annual	*Aman*	*Boro*
Fixed Effects	X	X	X
N	1428	1428	1428

Notes: Each column refers to an OLS specification where the outcome variable is the binary variable on perceptions of increases in droughts. The main regressors of interest are the annual or seasonal (*Aman* in col.2 and *Boro* in col.3) twenty-year average dryness and short-run deviations from the year prior to the production year. All regressions control for individual and year fixed effects. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B3: Ex-ante input decision. Contemporaneous weather realizations and irrigation decisions.

	Aman		Boro		
	Rainfed	STW	Rainfed	STW	DTW
	(1)	(2)	(3)	(4)	(5)
Deviation_t	0.0867	-0.0691	0.00204	-0.0180	0.0157
	(0.0734)	(0.0703)	(0.0480)	(0.0390)	(0.0237)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
N	1428	1428	1428	1428	1428
adj. R^2	0.560	0.573	0.749	0.665	0.588

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. The specification controls for perceptions of increases in droughts, the interaction term with long-run dryness and the set of controls as in baseline specification (10): seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects*: Individual, Year. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B4: Sub-sample analysis.

	Dependent variable: Share of irrigated cultivated land				
	(1)	(2)	(3)	(4)	(5)
Perc. Increase Drought	-0.0759***	-0.101***	-0.0746***	-0.0875***	-0.0785***
	(0.0210)	(0.0245)	(0.0243)	(0.0235)	(0.0218)
Perc. Increase in Drought × Long-run dryness	0.835***	0.872***	0.543*	0.757**	0.722**
	(0.243)	(0.305)	(0.288)	(0.295)	(0.292)
Sub-sample	Irrigated land $\neq 0$ in wave 1	Irrigated land $\neq 0$	Aman & Boro producers	No STW/DTW owners	At least one extreme drought
Mean Outcome	0.548	0.576	0.488	0.474	0.474
SD Outcome	0.296	0.276	0.323	0.332	0.334
N	1278	1212	1330	1270	1390
adj. R^2	0.563	0.502	0.695	0.716	0.700

Notes: The outcome variable is the average share of cultivated land in *Aman* or *Boro* growing seasons. Column (1) estimates the regression excluding farmers with share of irrigated land equal to zero in the first wave. Column (2) excludes farmers that never irrigate. Column (3) includes only farmers self-reporting the quantity of *Aman* and *Boro* rice produced in the first wave. Column (4) excludes farmers owning STWs or DTWs. Column (5) excludes unions where no drought occurred over the twenty years. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. All specifications include individual and year fixed effects, and the same controls as baseline regression in Table 1. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B5: Other adaptation responses to perceptions and dryness

	Livestock buffer			Off-farm work	Domestic labor in HH		
Outcome variable	Value Livestock Sold	Sold livestock	Consumed livestock	Has off-farm job	# agricultural workers	# crop farmers	# self-employed in agricultural activities
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Perc. Increase Drought	13644.1	-0.00841	0.0933	-0.0277	0.0350	0.0101	-0.00217
	(9901.2)	(0.0577)	(0.0699)	(0.0249)	(0.0295)	(0.0456)	(0.0498)
Perc. Increase in Drought × Long-run dryness	-210060.1	-0.215	-0.996	0.589	-0.780	-0.442	-0.00172
	(159026.5)	(0.700)	(0.800)	(0.385)	(0.571)	(0.515)	(0.612)
Mean Outcome	9418.782	0.500	0.627	0.141	0.109	0.835	0.939
N	1428	1428	1428	1428	1428	1428	1428
adj. R^2	0.086	0.176	0.139	0.681	0.487	0.737	0.705

Notes: Each column refers to an OLS specification on the sample of 714 individuals. All specifications include individual and year fixed effects, and the same controls as baseline regression in Table 1. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: $^{*}p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$. The outcome in column 1 is measured in Taka. Regressions in columns 2, 3, and 4 have a binary outcome variable.

Table B6: Monetized loss of inaccurate beliefs. Estimates using returns to irrigation from the literature.

