



Subjective Perceptions and Adaptation Strategies to Climate Change in Bangladesh

Guglielmo Zappalà

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**Subjective Perceptions and Adaptation
Strategies to Climate Change in Bangladesh**

Guglielmo Zappalà

JEL Codes: D83, Q12, Q15, Q51, Q54

Keywords: Adaptation, Agriculture and Environment, Belief, Climate Change





ANALYSIS AND POLICY IN ECONOMICS

PARIS SCHOOL OF ECONOMICS

Subjective Perceptions and Adaptation Strategies to Climate Change in Bangladesh

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Subjective Perceptions and Adaptation Strategies to Climate Change in Bangladesh

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Abstract

The aim of this paper is to analyze how subjective perceptions of climate change of farmers in Bangladesh affect the implementation of on-farm adaptation strategies to climate change. I present a model of subjective perceptions and adaptation in response to a change in climatic conditions. The empirical analysis is based on a unique national-representative panel dataset of rural households in Bangladesh and adopts a two-step approach disentangling the role of subjective perceptions on on-farm adaptation. I assess the accuracy of beliefs by comparing subjective probabilities to historical meteorological data and find considerable heterogeneity in beliefs and accuracy, depending on weather events and seasonal patterns. Moreover, I test whether farmers are subject to confirmation bias, finding that they tend to recall information and overweight evidence in a way that it confirms their own beliefs. The accuracy of farmers' beliefs explains differences in the adaptation decision-making process. A detailed comprehension of farmers' perceptions of climate change and adaptation strategies can significantly contribute to the design of adequate policies for agricultural security.

Keywords: Adaptation, Agriculture and Environment, Belief, Climate Change

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1 Introduction

Climate change represents one of the most important sources of risk for today's and future generations at the global level. Climate change-induced increases in temperatures, precipitation variations and frequency and intensity of extreme weather events such as floods, droughts and storms are posing major threats to natural resource-based activities. The Intergovernmental Panel on Climate Change (IPCC) estimates that climate change will have a dramatic impact on agricultural activities and a predicted global warming by 2°C would reduce agricultural output by 25% (Intergovernmental Panel on Climate Change, 2014). The projected changes in climate threaten in particular rural households and farmers, whose income depends on agricultural activities. These disruptive effects have laid the groundwork for a better understanding of potential adaptation strategies in developing countries, where vulnerability is presumably higher. Farmers might adapt by making changes in farming and land management decisions in order to avert the challenges posed by climate change and reduce its negative consequences. Adaptation is emerging as a relevant research area among climate change economists and scientists. However, theoretical and empirical research on adaptation has lagged behind in addressing the importance of cognitive and psychological factors that determine adaptation (Grothmann & Patt, 2005). Misconception about climate change and its potential damages can lead to an insufficient degree of adaptation or maladaptation, resulting in an even more negative impact of climate change. In this paper, I integrate and analyse the effect of farmers' subjective perceptions of climate change on their adaptation decision-making process in order to assess how beliefs are formed, what their main drivers are and how the nature of the behavioral responses to their beliefs shapes the adaptation outcomes.

This paper addresses three research questions. The first one examines whether historical weather affects subjective perceptions. The second research question explores the heterogeneous impact of actual gradual long-term weather events, such as changes in rainfall patterns and in temperatures, on individuals' perceptions as compared to extreme events, such as floods, droughts or storms. The third research question aims at understanding whether individuals who perceive climate change are more prone to undertake adaptation strategies to cope with climate change and whether the accuracy of beliefs explains differences in the adaptation decision-making process.

This paper relates to various strands of literature. Most important, it relates to a branch of the literature at the intersection between development and environmental economics that has started investigating the relationship between farmers' perceptions of climate change and adaptation strategies (Debela, Mohammed, Bridle, Corkrey, & McNeil, 2015; Deressa, Hassan, & Ringler, 2011; Elum, Modise, & Marr, 2017; Mertz, Mbow, Reenberg, & Diouf, 2009). The results of these articles are limited to small geographical zones, without sharp weather variations within the area. The studies lack of theoretical foundation and provide descriptive results based on small cross-sectional surveys tailored to the scope of the research. Moreover, the current state of the art of this strand of literature does not disentangle the different features of climatic changes that the farmers may perceive and does not match subjective perceptions and self-reported experiences of weather events with historical weather data. I contribute to this literature by exploiting a unique panel dataset

from a two-round survey at the rural household-level in Bangladesh, a geographical area in which subjective perceptions have never been investigated before. To the best of my knowledge, the match between survey data with meteorological and natural disaster data to compare subjective perceptions to objective historical weather, the tests in the heterogeneity in the effect of slow-onset as compared to sudden short-term weather events, and the effect of beliefs' accuracy on adaptation decision-making are novel in the literature.

Second, it relates to the growing literature on adaptation strategies to climate change in developing countries (Aragón, Oteiza, & Rud, [forthcoming](#); Auffhammer & Carleton, [2018](#); Di Falco, Veronesi, & Yesuf, [2011](#); Sesmero, Ricker-Gilbert, & Cook, [2018](#)), that has however neglected the link between perceptions and adaptations so far. The absence of empirical analysis on this relationship is mainly motivated by the lack of available data on farmers' perceptions of climate change. However, the lack of recognition of climate change is deemed to be one of the drivers of limited adaptation (Burke & Emerick, [2016](#)). Farmers might not adapt because they do not realize that climate is changing and adaptation is needed. In order to test this hypothesis, the literature usually explores whether farmers' responsiveness is a function of characteristics that are likely to shape their ability to learn about a changing climate. This paper contributes to this literature by integrating perceptions and a measure of accuracy of beliefs into the farmers' adaptation decision-making process and by including them in the empirical analysis.

Third, it is related to the literature that measures expectations and its impacts on various outcomes in developing countries (Alem & Colmer, [2018](#); Delavande, [2014](#); Delavande, Giné, & McKenzie, [2011](#); Giné, Townsend, & Vickery, [2015](#)). For the first time, a theoretical model of optimal expectations, built on Brunnermeier and Parker ([2005](#)) and used in Alem and Colmer ([2018](#)), integrates farmers' subjective probabilities of climatic changes in their adaptation decision-making process and opposes them to objective probabilities. The model also includes a direct measure of accuracy of beliefs defined as the difference between the prior subjective and historical distribution of weather events and natural disasters. Moreover, the empirical analysis integrates a test on confirmation bias (Kahneman & Tversky, [1973](#); Nickerson, [1998](#); Rabin & Schrag, [1999](#)), namely the tendency to recall information and overweight evidence in a way that it confirms one's beliefs.

I find that farmers' subjective perceptions of climatic changes are heterogeneously shaped by weather variations across growing seasons and the result is robust to a variety of specification checks. In addition, farmers are subject to confirmation bias, in particular when reporting droughts events. Finally, farmers' subjective probabilities of climatic changes are a powerful predictor of the implementation of adaptation strategies, even when controlling for objective probabilities in weather. The accuracy of farmers explains differences in the adaptation decision-making process and inaccurate farmers are more likely not to adapt.

By addressing questions of perceptions, adaptation strategies and climate change, these findings have important implications for the debate on public awareness and adaptations to climate change in developing countries by providing empirical evidence and a solid theoretical framework, necessary to inform environmental and agricultural policy.

The remainder of the paper is organized as follows. Section 2 provides the background and the context. Section 3 describes the data used in the empirical analysis. Section 4 presents the theoretical framework. Section 5 defines the empirical approach. Section 6 shows and discusses the main results and the key robustness checks, which are displayed in detail in the Appendix. Section 7 discusses some potential limitations in the analysis and Section 8 concludes.

2 Background and Literature Review

2.1 Context

Bangladesh is a South Asian country identified by the IPCC as one of the most vulnerable least developed countries (Intergovernmental Panel on Climate Change, 2014). It is the eighth-most populous country in the world and its administrative structure consists in eight divisions and sixty-four districts, each subdivided into *upazila* or *thana*, that are the second lowest level of regional administration in Bangladesh. The smallest rural administrative and local government units in Bangladesh are the unions. It has been ranked 7th on Global Climate Risk Index 2019 of the countries most affected by climate change since 1998 (Eckstein, Hutfils, & Wings, 2018). Due to its geographical position and its environmental features – being a flat, low-lying deltaic country - Bangladesh is exposed to disasters of different types, ranging from extreme temperatures, increasing number of severe floods, coastal erosions, higher frequency of cyclones and erratic rainfall. The climate of Bangladesh is considerably heterogeneous over the year and has rather marked seasonal variations (Thomas et al., 2013). More than 80% of the annual precipitation occurs during the monsoon season between June and September (see Figure A5) and recently the weather pattern has become more erratic with a shorter cool and dry season between November and February (see Figures A5 and A6) and a positive trend in the average yearly temperature between 1981 and 2012 (see Figure A10).

Bangladesh has a natural resources-based economy, predominant in agriculture, with more than 35% of the population living below the poverty line. Agriculture heavily depends on weather and there is evidence of the negative effect of increases in temperatures and changes in rainfall patterns (Aragón et al., forthcoming; Burke & Emerick, 2016; Schlenker & Roberts, 2009) on crops. The impact of climate change can thus be amplified in countries as Bangladesh that heavily rely on agriculture. Rain fed agriculture hinges upon seasonal rainfall and South Asian monsoon is the most important climatic phenomenon directly linked to the intensity and frequency of rainfall and drought in the country (Dastagir, 2015). Natural disasters such as floods, droughts and storms, that are expected to increase with climate change, can have both short- and long-term impacts on households, who mostly depend on agriculture, affecting savings, creditworthiness, loss of livelihoods and agricultural damages (Intergovernmental Panel on Climate Change, 2014; Maccini & Yang, 2009).

Bangladesh has a growing season extending throughout 12 months, that can be divided into three overlapping cropping seasons. The three seasons are articulated following the production of three different types

of rice, which is the staple and the most produced crop of Bangladesh (Johnson, 1982). The three main varieties of rice are *Aus*, that is sown from March to June, during the pre-monsoon season, the *Aman*, that is the dominant monsoon season rice (from July to October), and the *Boro*, that is the dry season irrigated rice, sown from November to February. The crop rice calendar of Bangladesh is extended to the other crops and determines three different growing seasons, characterized by different weather characteristics: *Kharif 1* is the pre-monsoon season that goes from March to June, rainfall is variable and temperatures are high. Besides the *Aus* rice, summer vegetables and pulses are grown during *Kharif 1*. *Kharif 2* is the second part of the *Kharif* season. It is the monsoon season occurring between July and October and it is characterized by heavy rain and floods. *Aman* is the major crop grown, while other fruits and summer vegetables can be grown on high lands. *Rabi* is the winter dry season going from November to February, with low or minimal rainfall and low temperatures. *Boro* rice, wheat, potato, tomato, cabbage, spinach, Chinese cabbage, cauliflower and oil seeds are examples of winter vegetables (Paul & Rashid, 2016). Therefore, three different growing seasons are defined, *Kharif 1*, *Kharif 2* and *Rabi*, extending the approach in Guiteras (2009) and Carleton (2017), who, in their studies set in India, define only the *Kharif* (monsoon crop) growing season and *Rabi* (winter crop). Time series of the average temperature and total precipitation by growing season over time between 1981 and 2012 in Bangladesh are reported in Figures A11 and A12 where it is possible to observe an increasing trend in average temperatures in each growing season and a decreasing trend of rainfall only in the *Rabi* season, that has become drier over time.

2.2 Beliefs and Subjective Perceptions

The philosophical and phenomenological literature has extensively investigated the relationship between belief and perception (Smith, 2001). The main open question still unanswered is whether the perception involves the belief in the object of perception. Contemporary philosophers have conjectured that perceiving something leads to having a particular perceptual belief about that object (Armstrong, 1969).

In the framework of climate change, studies on the perceptions of this phenomenon have been conducted both in developing (Ishaya & Abaje, 2008; Mertz et al., 2009; Vedwan & Rhoades, 2001) and developed (Aker & Bennett, 2011; Leiserowitz, 2006; Semenza et al., 2008) countries. In both settings, results confirm that the majority of the population has already perceived climate change. This, however, is not immediately linked to a spread belief in climate change, as there is still a lively debate on the narrative behind the phenomenon of *climate skepticism*, that is present both in emerging and developed economies (Lejano, 2019). Regarding the definition of perception of climate change, Whitmarsh and Capstick (2018) provide an adequate interpretation of this concept that denotes a range of psychological constructs, that include knowledge, attitudes, concern, beliefs and perceived risk. This term captures the cognitive, affective and evaluative dimensions of the internal representations of the individuals of the notion. These representations, however, are not exempt from influences of social processes and cultural context, that shape their formation (Whitmarsh, Seyfang, & O'Neill, 2011).

The articles that study the subjective perceptions of climate change have usually focused on the impact of different socio-demographic factors. Maddison (2007) and Ishaya and Abaje (2008) have concluded that farming experience has an important role in the perception of climate change, whereas Semenza et al. (2008) showed that higher income is associated with a stronger perception of the changes in climate. Other drivers of the perception of climate change such as gender, ethnic background and newspaper reading (Leiserowitz, 2006), education, access to extension services and soil types (Gbetibouo, 2009) have also been studied. There is a small strand of the literature in developing countries that has compared farm surveys with data records from meteorological stations, but this has always been limited to descriptive comparison (Hageback et al., 2005; Thomas et al., 2013; Vedwan & Rhoades, 2001).

A particular feature that characterizes the perception process is the distinction between sudden-onset weather events and gradual long-term climatic changes (Intergovernmental Panel on Climate Change, 2014). In fact, climate change is usually interpreted as a long-term shift in climate patterns and usually refers to slow-onset changes such as increases in temperature and changes in rainfall patterns. Nevertheless, climate change can also be perceived through the increase in the frequency and intensity of extreme events such as floods, droughts, tornadoes, cyclones and hailstorms. In this regard, there is a strand in the psychological literature that investigates the different impact that gradual changes and extreme weather events can have on subjective perceptions. The theoretical background behind this hypothesis associates more power to experiential processing than to analytical processing in driving decision-making and behavior. Therefore, close experiences of climate change could influence climate opinions and perceptions more than longer-term, gradual or distant climatic change. Studies (Druckman & Shafraneck, 2017; Fownes & Allred, 2019; Hamilton & Stampone, 2013; Joireman, Truelove, & Duell, 2010; Risen & Critcher, 2011) have concluded with results that confirm this hypothesis.

Another cognitive bias that can be related to the personal experience of climate change and the formation of subjective beliefs is the confirmation bias (Kahneman & Tversky, 1973; Nickerson, 1998). An individual suffers from confirmation bias if she tends to misinterpret ambiguous evidence as confirming her current beliefs (Rabin & Schrag, 1999). Coupled with the confirmation bias is the availability bias (Kahneman and Tversky, 1982), that arises 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 and Tversky, 1982: 11) and that has already been studied in the context of how individuals form beliefs over the likelihood of natural disasters (Gallagher, 2014). The introduction of such biases in the beliefs formation process of the agents relaxes the assumption of Bayesian rationality, through which agents start with subjective beliefs over different possible states of the world, they learn about an unobserved environmental change by observing the weather and then use Bayes' rule to update the prior beliefs (Kelly, Kolstad, & Mitchell, 2005).

Literature on climate change has also introduced in the theoretical agents' learning models the "recency bias" (Kala, 2017). This corresponds to the tendency of an individual to most easily remember something that has happened recently, compared to remembering something that may have occurred long time before.

Even in robust learning models, this bias persists since agents use old information in more forecasts and the agent would best respond by treating the earlier signals as less informative.

The analysis of subjective perception of climate change and its drivers is relevant in order to understand whether, besides technological, economic and ecological limitations, there can be "social barriers" that hamper adaptation to climate change (Raymond & Spoehr, 2013). Social barriers are defined as normative, cognitive and institutional obstacles to adaptation, where the first refer to the interactions between the individual and the social environment and the second refer to individual psychological and thought processes (Weber, 2016). Directly observing subjective perceptions can allow to empirically test the hypothesis that lack of adaptation is driven by a difficulty in recognizing changes in climate and effectively adapt to them.