Reference	Geographical Context	Crop Production	Irrigation technology	$\Delta yield/\Delta irrigation$	Median value loss $ [IQR]
Haque (1975)	Bangladesh	*Aman* rice	STW	2490kg ha^{-1}	$102.80 [$95.63,$115.98]
		Boro rice	STW	3504.74kg ha^{-1}	$23.55 [$12.11,$42.06]
Bhandari (2001)	Nepal	Rice	STW	850kg ha^{-1}	*Aman*: $35 [$32.64, $39.57]
					Boro: $5.7 [$2.86, $10.2]
Mandal and Singh (2004)	West Bengal (India)	*Kharif* rice	STW	500kg ha^{-1}	*Aman* :$20.64 [$19.2, $23.28]
		Rabi rice	STW	1100kg ha^{-1}	*Boro*: $7.40 [$3.7, $13.2]
Parvin and Rahman (2009)	Bangladesh	*Boro* rice	-	3220 kg ha^{-1}	$21.64 [$10.82, $38.64]
Sekhri (2014)	rural India	mixed	access to groundwater	1235.53 rupees ha^{-1} *	*Aman*: $2.04 [$1.90, $2.31]
					Boro: $.33 [$.16, $.59]
Jones et al. (2022)	Rwanda	dry season crops	hillside irrigation schemes	375-562.5 USD ha^{-1} †	*Boro*: $5.25-7.88 [$2.63-3-94, $9.38-14.06]

* The effect is computed at the district level exploiting variation in the technology required to access groundwater at a depth of eight meters. Agricultural yields are originally reported in rupees per acre and converted to USD using the exchange rate in the study period: 1 USD = 62 rupees.

† Dry season goes from June to August, when in Bangladesh is the monsoon season. I use the exchange rate in the study period reported in Jones et al. (2022): 800 RwF = 1 USD. The effect is mostly driven by changes in agricultural production, shifting from staples (primarily maize and beans) to horticulture.

A.5 Heterogeneity by socio-demographic characteristics

Table B7: Baseline estimates. Heterogeneity by age.

	Irrigated		STW		DTW	
	18-44	45+	18-44	45+	18-44	45+
	(1)	(2)	(3)	(4)	(5)	(6)
Perc. Increase in Drought (β_1)	-0.0689**	-0.128***	-0.0484	-0.121***	0.00485	0.0408
	(0.0303)	(0.0298)	(0.0350)	(0.0359)	(0.0194)	(0.0256)
Perc. Increase in Drought × Long-run dryness (β_2)	0.576	1.265***	0.769*	1.105***	-0.357	-0.463
	(0.431)	(0.356)	(0.445)	(0.419)	(0.246)	(0.299)
Controls	X	X	X	X	X	X
Fixed Effects	X	X	X	X	X	X
p-value ($\beta_1 + \beta_2$)	0.2109	0.0008	0.0851	0.0122	0.1300	0.1277
Mean Outcome	0.495	0.482	0.316	0.284	0.066	0.070
SD Outcome	0.331	0.324	0.365	0.344	0.184	0.198
N	675	753	675	753	675	753
adj. R^2	0.695	0.695	0.681	0.679	0.548	0.631

Notes: Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: $^{*}p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls*: Annual deviation in excess dryness relative to twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects*: Individual, Year.

Table B8: Baseline estimates. Heterogeneity by education.

	Irrigated		STW		DTW	
	No education	$\geq$ one year	No education	$\geq$ one year	No education	$\geq$ one year
	(1)	(2)	(3)	(4)	(5)	(6)
Perc. Increase in Drought (β_1)	-0.0515**	-0.111***	-0.0481	-0.0961***	0.0247	0.0182
	(0.0257)	(0.0271)	(0.0513)	(0.0290)	(0.0217)	(0.0231)
Perc. Increase in Drought $\times$ Long-run dryness (β_2)	0.299	1.163***	0.332	1.185***	-0.310	-0.414
	(0.285)	(0.379)	(0.517)	(0.371)	(0.252)	(0.258)
Controls	X	X	X	X	X	X
Fixed Effects	X	X	X	X	X	X
p-value ($\beta_1 + \beta_2$)	0.3516	0.0035	0.5458	0.0021	0.2260	0.1007
Mean Outcome	0.489	0.488	0.304	0.295	0.066	0.070
SD Outcome	0.335	0.321	0.360	0.349	0.190	0.192
N	666	762	666	762	666	762
adj. R^2	0.762	0.649	0.701	0.668	0.656	0.548

Notes: Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: $^{*}p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls*: Annual deviation in excess dryness relative to twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects*: Individual, Year.

Table B9: Heterogeneity by age and education in Aman

	Age				Education			
	Rainfed		STW		Rainfed		STW	
	18-44	45+	18-44	45+	No education	$\geq$ one year	No education	$\geq$ one year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Perc. Increase in Drought (β_1)	0.0804***	0.118***	-0.0542*	-0.0679**	0.0744**	0.102***	-0.0461	-0.0496**
	(0.0303)	(0.0455)	(0.0296)	(0.0299)	(0.0340)	(0.0382)	(0.0345)	(0.0247)
Perc. Increase in Drought $\times$ Long-run dryness (β_2)	-0.614**	-0.890**	0.666**	0.601**	-0.401	-0.951***	0.407*	0.683**
	(0.263)	(0.412)	(0.286)	(0.279)	(0.255)	(0.348)	(0.237)	(0.268)
Controls	X	X	X	X	X	X	X	X
Fixed Effects	X	X	X	X	X	X	X	X
p-value ($\beta_1 + \beta_2$)	0.0309	0.0459	0.0256	0.0412	0.1657	0.0101	0.0916	0.0131
Mean Outcome	0.751	0.773	0.183	0.145	0.759	0.766	0.169	0.158
SD Outcome	0.411	0.399	0.366	0.331	0.410	0.400	0.354	0.344
N	675	753	675	753	666	762	666	762
adj. R^2	0.550	0.567	0.502	0.634	0.598	0.524	0.545	0.589

Notes: Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: $^{*}p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls*: Seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects*: Individual, Year.

A.6 Robustness Checks

A.6.1 Subjective Perceptions and Adaptive Decisions

Table C1: Baseline results. Spatial and temporal cutoffs for standard errors adjustment.

Dependent variable: Share of cultivated land	Irrigated	STW	DTW
	(1)	(2)	(3)
Panel A: 100 km and 2-year cutoffs			
Perc. Increase in Drought (β_1)	-0.0821***	-0.0626**	0.0190
	(0.0278)	(0.0285)	(0.0221)
Perc. Increase in Drought × Long-run dryness (β_2)	0.600**	0.543**	-0.260
	(0.267)	(0.261)	(0.195)
Panel B: 200 km and 5-year cutoffs			
Perc. Increase in Drought (β_1)	-0.0821***	-0.0626**	0.0190
	(0.0258)	(0.0305)	(0.0187)
Perc. Increase in Drought × Long-run dryness (β_2)	0.600**	0.543*	-0.260
	(0.271)	(0.286)	(0.189)
Panel C: 400 km and 2-year cutoffs			
Perc. Increase in Drought (β_1)	-0.0821***	-0.0626**	0.0190
	(0.0200)	(0.0264)	(0.0149)
Perc. Increase in Drought × Long-run dryness (β_2)	0.600***	0.543**	-0.260
	(0.220)	(0.271)	(0.183)
Panel D: 400 km and 5-year cutoffs			
Perc. Increase in Drought (β_1)	-0.0821***	-0.0626**	0.0190
	(0.0217)	(0.0279)	(0.0160)
Perc. Increase in Drought × Long-run dryness (β_2)	0.600**	0.543*	-0.260
	(0.237)	(0.284)	(0.167)
Panel E: 800 km and 5-year cutoffs			
Perc. Increase in Drought (β_1)	-0.0821***	-0.0626**	0.0190
	(0.0205)	(0.0243)	(0.0144)
Perc. Increase in Drought × Long-run dryness (β_2)	0.600***	0.543**	-0.260
	(0.221)	(0.243)	(0.161)
Panel F: 800 km and 999-year cutoffs			
Perc. Increase in Drought (β_1)	-0.0821***	-0.0626**	0.0190
	(0.0222)	(0.0259)	(0.0155)
Perc. Increase in Drought × Long-run dryness (β_2)	0.600**	0.543**	-0.260
	(0.237)	(0.257)	(0.159)
N	1428	1428	1428

Notes: The outcome variable is the average share of cultivated land across the two main growing seasons under any irrigation status (column 1), irrigated with STW (column 2) and with DTW (column 3). Spatial and temporal cutoffs are varying and reported in the heading of each panel. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions control for 20-year long-run average exposure to dryness, seasonal year-to-year deviation in excess dryness relative to long-run average, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings, weighted share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam by hectares; individual and year fixed effects.

Table C2: Baseline results by growing season. Spatial and temporal cutoffs for standard errors adjustment.