2.3 Adaptation Strategies

The IPCC has defined the adaptive capacity as the ability of systems, institutions and humans to adjust to climate change, including climate variability and extremes, in order to alleviate potential damages and cope with the consequences (Intergovernmental Panel on Climate Change, 2014). Thus, implementing an adaptation strategy should increase the capacity of a system to survive external shocks or change. The International Food Policy Research Institute (IFPRI) has defined adaptation as the process of improving the ability to cope with changes in climatic conditions both in the short term, e.g. seasonal or annual, and in the long term, e.g. in decades (Nhemachena & Hassan, 2007).

Agriculture has been identified as the primary channel through which the impacts of climate change are transmitted to poor and rural households. The literature (Di Falco et al., 2011) has identified a number of potential climate change adaptation strategies that rural households have undertaken in order to tackle the negative effects of climate change on agriculture. Adaptation strategies can be classified into three main categories: i) reallocation of economic activities through the diversification between on-farm and off-farm activities (Barrett, Reardon, & Webb, 2001; Colmer, 2018; Molua, 2011); ii) changes in consumption and savings patterns (Fafchamps, Udry, & Czukas, 1998; Hisali, Birungi, & Buyinza, 2011; Kazianga & Udry, 2006); iii) on-farm production decisions (Binswanger & Rosenzweig, 1993; Hassan & Nhemachena, 2008).

In the first type of adaptation strategies, farmers could decide to leave agriculture because of considerable losses in productivity due to climate change and choose to seek employment in other sectors of the economy such as industry or services. Bryan, Chowdhury, and Mobarak (2014) found that Bangladeshi rural households respond to incentives that relax their liquidity constraint when they make seasonal migration decisions during the lean period. This decision might include geographical relocation, with households choosing to migrate to more productive regions across states. Gray and Mueller (2012) have investigated population mobility in Bangladesh driven by natural disasters and found that, despite natural disasters having relevant effects on long-term population mobility in rural Bangladesh, exposure to them does not have significant positive effects on overall mobility and it might reduce mobility by increasing labor needs at the origin or by removing the resources necessary to migrate.

Rural households and farmers might also change their consumption and savings behavior in response to natural disasters and climatic changes exposure. Forward-looking agents would usually save to smooth their consumption during disasters or in the aftermath of them. Eskander, Fankhauser, and Jha (2016) showed that Bangladeshi rural households tend to shift from farm to non-farm employment in order to tackle negative shocks in the household income from exposure to floods and storms but maintain similar levels of savings.

A final set of strategies includes on-farm adaptation strategies. These strategies are usually implemented by households who cannot bear the cost of migrating or seeking an off-farm employment, and who heavily rely on the agricultural income. Therefore, they find more efficient to adjust their farming practices, bearing a cost of effort in terms of adaptation and learning new techniques. For this reason, these adaptation strategies are mostly related to gradual changes in climate such as changes in temperatures or precipitation, whereas migrating or seeking off-farm employment would be the most effective strategy in response to exposure to extreme natural disasters such as cyclones or tornadoes. Examples of on-farm adaptation strategies are changes of cropping practices - in terms of timing and variety of plantations - diversification between crop and livestock activities, adjustment of quantities of inputs applied or the update of technological methods (Aragón et al., forthcoming). This set of strategies extends also to soil conservation techniques, shading and planting trees, change in the use of irrigation/groundwater and other watering strategies (Deressa et al., 2011). Maddison (2007) suggests that stratifying the adaptation strategies by different changes in climate and perceptions, such as increases in precipitations, increases in temperatures, increases in cold waves or changes in the timing of rainfall, would provide greater insights on the adaptation decision-making process. For example, if temperatures are perceived to change, farmers might change variety of plantations or increase the use of water conservation techniques and the use of shading and sheltering techniques (Lobell & Burke, 2009). Furthermore, for a perceived change in precipitation and its timing, farmers would tend to respond by varying the planting date (Kala, 2017).

It might be argued that if farmers behave as forward-looking agents and they anticipate disaster shocks, they could adapt to them. However, such shocks cannot be perfectly anticipated because of their increasing high frequency, especially in south-east Asia (Mirza, 2011). Even though farmers usually show experience of coping strategies by considering seasonal risks and uncertainties in agriculture, the magnitude and frequency of stresses and shocks deriving from climate change are changing (Davies, Guenther, Leavy, Mitchell, & Tanner, 2009), making it more difficult for them to adapt on time. For this reason, studying the subjective perceptions of climate change and their drivers can shed light on the adaptation decision-making process.

3 Data

3.1 Household Data

Household-level data for Bangladesh are taken from the Bangladesh Climate Change Adaptation Survey (BCCAS), that consists in a two-round survey. It is 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 (administrative units) in Bangladesh. The survey is funded by the United States Agency for International Development (USAID) and it was designed and supervised by the IFPRI together with the Center for Development Studies (ZEF) and the Data Analysis and Technical Assistance Limited (DATA). It was administered by the Bangladesh Centre for Advanced Studies. The first round of the survey was conducted from December 2010 to February 2011, and it covers data from the previous production year, between December 2009 and December 2010. The dataset provides information at the national level on demographic characteristics, land tenure, crop management, incidence and perception of climatic shocks and adaptation options for Bangladeshi rural households. A follow-up second round of the survey (International Food Policy Research Institute, 2014b) was conducted in the following year, in September 2012, and it covers data from the previous production year between September 2011 and August 2012. A timeline of the survey rounds with respect to the three agricultural growing seasons identified earlier for Bangladesh is reported in Figure A2.

The respondent is the head of the household. 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). An agricultural household is defined as such if it complies with at least one of the following requirements: i) it was operating cultivate land (either owned, leased, shared or mortgaged); ii) it owned 5 or more livestock; iii) it raised 50 or more poultry.

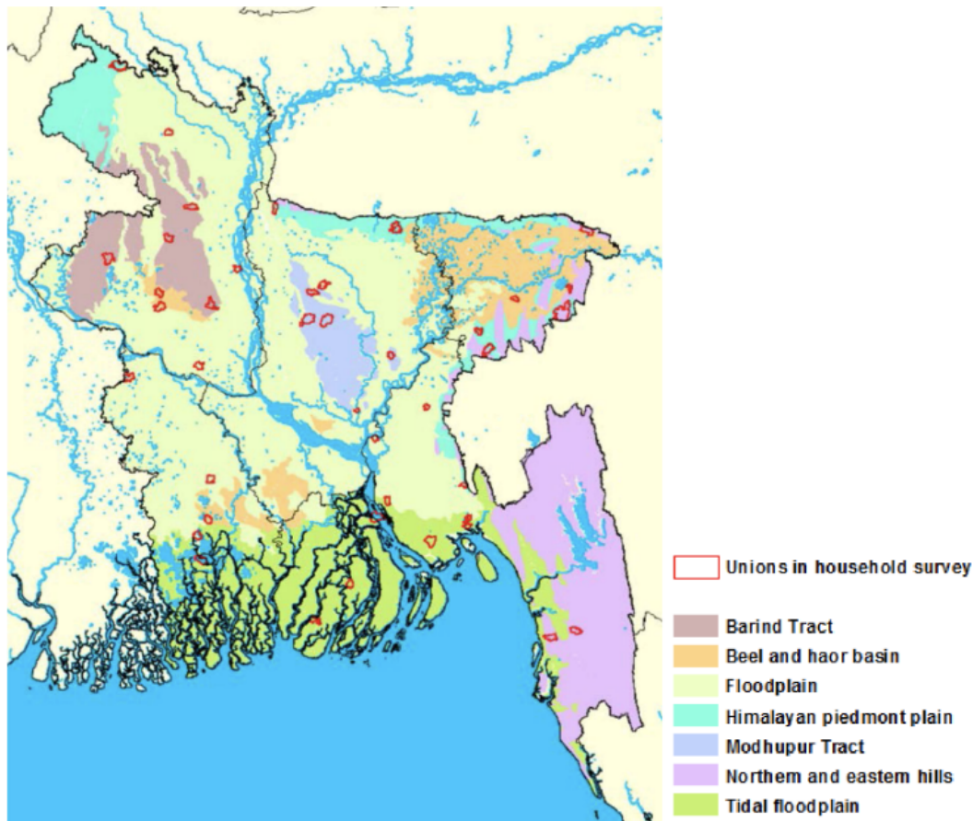
Bangladesh is divided into seven broad agro-ecological zones (AEZs), as grouped by the Bangladesh Centre for Advanced Studies (2014), based on the 30 AEZs categorization operated by the Soil Resource Development Institute (SRDI). The BCCAS covered 40 unions selected to represent proportionally the 7 AEZs, which are Barind Tract, *Beel* and *Haor* Basins, Floodplain, Himalayan Piedmont Plain, Modhupur Tract, Northern and Eastern Hills and Tidal Floodplains, that present very heterogeneous climatic characteristics. The heterogeneity in monthly precipitations across AEZs is documented in Figure A4. The number of unions randomly selected from each AEZ is reported in Table I. For each sample union, twenty agricultural households were randomly drawn from a single village in each union, for a total sample of 800 households. Figure I shows the location of the unions in the survey and the seven different AEZs in Bangladesh. Based on such agroecozone stratification, the sample was built to be national representative. However, the absence of a recent agricultural census made it impossible to assign weights. Therefore, observations are unweighted. More than 97%, or 766 out of 800 households, from the first round have been reinterviewed in the second round. The remaining 34 households could not be interviewed because they migrated or were not at home at the time of the survey. In particular, only 15 migrated. Given that the interest of the research is on subjective

perceptions, the final sample includes only those households who have been surveyed in both waves, did not move between the two rounds and whose respondent was the same in both waves. For this reason, the resulting final sample is a balanced panel dataset with two periods and 714 observations each. The geographical distribution of the households included in the final estimation sample is reported in Table A1. There are no substantial differences in the geographical distribution of the full and final estimation sample, which provides support to the absence of bias when focusing only on the 714 remaining households.

Table 1: Number of unions and households per AEZ covered in the BCCAS

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

Figure 1: Map of Study Site with Agroecological Zones



Source: Thomas et al. (2013)

Households Table 2 presents key summary statistics of the households and their agricultural characteristics by survey wave and defines the setting for the empirical analysis. Most of the households have a male head (94%). The average number of years of education for the head of the household is 3.5, that would imply an incomplete primary education, confirmed by the fact that the literacy rate among the heads of the household is around 50%. There are on average 5 members in the household. The average farm does not seem to rely on hired labor force for farming, whereas above 70% of the households has at least one member of the household self-employed in farming activities. Child labor force occurs only in less than one fifth of the households. Most of the rural households (around 90%) own livestock (cattle, buffaloes, goats, sheep, pigs, chicken or ducks), whereas only less than a third of the sample owns fishery assets. This provides support to the fact that most of the households are mainly focused on farming activities and fishery is only a supplementary activities that can be either performed on the south coast or on tidal ponds. Even though the ownership of a tractor or power tiller is not very spread (around 2% of the sample), households usually own other agricultural equipment such as plough or threshers. In the first round, the average area of land holdings is around 0.68 hectares and the average cultivable land is 0.56 hectares¹. There is considerable heterogeneity in the soil type of the cultivable/arable land held by an household, that predominantly is clay-loam. The total cultivable land reported by the households in the survey is subject to different operational status: around half of the cultivable land is owned by the household. Around 30% of the cultivable land of an household was rented in the first round, with the average share dropping to around 20% in the second round. These are the two most common statuses of cultivable land in the sample that make up to 75% of the total cultivable land of an household across waves. Remaining options such as mortgage, rent out or fallow have small non substantial shares.

¹This computation is a result of the conversion from the decimal unit of measure used in the survey and considers the sizes of all cultivable land holdings declared.

Table 2: Summary Statistics of BCCAS estimation sample by survey wave

	Mean		SD	
	2011	2012	2011	2012
<i>A. Household characteristics</i>				
Age of head of household (complete years)	46	47.9	13.5	13.5
Head of Household is male	.945	.945	.227	.227
Head of Household can read and write	.483	.462	.5	.499
Completed years of education by head of household	3.49	3.49	4.19	4.21
Number of children in the household	2.23	2.09	1.51	1.42
Household size	5.05	5.46	2.21	2.46
Number of agricultural workers in household	.113	.105	.396	.384
At least 1 HH member is self-employed in HH farming activities	.745	.71	.436	.454
Number of self-employed in farming activities in household	.959	.919	.762	.75
Child works	.169	.231	.375	.422
Log(Unpaid Debt) in 2010 USD	2.36	4.17	2.72	2.78
Receives information from extension agents	.176	.359	.381	.48
Receives farmer-to-farmer exchange visits as extension	.056	.049	.23	.216
Livestock Ownership	.899	.901	.301	.299
Ownership of fishery assets	.237	.368	.425	.483
Ownership of tractor	.0196	.0224	.139	.148
Ownership of other agricultural assets	.741	.899	.438	.301
<i>B. Agricultural characteristics</i>				
Total area land holdings in hectares	.68	.793	1.3	1.3
Total area cultivable land in hectares	.56	.69	1.2	1.27
Weighted proportion of clay cultivable land	.039	.0293	.183	.158
Weighted proportion of loam cultivable land	.252	.171	.422	.358
Weighted proportion of sandy cultivable land	.0283	.0219	.15	.131
Weighted proportion of clay-loam cultivable land	.468	.505	.486	.481
Weighted proportion of sandy-loam cultivable land	.213	.272	.395	.425
Weighted proportion of cultivable land owned	.52	.418	.434	.401
Weighted proportion of cultivable land rented in (Cash/Share)	.298	.205	.418	.323
Weighted proportion of cultivable land mortgaged in	.0816	.101	.239	.235
Weighted proportion of cultivable land rented out (Cash/Share)	.0516	.0563	.186	.197
Weighted proportion of cultivable land mortgaged out	.0257	.0455	.115	.15
Weighted proportion of cultivable land fallow	.00901	.00126	.0852	.0197

Notes: Proportions of cultivable land is weighted by the size of the plot of type cultivable/arable as reported by the household in the survey.

Subjective Perceptions Concerning the subjective perceptions of climate change, the survey contains five questions on different features of climate change that the respondent might have perceived: increases in floods, increases in droughts, increases in cold, increases in erratic and unseasoned rainfall and decreases in precipitations. The mean and standard deviation for each subjective perception by survey wave is reported in [Table 3](#). There are considerable differences across waves in the share of respondents who perceived increases in droughts, increases in unseasoned and erratic rainfall and decreases in precipitations. The latter clashes with the historical weather evidence on the period between the two waves, from February 2011 to September 2012. In fact, in this period of time, Bangladesh experienced two floods and two storms (Eskander et al., [2016](#)). A flood occurred in July 2011 and another one in June 2012, with the former causing also 17 deaths from rain-triggered landslides and the latter causing 139 deaths and affecting more than 5 million people². Bangladesh has also been hit by two cyclonic storms in April 2011 and 2012, respectively causing 13 and 25 deaths. The differences across waves in the subjective perceptions might be explained by the open-endedness feature of the question in the first wave, asking farmers to explain the features of perceived climate changes. This might make room for interview bias and negligence of the respondent in providing complete answer, compared to multiple choice questions that include all specific cases (Shapiro, [1970](#)).

Table 3: Summary statistics on subjective perceptions of climate change by survey wave

	N	Mean	SD
2011			
Perceived any changes in climate over the last 20 years	714	0.66	0.47
Perceived an increase in floods	714	0.11	0.31
Perceived an increase in droughts	714	0.25	0.43
Perceived an increase in cold	714	0.20	0.40
Perceived an increase in unseasoned/erratic rain	714	0.27	0.45
Perceived a decrease in precipitations	714	0.22	0.42
2012			
Perceived any changes in climate over the last 20 years	714	0.99	0.06
Perceived an increase in floods	714	0.17	0.38
Perceived an increase in droughts	714	0.92	0.26
Perceived an increase in cold	714	0.13	0.34
Perceived an increase in unseasoned/erratic rain	714	0.87	0.34
Perceived a decrease in precipitations	714	0.88	0.32
Total			
Perceived any changes in climate over the last 20 years	1428	0.83	0.38
Perceived an increase in floods	1428	0.12	0.33
Perceived an increase in droughts	1428	0.59	0.49
Perceived an increase in cold	1428	0.17	0.37
Perceived an increase in unseasoned/erratic rain	1428	0.57	0.50
Perceived a decrease in precipitations	1428	0.55	0.50
Observations	1428		

Notes: A farmer is considered to have perceived a change in climate over the 20-year period preceding the year of the interview if she has answered "Yes" to at least one of the question on perceptions below.