	Aman		Boro		
Dependent variable: Share of cultivated land	Rainfed	STW	Rainfed	STW	DTW
	(1)	(2)	(3)	(4)	(5)
Panel A: 100 km and 2-year cutoffs					
Perc. Increase in Drought (β_1)	0.0871***	-0.0498**	0.0229	-0.0234	0.0188
	(0.0296)	(0.0203)	(0.0201)	(0.0232)	(0.0214)
Perc. Increase in Drought × Long-run dryness (β_2)	-0.545**	0.437**	0.275	0.0254	-0.296
	(0.276)	(0.219)	(0.306)	(0.333)	(0.220)
Panel B: 200 km and 5-year cutoffs					
Perc. Increase in Drought (β_1)	0.0871***	-0.0498**	0.0229	-0.0234	0.0188
	(0.0280)	(0.0202)	(0.0176)	(0.0237)	(0.0194)
Perc. Increase in Drought × Long-run dryness (β_2)	-0.545*	0.437*	0.275	0.0254	-0.296
	(0.285)	(0.243)	(0.285)	(0.318)	(0.215)
Panel C: 400 km and 2-year cutoffs					
Perc. Increase in Drought (β_1)	0.0871***	-0.0498***	0.0229	-0.0234	0.0188
	(0.0225)	(0.0168)	(0.0142)	(0.0177)	(0.0158)
Perc. Increase in Drought × Long-run dryness (β_2)	-0.545**	0.437**	0.275	0.0254	-0.296
	(0.234)	(0.203)	(0.229)	(0.269)	(0.189)
Panel D: 400 km and 5-year cutoffs					
Perc. Increase in Drought (β_1)	0.0871***	-0.0498***	0.0229	-0.0234	0.0188
	(0.0243)	(0.0184)	(0.0152)	(0.0190)	(0.0168)
Perc. Increase in Drought × Long-run dryness (β_2)	-0.545**	0.437**	0.275	0.0254	-0.296
	(0.245)	(0.212)	(0.250)	(0.286)	(0.204)
Panel E: 800 km and 5-year cutoffs					
Perc. Increase in Drought (β_1)	0.0871***	-0.0498***	0.0229	-0.0234	0.0188
	(0.0224)	(0.0176)	(0.0139)	(0.0172)	(0.0150)
Perc. Increase in Drought × Long-run dryness (β_2)	-0.545***	0.437**	0.275	0.0254	-0.296
	(0.208)	(0.176)	(0.236)	(0.247)	(0.191)
Panel F: 800 km and 999-year cutoffs					
Perc. Increase in Drought (β_1)	0.0871***	-0.0498***	0.0229	-0.0234	0.0188
	(0.0241)	(0.0191)	(0.0150)	(0.0185)	(0.0161)
Perc. Increase in Drought × Long-run dryness (β_2)	-0.545**	0.437**	0.275	0.0254	-0.296
	(0.220)	(0.185)	(0.256)	(0.265)	(0.206)
N	1428	1428	1428	1428	1428

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). Spatial and temporal cutoffs are varying and reported in the heading of each panel. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions control for 20-year long-run seasonal average exposure to dryness, seasonal year-to-year deviation in excess dryness relative to long-run average, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings, weighted share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam by hectares; individual and year fixed effects.

Table C3: Baseline results. Clustered standard errors at the grid cell-level.

Dependent variable: Share of cultivated land	Irrigated	STW	DTW
	(1)	(2)	(3)
Perc. Increase in Drought (β_1)	-0.0821***	-0.0626*	0.0190
	(0.0293)	(0.0353)	(0.0320)
Long-run dryness (β_2)	-1.971	-1.018	-0.406
	(1.301)	(1.937)	(1.134)
Perc. Increase in Drought $\times$ Long-run dryness (β_2)	0.600*	0.543*	-0.260
	(0.305)	(0.304)	(0.257)
Controls	X	X	X
Fixed Effects	X	X	X
p-value ($\beta_1 + \beta_2$)	0.0784	0.0907	0.3048
Mean Outcome	0.489	0.299	0.068
SD Outcome	0.327	0.354	0.191
N	1428	1428	1428
adj. R^2	0.698	0.682	0.593

Notes: The outcome variable is the average share of cultivated land across the two main growing seasons under any irrigation status (column 1), irrigated with STW (column 2) and with DTW (column 3). Standard errors are clustered at the grid cell-level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls*: year-to-year deviation in excess dryness relative to twenty-year long-run average, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects*: Individual, Year.