²Author's calculation from EM-DAT database (D. Guha-Sapir, R. Below, Ph. Hoyois - EM-DAT: The CRED/OFDA International Disaster Database – www.emdat.be – Université Catholique de Louvain – Brussels – Belgium).

Adaptation Strategies Farmers can choose among a wide set of adaptation strategies to climate change, which has already been described in subsection 2.3. The survey asks in a specific module whether the household has made any changes to its farming practices due to noticed long-term shifts in temperature and rainfall changes and variability. Focusing on on-farm adaptation strategies, around 90% of the households in the sample has undertaken at least an adaptation strategy. Summary statistics for each adaptation strategy by survey wave are reported in Table 4. The adaptation strategy that is implemented most often in wave 1 is a change in crop variety, whereas in wave 2, three out of four households have changed the rate of fertilizer application.

Table 4: Summary Statistics on on-farm adaptation strategies by survey wave

	Mean		SD	
	2011	2012	2011	2012
Implemented on-farm adaptation strategy	.894	.915	.309	.28
Change crop variety	.592	.723	.492	.448
Change paddy variety	.189	.248	.392	.432
Increase amount of land under production	.0924	.104	.29	.305
Decrease amount of land under production	.0574	0	.233	0
Implement soil and water management techniques	.056	.0616	.23	.241
Mix crop and livestock production	.0266	.007	.161	.0834
Integrated crop and fish farming production	.0168	.0056	.129	.0747
Change field location	.07	.0574	.255	.233
Build a water harvesting scheme for crops	.123	.132	.329	.338
Build a water harvesting scheme for livestock	.0098	.0042	.0986	.0647
Build a diversion ditch	.14	.204	.347	.404
Plant trees for shading	.0238	.0378	.153	.191
Irrigated	.576	.49	.495	.5
Irrigated more	.577	.569	.494	.496
Change planting dates	.382	.333	.486	.472
Plant earlier in Kharif 1	.0588	.0378	.235	.191
Plant earlier in Kharif 2	.178	.0812	.383	.273
Plant earlier in Rabi	.123	.13	.329	.337
Plant later in Kharif 1	.13	.157	.337	.364
Plant later in Kharif 2	.0448	.077	.207	.267
Plant later in Rabi	.0784	.133	.269	.34
Change fertilizer application	.581	.749	.494	.434
Higher rate of fertilizer application	.555	.724	.497	.447
Lower rate of fertilizer application	.035	.0336	.184	.18

Notes: A household is considered to have implemented an on-farm adaptation strategy if it has answered "Yes" to at least one of the strategies in the table. An example of a soil and water management technique is contour plowing.

On-farm adaptation strategies can be grouped into four different categories, following Gorst, Dehlavi, and Groom (2018): alterations in crop timing, crop switching, agricultural inputs or the adoption of soil or water conservation technologies. A thorough analysis of the different adaptation strategies can shed light on the different changes in climate that are experienced by a household. The empirical analysis of this paper focuses on four adaptation strategies that are most widely adopted by the households in the sample and that relate to each of the categories of on-farm adaptation. Summary statistics by survey wave on the subset of adaptation strategies of interest are reported in Table 5. Changes in crop variety can be undertaken as a response to changes in the frequency and amount of precipitations and to changes in temperatures, since certain crops might grow better in more adverse conditions. Changes in planting dates and crop timing are usually implemented to cope with adverse seasonal climatic conditions, for instance erratic rainfall or higher average temperatures. Input alteration is related to changes in the amount of available input used and could relate to higher rate of fertilizer application in the case of drought events, low or more erratic precipitations (Yin et al., 2016). Farmer may also adopt new water conservation techniques, an example would be to increase the amount of irrigation applied to crops in order to counter extreme heat, drought events or low precipitations.

Table 5: Summary Statistics on On-Farm Adaptation Strategies by survey wave

	Mean		SD	
	2011	2012	2011	2012
Implemented on-farm adaptation strategy	.88	.887	.326	.317
Change crop variety	.592	.723	.492	.448
Irrigated more	.577	.569	.494	.496
Change planting dates	.382	.333	.486	.472
Higher rate of fertilizer application	.555	.724	.497	.447

Notes: A household is considered to have implemented an on-farm adaptation strategy if it has answered "Yes" to at least one of the strategies in the table.

A cross-tabulation of subjective perceptions of climatic changes of farmers and on-farm adaptation strategies taken in response to changes in climate is reported in Table 6. It shows that farmers who perceived changes in temperature, for example an increase in cold, tend to adapt by changing crop varieties, perhaps moving to more cold-resistant crops. Likewise, farmers who perceived increases in droughts and erratic rainfalls tend to cope by increasing the rate of fertilizers and changing crops for instance to drought-resistant varieties.

Table 6: Adaptation Strategies and Subjective Perceptions (%)

Adaptation Strategy	Subjective perception					
	Increase Flood	Increase Drought	Increase Cold	Erratic Rainfalls	Decrease Precipitations	Total
Change crop variety	8.96	40.55	11.76	41.46	37.75	65.76
Irrigated more	5.46	35.29	10.99	35.08	34.24	57.28
Change planting dates	6.23	22.06	6.30	20.73	18.49	35.78
Higher rate of fertilizer	9.24	41.46	10.71	39.92	39.22	63.94
Total	13.80	58.72	16.53	57.00	55.25	74.23

Notes: Each cell represents the percentage of households across survey waves who have perceived a change in climate characteristics in the column and implemented an adaptation strategy in the row.

3.2 Historical Weather Data

Historical weather data are taken from the European Centre for Medium-Range Weather Forecasts (ECMWF)’s ERA5-Land monthly averaged dataset³. ERA5 is the fifth generation of ECMWF atmospheric reanalyses of the global climate. It is a high-quality reanalysis dataset that provides a consistent view of the evolution of weather variables over time at a finer resolution compared to ERA5. The use of reanalysis technique combines model data with observations from all over the world and ensures a globally complete and consistent dataset with climate models. Using reanalysis data solves the endogeneity concern that would result from the weather stations placement, and variation in the data collection quality. It also produces a consistent best estimate of atmospheric parameters over time and space (Auffhammer, Hsiang, Schlenker, & Sobel, 2013). ERA5-Land provides information on the water and energy cycles at surface level during several decades. The original spatial resolution of the ERA5-Land reanalysis dataset is 9 kilometres on a reduced Gaussian grid (TCO1279), and the data has been regridded to a regular latitude-longitude grid of 0.1x0.1 degree-scale. In particular, this dataset provides estimates of monthly average surface air temperature monthly and monthly total precipitation. The monthly average reanalysis data are obtained by averaging all daily data. These estimates cover the entire Bangladesh over the period from 1981 to 2012, the year of the second round of the survey⁴. The temperature variable measures the temperature of the air at 2 metres above the surface of land, sea or in-land water, where 2-metres temperature is computed by interpolating between the lowest model level and the Earth’s surface, considering the atmospheric conditions. Temperature is initially measured in Kelvin and is converted to degrees Celsius (°C) by subtracting 273.15. The precipitation variable measures the accumulated liquid and frozen water, including rain and snow, that falls to the Earth’s surface. It is the sum of large-scale precipitation and convective precipitation. The former embeds precipitation generated by large-scale weather patterns, while the latter is generated by convection, occurring when air, being at lower levels in the atmosphere, is warmer and less dense than the air above and therefore rises. However, total precipitation does not include fog, dew or the precipitation evaporating in the atmosphere before it lands at the surface of the Earth. Monthly mean precipitation data are initially measured in metres, being the depth

³<https://doi.org/10.24381/cds.68d2bb30>

⁴The first available year of data is 1981. In 2020, the ERA5 coverage will be extended to 1950. For further information, please see [here](#).

the water would have had, had it spread uniformly over the grid box. The variable has been converted to millimetres. Given that the variable is of monthly averaged reanalysis type, data are produced by averaging all daily data. In order to obtain an average of the total monthly rainfall, data are multiplied by the number of days in each month.