Table C4: Baseline results by growing season. Clustered standard errors at the grid cell-level.

	Aman		Boro		
Dependent variable: Share of cultivated land	Rainfed	STW	Rainfed	STW	DTW
	(1)	(2)	(3)	(4)	(5)
Perc. Increase in Drought (β_1)	0.0871**	-0.0498*	0.0229	-0.0234	0.0188
	(0.0361)	(0.0246)	(0.0233)	(0.0298)	(0.0287)
Long-run dryness (β_2)	-0.634	0.539	0.551	2.761*	-0.561
	(0.792)	(0.603)	(2.231)	(1.385)	(0.965)
Perc. Increase in Drought × Long-run dryness (β_2)	-0.545*	0.437*	0.275	0.0254	-0.296
	(0.279)	(0.233)	(0.338)	(0.391)	(0.290)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
p-value ($\beta_1 + \beta_2$)	0.0880	0.0811	0.3734	0.9959	0.3291
Mean Outcome	0.763	0.163	0.260	0.435	0.112
SD Outcome	0.405	0.348	0.411	0.470	0.300
N	1428	1428	1428	1428	1428
adj. R^2	0.560	0.572	0.750	0.669	0.583

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are clustered at the grid cell-level. Significance levels: $^{*}p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls*: Seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects*: Individual, Year.

Table C5: Subjective perceptions and irrigation status

Dependent variable: Share of cultivated land	Irrigated (1)	STW (2)	DTW (3)
Perc. Increase in Drought (β_1)	-0.0821***	-0.0626**	0.0190
	(0.0244)	(0.0292)	(0.0178)
Long-run dryness (β_2)	-1.971*	-1.018	-0.406
	(1.038)	(1.458)	(0.905)
Perc. Increase in Drought $\times$ Long-run dryness (β_3)	0.600**	0.543**	-0.260
	(0.257)	(0.273)	(0.183)
Controls	X	X	X
Fixed Effects	X	X	X
p-value ($\beta_1 + \beta_3$)	0.0022	0.0556	0.1542
Mean Outcome	0.489	0.299	0.068
SD Outcome	0.327	0.354	0.191
N	1428	1428	1428
adj. R^2	0.698	0.682	0.593

Notes: The outcome variable is the average share of cultivated land across the two main growing seasons under any irrigation status (column 1), irrigated with STW (column 2) and with DTW (column 3). Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls*: year-to-year deviation in excess dryness relative to twenty-year long-run average, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects*: Individual, Year.

Table C6: Subjective perceptions and irrigation status by growing season

	Aman		Boro		
Dependent variable: Share of cultivated land	Rainfed	STW	Rainfed	STW	DTW
	(1)	(2)	(3)	(4)	(5)
Perc. Increase in Drought (β_1)	0.0871***	-0.0498***	0.0229	-0.0234	0.0188
	(0.0265)	(0.0188)	(0.0167)	(0.0227)	(0.0185)
Long-run dryness (β_2)	-0.634	0.539	0.551	2.761**	-0.561
	(0.823)	(0.732)	(1.977)	(1.216)	(0.834)
Perc. Increase in Drought × Long-run dryness (β_3)	-0.545**	0.437*	0.275	0.0254	-0.296
	(0.276)	(0.236)	(0.267)	(0.303)	(0.200)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
p-value ($\beta_1 + \beta_3$)	0.0423	0.0470	0.2592	0.9947	0.1622
Mean Outcome	0.763	0.163	0.260	0.435	0.112
SD Outcome	0.405	0.348	0.411	0.470	0.300
N	1428	1428	1428	1428	1428
adj. R^2	0.560	0.572	0.750	0.669	0.583

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls*: seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects*: Individual, Year.

Table C7: Baseline results by growing season. Hectares of cultivated land as outcome variable.

	Aman		Boro		
Dependent variable: Hectares of cultivated land	Rainfed	STW	Rainfed	STW	DTW
	(1)	(2)	(3)	(4)	(5)
Perc. Increase in Drought (β_1)	0.0894**	-0.0334**	0.0236	-0.0168	0.0310**
	(0.0386)	(0.0146)	(0.0196)	(0.0144)	(0.0126)
Long-run dryness (β_2)	-1.071**	1.145**	-0.816	2.073**	-0.718
	(0.467)	(0.471)	(1.272)	(1.029)	(0.711)
Perc. Increase in Drought × Long-run dryness (β_3)	-0.656*	0.134	-0.477*	0.282	-0.193
	(0.398)	(0.150)	(0.280)	(0.195)	(0.155)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
p-value ($\beta_1 + \beta_3$)	0.0806	0.4676	0.0934	0.1596	0.2702
Mean Outcome	0.502	0.080	0.185	0.257	0.050
SD Outcome	1.230	0.227	0.479	1.122	0.184
N	1428	1428	1428	1428	1428
adj. R^2	0.968	0.652	0.812	0.973	0.498

Notes: The outcome variable is the total hectares of cultivated land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: $^{*}p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls*: Seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects*: Individual, Year.