I use spatial interpolation to compensate for the locational mismatch between the union coordinates of the households in the BCCAS and the gridded weather data from ERA5. For each month of each year, I estimate the average temperature and total precipitation that each household is exposed to by aggregating up from grid data to union centroid and weighting the average by the inverse squared distance from the union centroid, the finest geographical level coordinate available in the survey data⁵. To test for robustness, all the variables from weather data are created for bounding distances of 20, 30 and 40 km.

A wide set of weather variables is built in order to test for the robustness of the results. First, average precipitation and average temperature in the previous 5, 10 and 20 years are computed. I compute also their squares in order to control for the potential non-linear impact that weather shocks can have both on agriculture and the economy (Schlenker & Roberts, 2006). In particular, Schlenker and Roberts (2009) show the existence of an inverted U-shape relation between yields and precipitation levels and identify a breaking point at around 29°C and 32°C after which the impact of an increase in temperature on crop yields is negative. I also compute cumulative growing season rainfall and average growing season temperature as explanatory climatic variables, in the spirit of Auffhammer and Carleton (2018). Analysis using growing season variables examines the effect of each of the three growing seasons in Bangladesh in the same econometric specification (Auffhammer & Carleton, 2018; Auffhammer, Ramanathan, & Vincent, 2012). Variables are built both as measures of the cumulative precipitation and average temperature in the year of the survey and also averaged for different time horizons (5, 10 and 20 years). Moreover, short-run and long-run differences in average temperature and cumulative precipitation are computed for different time horizons, 1, 5, 10 and 20 years from the year of the survey. A final set of variables is built using the literature on weather anomalies. Following Nicholson (1993) and Marchiori, Maystadt, and Schumacher (2012), temperature and precipitation anomalies are built as follows: they are computed as the deviations from the union's long-term mean, divided by the long-run standard deviation. The long-run is considered to be the 1981-2012 period. This time span is aligned with literature investigating anomalies. In fact, Hansen, Sato, and Ruedy (2012) adopt a 30-year period as long-run base period, being long enough to provide sufficient data for statistical analyses and consistent with the period used by most weather and climate services. Weather anomaly, either precipitation or temperature, is defined as follows:

$$\text{Anomaly}_{ut} = \frac{W_{ut} - \mu_u^{LR}}{\sigma_u^{LR}} \quad (1)$$

⁵I thank Timothy Thomas (IFPRI) for his kind provision of geographical coordinate of the surveyed union centroids. The initial coordinates of survey centroids available in the BCCAS dataset did not match with Bangladesh geographic boundaries. See Figure A1 for a map of the union centroids.

where W_{ut} is the level of either precipitation or temperature in union u in year of interview t , μ_u^{LR} is union u 's 1981-2012 average value and σ_u^{LR} is union u 's 1981-2012 standard deviation value over the long-run (LR) period. The use of anomalies is justified by Barrios, Bertinelli, and Strobl (2010), since these measures eliminate possible scale effects and they describe how far weather conditions in a given year are from a norm that is given by the long-term mean. Furthermore, Blanc and Schlenker (2017) describe "weather anomalies" as "ideal right-hand side variables" since "they are random and exogenous".

The definition of past climatic anomalies in union u can be refined following the methodology adopted by Coniglio and Pesce (2015). First, the long-term monthly mean and standard deviation of precipitation and temperature is computed, respectively p_m and t_m for the long-term monthly mean where $m \in M[\text{January, February, ..., December}]$ and $p_{SD,m}$ and $t_{SD,m}$ for the long-term monthly standard deviation. The long-term is defined as the period 1981-2005, where the starting year is chosen according to the first available year in the historical weather data, and the final year is chosen in order to exclude the five years preceding the year of the first wave of the survey (2011). The new anomaly variable distinguishes between anomalies that are above or below one long-term standard deviation with respect to long-term first month-specific moment. In the spirit of Coniglio and Pesce (2015), the anomalies above one standard deviation from the long-term mean are defined as positive, whereas those below one standard deviation from the long-term mean are defined as negative. The formulas below show the construction of the anomalies measures for precipitation and can be applied symmetrically to temperature:

$$p_{(+)\text{anomalies}} = \frac{\sum_{x=y-1}^{y-5} \sum_{m=1}^M \max[0, p_{x,m} - (\bar{p}_m + \bar{p}_{SDm})]}{5} \quad (2)$$

$$p_{(-)\text{anomalies}} = \frac{\left| \sum_{x=y-1}^{y-5} \sum_{m=1}^M \min[0, (\bar{p}_m - \bar{p}_{SDm}) - p_{x,m}] \right|}{5} \quad (3)$$

where x is the year index that assumes values ranging between 5 years before the year of the interview and the year before the interview, therefore neglecting contemporaneous anomalies and assuming that the reaction to climatic shocks is likely to occur with a time lag (Coniglio & Pesce, 2015).

Due to the monthly frequency of weather data, it is not possible to build cumulative growing season rainfall nor cumulative exposure to heat during the growing season, using measures widely adopted in the literature as average degree days (DD) and harmful degree days (HDD) (Schlenker & Roberts, 2006). Future research should prioritise the use of higher frequency weather data in order to build these explanatory variables.

3.3 Extreme Events and Natural Disasters Data

The third source of data concerns extreme events and natural disasters occurred in Bangladesh from the EM-DAT 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, therefore necessitating a request for external assistance. 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.

Between 2000 and 2012, Bangladesh has experienced 91 natural disasters, among which droughts, earthquakes, extreme temperatures, floods, landslides and storms, which have in turn triggered associated disasters such as broken dams, rains, hail, tsunamis. These disasters have resulted in almost 10,000 deaths and \$5,900 million in losses from damage to property, crops, and livestock (EM-DAT, 2020)⁶. The database includes information on the locations within the country that have been hit by the natural disaster. Locations vary according to the disaster reported (e.g. districts, cities, regions). The geographical level at which there is the best match with the geographical locations of the households is at the district level. Consequently, each district in the survey can be associated to the number of natural disasters - cold waves, droughts, floods and precipitation - 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). The choice of the time periods and of the natural disasters is coherent with the questions asked in the household survey on the incidence of climatic shocks in the previous 5 years and between the two waves of the survey. This approach allows to create specific measures for each wave. The modelling of natural disasters at the district level, broader than the union level used for temperature and precipitation data, is justified by two reasons. First, districts are the finest geographical level that can be matched with the household locations using EM-DAT data. Second, it is expected that natural disasters occurrence does not vary at union level, but rather hits all unions within the same district. Moreover, it is out of the purpose of the research to analyse the heterogeneous impact in the intensity of natural disasters across unions within a district, but rather the goal is to assess the effect of the frequency of natural disasters on individuals' perceptions of climate change.

4 Theoretical Framework

4.1 Subjective Perceptions

This section provides a theoretical model that frames the process of adaptation to climate change in two steps. The first step consists in analysing whether farmers perceive a change in climate, and the second step consists in farmers making a decision on whether to adapt or not, depending on their subjective probabilities and accuracy of beliefs about climatic changes. This approach has been frequently adopted in the empirical literature through the implementation of an Heckman (1979) selection model (Asayehegn, Temple, Sanchez, & Iglesias, 2017; McBride & Daberkow, 2003). Maddison (2007) adopted this two-step process of adaptation in Africa at the regional level, with results that are too highly aggregated to be of any help for addressing

⁶Author's computation from EM-DAT database (D. Guha-Sapir, R. Below, Ph. Hoyois - EM-DAT: The CRED/OFDA International Disaster Database – www.emdat.be – Université Catholique de Louvain – Brussels – Belgium).

country-specific perceptions and adaptations to climate change.