Table C8: Baseline results by growing season. Extensive margin of irrigation status as outcome.

	Aman		Boro		
	(1)	(2)	(3)	(4)	(5)
	Rainfed	STW	Rainfed	STW	DTW
Perc. Increase in Drought (β_1)	0.0847***	-0.0648***	0.0101	-0.0154	0.0162
	(0.0304)	(0.0221)	(0.0216)	(0.0243)	(0.0200)
Long-run dryness (β_2)	-0.212	0.705	2.702	4.254***	-0.131
	(1.054)	(0.656)	(2.543)	(1.258)	(0.969)
Perc. Increase in Drought × Long-run dryness (β_3)	-0.777**	0.482**	-0.474	-0.0904	-0.217
	(0.375)	(0.239)	(0.379)	(0.355)	(0.197)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
p-value ($\beta_1 + \beta_3$)	0.0541	0.0651	0.2195	0.7644	0.2941
Mean Outcome	0.819	0.204	0.363	0.496	0.135
SD OUtcome	0.385	0.403	0.481	0.500	0.342
N	1428	1428	1428	1428	1428
adj. R^2	0.456	0.582	0.621	0.641	0.618

Notes: The outcome variable is a dummy variable that takes value 1 if the share of cultivated land under each irrigation status or rainfed is strictly positive and zero otherwise. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: $^{*}p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls*: Seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects*: Individual, Year.

Table C9: Reverse Causality: Irrigation status and subjective perceptions

	Perc. Increase in Drought in wave 2			Δ Perc. Increase in Drought		
	(1)	(2)	(3)	(4)	(5)	(6)
Avg share of irrigated land in wave 1	0.0283			-0.00667		
	(0.0973)			(0.137)		
Avg share of irrigated land in Aman in wave 1		0.00228			-0.0518	
		(0.0452)			(0.0760)	
Avg share of irrigated land in Boro in wave 1			0.0399			0.0806
			(0.111)			(0.143)
N	714	714	714	714	714	714
adj. R^2	0.152	0.152	0.153	0.112	0.113	0.113

Notes: The table estimates the potential reverse causality of past adaptation decisions on future perceptions. Each column refers to an OLS specification where the sample is a cross-section of 714 rural households' respondents. The dependent variable is the dichotomous variable on the perceived increase in drought measured in the second wave of the survey in columns 1-3 and the difference between perceived increase in drought in wave 2 and wave 1 in columns 4-6. The main regressors of interest are the share of irrigated cultivated land in the first wave. All regressions control for: main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings, age, gender and years of education of the respondent, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam, weighted by hectares. All regressions also control for union fixed effects. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A.6.2 Salience

Table C10: Salience of objective drought events and irrigation status in *Boro*

	Objective Drought			Most Harmful Objective Drought		
Dependent variable: Share of cultivated land	Rainfed	STW	DTW	Rainfed	STW	DTW
	(1)	(2)	(3)	(4)	(5)	(6)
Obj Drought$_{t-1}$	-0.0942**	-0.0550*	0.0614**	0.00724	-0.134***	0.122***
	(0.0436)	(0.0335)	(0.0278)	(0.0205)	(0.0313)	(0.0266)
Perc. Increase in Drought	0.0192	-0.0256	0.0212	0.0221	-0.00916	0.00583
	(0.0172)	(0.0227)	(0.0183)	(0.0160)	(0.0221)	(0.0180)
Perc. Increase in Drought × Long-run dryness	0.311	0.0465	-0.320	0.266	0.203	-0.457*
	(0.258)	(0.310)	(0.199)	(0.266)	(0.263)	(0.235)
Controls	X	X	X	X	X	X
Fixed Effects	X	X	X	X	X	X
N	1428	1428	1428	1428	1428	1428
adj. R^2	0.751	0.669	0.584	0.750	0.679	0.604

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in the *Boro* growing season. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: $^{*}p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls*: 20-year long-run seasonal average exposure to dryness, Seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects*: Individual, Year.

A.6.3 Overestimation

Table C11: Extent of overestimating drought frequency using other objective drought cutoffs.

	Moderate Droughts					Severe Droughts				
	Aman		Boro			Aman		Boro		
Dependent variable: Share of cultivated land	Rainfed	STW	Rainfed	STW	DTW	Rainfed	STW	Rainfed	STW	DTW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Drought	-0.0169***	0.0111*	0.00489	-0.00286	0.00213	-0.00595	0.000368	-0.00123	-0.00866	0.00794*
	(0.00629)	(0.00592)	(0.00493)	(0.00517)	(0.00474)	(0.00970)	(0.00870)	(0.00709)	(0.00732)	(0.00479)
Controls	X	X	X	X	X	X	X	X	X	X
Fixed Effects	X	X	X	X	X	X	X	X	X	X
N	1428	1428	1428	1428	1428	1428	1428	1428	1428	1428
adj. R^2	0.563	0.574	0.750	0.669	0.583	0.559	0.572	0.750	0.669	0.584

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: $^{*}p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls*: 20-year long-run seasonal average exposure to dryness, seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects*: Individual, Year.

A.6.4 Alternative Drought Events Source

In Section 6.3, I examine the role of overestimating drought events in the irrigation decisions of farmers. To test for the robustness of the results, I also use another source of objective drought events to compute the objective counterfactual of the number of drought occurred. I use the EM-DAT (2022) database collected by the Centre for Research on the Epidemiology of Disasters (CRED) at the Catholic University of Louvain. The EM-DAT database has worldwide coverage, and contains data on the occurrence and effects of natural disasters from 1900 to the present. A disaster is defined by the CRED as a natural event that overwhelms local capacity, necessitating a request for external assistance. The database includes information on the locations within the country that have been hit by the natural disaster. In order to be recorded in the EM-DAT database, a disaster needs to satisfy at least one of the following criteria: i) 10 or more people are reported to have been killed; ii) 100 people have been reported affected; iii) a state of emergency is declared; iv) international assistance is called for. The use of this source for objective records of extreme events might be problematic due to the potential threshold and accounting biases in loss information that the database could suffer from (Gall et al., 2009). Nevertheless, the use of loss information is out of the scope of this research, which is limited to analyse the number of drought events recorded. Limits in the use of EM-DAT records as objective measures have been discussed in the literature (Cavallo et al., 2013; Felbermayr & Gröschl, 2014; Noy, 2009). Given the threshold conditions that the disaster needs to satisfy to be recorded, potential measurement error in the data would bias downward the information from the database.

I adopt the same methodology used in Section 3.2 to compute the objectively recorded number of drought events that have occurred in the five years before the first wave of the survey (between 2006 and 2010) and between the first and the second wave (2011 and 2012). Following this approach, round-specific measures of accuracy are created comparing the number of self-reported drought events by the household and the recorded number of drought events as reported by EM-DAT:

$$\Delta \text{ Drought}_{it} = \text{self-reported } \#_{it} - \text{objective } \# \text{ droughts}_{ut} \tag{13}$$

These round-specific measures of accuracy infer whether respondents overestimate or underestimate the number of drought events that they have experienced.

Table C12: Extent of overestimating drought frequency using EM-DAT objective drought records.

	Aman		Boro		
Dependent variable: Share of cultivated land	Rainfed	STW	Rainfed	STW	DTW
	(1)	(2)	(3)	(4)	(5)
Δ Drought	-0.00435	0.00211	0.00943	-0.0155	0.0155**
	(0.0156)	(0.0149)	(0.00838)	(0.00943)	(0.00730)
Perc. Increase in Drought	0.0885***	-0.0505**	0.0202	-0.0191	0.0144
	(0.0289)	(0.0209)	(0.0178)	(0.0235)	(0.0183)
Perc. Increase in Drought × Long-run dryness	-0.550**	0.440*	0.296	-0.00877	-0.262
	(0.277)	(0.238)	(0.269)	(0.308)	(0.199)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
N	1428	1428	1428	1428	1428
adj. R^2	0.559	0.572	0.397	0.750	0.669

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: $^{*}p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls*: 20-year long-run seasonal average exposure to dryness, seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects*: Individual, Year.