The first step of this process aims at considering farmer's subjective perceptions of climate change as a function of socio-demographic characteristics and historical weather variables. Subjective perceptions ω can initially be modelled as follows:

$$\omega = f(R, T, X) \quad (4)$$

where historical weather variables refer to precipitation R and temperature T , and X includes a set of socio-demographic characteristics that drive subjective perceptions. An example is the age of the responding farmer, which is a measure of experience in farming, that could result in a positive marginal effect of age on subjective perceptions, as confirmed by the literature about experienced farmers more likely to perceive climate change (Ishaya & Abaje, 2008; Maddison, 2007). However, it might also be the case that aged individuals are more reluctant to admit that a change in climate is occurring and can therefore be identified as *climatoskeptic* (Frumkin, Fried, & Moody, 2012). Other socio-economic mechanisms that can drive subjective perceptions are the literacy rate of the farmer and access to extension services on crop and livestock production. In particular, the literature has showed a strong positive relationship between receiving extension advices and awareness of climate change (Ado, Leshan, Savadogo, Bo, & Shah, 2019; Deressa et al., 2011; Nhemachena & Hassan, 2007).

The role of historical weather on formation of subjective perceptions of climate change might depend on the frequency, magnitude and temporal proximity of the event. The literature (Intergovernmental Panel on Climate Change, 2014) tends to classify the weather events that adversely affect the household and/or its farming activities in two subsets that integrate differences in intensity and time dimension of the change:

- **Extreme events:** Floods, Droughts, Tornadoes, Cyclones, Hailstorms.
- **Gradual long-term:** Sea Level Rise, Salinity Increase, Frequent Rainfall, Temperature Increase, Temperature Variability, Soil/River Erosion.

From this setup, three testable implications on the mechanisms through which climate change affects the perceptions of farmers are stated in the form of propositions.

Proposition 1 Farmers' subjective perceptions of climate change are driven by historical meteorological variables.

The first proposition focuses on the comparative statics analysis of changes in perceptions as a result of exogenous changes in temperature and precipitations (Myers, Maibach, Roser-Renouf, Akerlof, & Leiserowitz, 2013). There are two underlying assumptions of this proposition that are central to the model. First, farmers take climatic changes as exogenous and the adaptation strategies that they can implement do not alter the exogenous changes of climate, but only reduce the direct impact that future climatic changes can have on

the household. Second, beliefs are formed before the adaptation action is chosen and they do not depend on past adaptation actions. This assumption rules out the potential historical restraints on current actions that could be imposed by past actions and that would bias the results. The introduction of a long history of transient shocks reduces the bias introduced by historical restraints (Lemoine, 2018). In Equation 4 past actions are not introduced in the functional form since Nickell (1981) showed that when using a within-group estimator, the lagged dependent variable is correlated with the error term.

The marginal effect of historical meteorological change on subjective perceptions can be heterogeneous not only across different time dimensions and between gradual changes in precipitations and in temperatures, but also within the same time span across growing seasons. Because of the considerable heterogeneity in cumulative precipitations and in average temperature across growing seasons and a crop calendar in Bangladesh that extends throughout 12 months, the theoretical implications of the model can be refined in the form of the following proposition. The literature has already integrated the implications of such proposition in the empirical analysis (Auffhammer & Carleton, 2018; Carleton, 2017; Guiteras, 2009).

Proposition 2 Farmers' subjective perceptions of climate change are shaped heterogeneously by different historical climatic changes in the growing seasons.

Not all the climatic changes are linear over time nor is their effect on perceptions. The specification of a non-linear functional form representing the effect of historical weather on perceptions is a first step towards this direction. A further refinement takes as its starting point the literature on weather anomalies in temperature and precipitations (Coniglio & Pesce, 2015; Marchiori et al., 2012). The inclusion of both temperature and precipitation anomalies provides a fairly complete picture of the true extent of weather anomalies (Intergovernmental Panel on Climate Change, 2007). The empirical evidence agrees on the strong and direct impact of weather anomalies on agricultural activities, whereas the effect of weather anomalies has never been compared to the effect of gradual long-term changes outside of psychological literature (Druckman & Shafranek, 2017; Joireman et al., 2010). This implication can be formulated in the form of the following proposition.

Proposition 3 Gradual and long-term changes in temperatures and precipitations do not have an impact on farmers' subjective perceptions, whereas temperature and precipitation anomalies do.

Similarly, the relationship between subjective perceptions and historical meteorological data can be refined in its functional form by including the number of extreme events and natural disasters experienced in the 5-year period preceding the first round of the survey and in the time period between the first and the second rounds. The choice of a short time dimension is supported by the psychological and economic literature that agrees on perception and evaluation of adaptation options being a result of a reinforcement learning

that gives recent events more weight than distant ones (Marx et al., 2007; O'Connor, Yarnal, Dow, Jocoy, & Carbone, 2005; Weber, 2010). The function that defines subjective perceptions can be thus expressed as:

$$\omega = f(R, T, D, X) \quad (5)$$

where D is the number of extreme weather events and natural disasters. This functional form tests only the relationship between changes in the frequency of extreme events and natural disasters, such as droughts, floods and cold waves, and subjective perceptions of these events, neglecting the changes in the intensity. This implication is formulated as an additional proposition.

Proposition 4 By controlling for historical gradual changes in temperature and precipitation, the frequency of extreme events and natural disasters shapes the subjective perceptions of these events.

A new specification of the relationship between subjective perceptions of a change in climate and weather data is formulated in order to test whether farmers are subject to confirmation bias. Confirmation bias is a cognitive bias according to which agents have the tendency to recall information and overweight evidence in a way that it confirms their beliefs or hypotheses (Kahneman & Tversky, 1973; Rabin & Schrag, 1999). A particular type of the confirmation bias is the "selective recall" or "access-biased memory" (Hastie & Park, 1986), which states that agents remember evidence selectively to reinforce their beliefs, even if they gather and interpret evidence in a neutral manner. Psychological literature (Akerlof, Maibach, Fitzgerald, Ceden, & Neuman, 2013; Myers et al., 2013; Shao, 2016) has concluded that memory of experiences with climate change can shape climate change beliefs, however, it has neglected the two-way interaction between self-reported evidence and beliefs stemming from confirmation bias. Beliefs, in fact, feed back into the process of recalling evidence because of the selective recall bias. This phenomenon can be expressed by a new functional form in which the interaction between self-reported evidence of weather events and subjective perceptions is modelled as follows:

$$WE = f(\omega, X) \quad (6)$$

where WE is the number of self-reported weather events that adversely affected the household and/or its farming activities in the last five years. This functional form generates a testable implication that can be formulated in the form of a proposition.

Proposition 5 Farmers' subjective perceptions are subject to confirmation bias, through the selective recall phenomenon. They tend to remember evidence selectively to reinforce their beliefs. In other words, surveys' responses to questions asking to self-report the number of weather events experienced by the farmer should be a confirmation of the individual's subjective perception of a change in such climate characteristics.

The ambiguity in the belief about climate change is explained by the literature with the "directional motivated reasoning" (Dietz, 2013), namely agents who are skeptical about climate change reject credible scientific information and evidence because it counters their standing beliefs. For this reason, the literature is exploring the role of directional motivations, and in particular confirmation bias, in the context of public awareness and understanding of climate change (Druckman & McGrath, 2019).

4.2 Behavioral Response: Adaptation Strategies

The second step of the model concerns the adaptation decision-making process in relation to subjective probabilities of a future shock. The household can alleviate the impact by implementing an adaptation strategy. The theoretical model relies on the optimal expectations framework proposed by Brunnermeier and Parker (2005) and used in Alem and Colmer (2018). In this setting, beliefs about future states of the world enter directly into the current utility function of an individual, such that the agents care both about current and expected future utility. If an individual's subjective probability about a future shock is different from the true objective probability, then her beliefs about the future will affect her decisions today and thus her current utility.

Consider a world in which there is uncertainty about future utility and ambiguity about the future states of the world. There are two states of the world $s_t \in \{0, 1\}$, such that $s_t = 1$ indicates that a weather shock affecting negatively the agent's utility will take place, and $s_t = 0$ means that the agent will not experience such a negative shock. Let $p(s_t | \underline{s}_{t-1})$ be the true objective probability that the state $s_t \in \{0, 1\}$ is realized, conditional on the state history $\underline{s}_{t-1} = (s_1, s_2, \dots, s_{t-1}) \in \{0, 1\}$. A novel introduction in this model as in Brunnermeier and Parker (2005) stands in agents having subjective probabilities that may not coincide with the true objective probabilities, because of subjective assessments of the likelihoods of ambiguous events. This assumption differs from the standard neoclassical model.

Consider a risk-neutral agent who has a conditional subjective probability $\hat{p}(s_t | \underline{s}_{t-1})$ that is based on historical meteorological history. At time t , the individual makes a decision a_t , where $a_t \in \{0, 1\}$, before the state of the world s_t is revealed. The agent can either implement an adaptation strategy to climate change, $a_t = 1$, or decide not to adapt, $a_t = 0$. If $s_t = 1$, the benefit of adapting is $U(\bar{y})$, but she incurs direct damage \underline{D} from the weather shock and bears cost of adaptation $c(a)$ in any state, linear and additive to utility, that can be both monetary or in terms of effort e_i , where $c(1) = c$. If $s_t = 0$, the benefit of adapting is $U(\underline{y})$ (where $U(\underline{y}) < U(\bar{y})$). The benefit of not adapting is normalized to 0 if $a_t = 0$ (where $0 < U(\underline{y}) < U(\bar{y})$) and costs of adaptation are saved (i.e., $c(0) = 0$). However, if $s_t = 1$ and there is no adaptation ($a_t = 0$), the agent incurs a higher damage \bar{D} . If state $s_t = 0$ and the agent chooses not to adapt ($a_t = 0$), the total benefit will be $U(\underline{y})$. This means that the benefit $U(\underline{y})$ is the same when $s_t = 0$, irrespective of the choice of the agent. Agents will choose to adapt if the perceived utility or profit is greater than not doing it. As utility is not directly observed, the actions of the agents are observed through the choice they make that

enters directly in the utility function.

Agents have priors $\hat{\omega}$ of the state $s_t = 1$ (i.e. $\hat{p}(s_t = 1 | \underline{s}_{t-1})$) that might differ from the objective probability ω . Following Giné et al. (2015), I define $\nu = |\hat{\omega} - \omega|$ as a proxy for accuracy such that agents with larger ν have more inaccurate priors⁷. The expected utility of the agent at time t is defined as:

$$\hat{\mathbb{E}}[U(a_1, a_2, \dots, a_T) | \underline{s}_t] \quad (7)$$

where $\hat{\mathbb{E}}$ is the subjective expectations operator that is associated with \hat{p} , and depends on the available information at time t to individual i . The agent will decide to adapt if the expected gains from adapting are positive. The gains from adapting Ω is the difference in expected subjective utility between adapting and not adapting:

$$\begin{aligned} \Omega &= \hat{\mathbb{E}}U(\text{Adapt}) - \hat{\mathbb{E}}U(\text{Not Adapt}) \\ &= \hat{p}(s_t = 1)[U(\bar{y} - c - \underline{D})] + \hat{p}(s_t = 0)[U(\underline{y} - c)] - [\hat{p}(s_t = 1)U(-\bar{D}) + \hat{p}(s_t = 0)U(\underline{y})] \\ &= \hat{\omega}[U(\bar{y} - c - \underline{D})] + (1 - \hat{\omega})[U(\underline{y} - c)] - [\hat{\omega}U(-\bar{D}) + (1 - \hat{\omega})U(\underline{y})] \\ &= \hat{\omega}U(\bar{y} - \underline{D}) - \hat{\omega}U(-\bar{D}) - c \end{aligned} \quad (8)$$

Let ω^* be the probability of state $s_t = 1$ such that $\hat{\omega}U(\bar{y} - \underline{D}) - \hat{\omega}U(-\bar{D}) = c$, i.e. $\Omega = 0$, and the agent is indifferent between adapting or not. The objective probability ω is assumed to satisfy $\omega > \omega^*$. The expected gains of adapting depend positively on subjective probabilities $\hat{\omega}$, implying that farmers with higher beliefs $\hat{\omega}$ are more likely to adapt at time t . This result is stated in the next proposition.

Proposition 6 A farmer who has a too low subjective probability of state $s_t = 1$ (i.e. $\hat{\omega} < \omega$) will not implement an adaptation strategy in order to cope with the negative weather shock. The probability of adapting at time t is (weakly) increasing in belief $\hat{\omega}$ of state $s_t = 1$.

If the subjective probability of a negative weather shock does not coincide with the true probability, the utility of the farmer $\hat{\mathbb{E}}[U(\cdot) | \underline{s}_t]$ depends on the expected future utility or anticipated utility as defined by Alem and Colmer (2018), such that the subjective probability will have a direct impact on utility through its impact on the decision a_t . Following Brunnermeier and Parker (2005), I consider the canonical model with time-separable utility flows and exponential discounting, such that utility at time t is modelled as:

⁷This model has no dynamic linkages and the agent solves a series of static decisions problems. Future research should focus on the introduction of a signal r correlated to the state s and on the farmer's decision to update the prior or not given that she has prior $\hat{\omega}$, in a multi-period version of the model where each period is subdivided into the sub-periods where farmers decide or not to update the prior. The most straightforward conclusion is that if the prior was always updated at each period, it would eventually converge to the true probability ω and the farmer would be perfectly accurate.

$$\hat{\mathbb{E}}[U(\cdot)|\underline{s}_t] = \beta^{t-1} \left(\sum_{\tau=1}^{t-1} \beta^\tau u_{t-\tau}(\cdot) + u_t(\cdot) + \hat{\mathbb{E}} \left[\sum_{\tau}^{T-t} \beta^\tau u_{t+\tau}(\cdot|\underline{s}_t) \right] \right) \quad (9)$$

the sum of memory utility from past adaptation decisions, flow utility from the current adaptation decision, and anticipatory utility from future adaptation decisions. In this regard, it is possible to examine the different drivers of the adaptation decision and distinguish them according to their time dimension. The memory utility includes those events in the past such as the objective past weather realizations and the number of historical weather events that adversely affected the household in $t - \tau$, where $\tau \in \{1, \dots, t - 1\}$. The flow utility from the current adaptation decision is based on socio-demographic characteristics of the individual, farm and household characteristics and on the contemporaneous weather at time t . Finally, anticipatory utility is modelled as both subjective and objective.

The subjective beliefs of agents are a complete set of conditional probabilities following any history of events, $\hat{p}(s_t|\underline{s}_{t-1})$, meaning that the subjective belief on the probability that a weather shock will occur in the future depends on the past history of the shocks. Agents who have experienced more shocks in the past might believe that they are more likely to experience a shock in the future. I rely on Brunnermeier and Parker (2005) for the assumption underlying the definition of optimal expectations. If agents have rational expectations, such that $\hat{p}(s_t|\underline{s}_{t-1}) = p(s_t|s_{t-1})$, meaning that subjective and objective probabilities coincide, then utility at time t only depends on present adaptation decision and anticipatory utility does not enter the utility function. This would occur if an exact weather forecast was available. If this was the case, the agent would take the optimal decision a^* as the solution of the maximization problem. However, in the case in which subjective probabilities are different from the true probability of a weather shock, there is a gap between the objective and the subjective dimension. The maximization problem of the agent will therefore be harmed by the wedge between the two probabilities and the agent will not take the optimal choice a^* that maximizes his expected utility. In this case, memory utility and anticipatory utility enter the utility function.

4.3 Expected Utility

Expected utility from adapting for a farmer with subjective probability $\hat{\omega}$ is denoted $\hat{\mathbb{E}}U(\hat{\omega})$, where $\hat{\mathbb{E}}$ indicates that the expectation is taken over the prior $\hat{\omega}$. Expected utility is thus:

$$\hat{\mathbb{E}}U(\hat{\omega}) = \begin{cases} \hat{\omega}U(-\overline{D}) + (1 - \hat{\omega})U(\underline{y}) & \text{if } \hat{\omega} < \omega^* \\ \hat{\omega}[U(\overline{y} - c - \underline{D})] + (1 - \hat{\omega})[U(\underline{y} - c)] & \text{if } \hat{\omega} \geq \omega^* \end{cases} \quad (10)$$

Expected utility for the same farmer with subjective probability $\hat{\omega}$ but taking over the objective probability ω of state $s_t = 1$ is

$$\mathbb{E}U(\hat{\omega}) = \begin{cases} \omega U(-\bar{D}) + (1 - \omega)U(\underline{y}) & \text{if } \hat{\omega} < \omega^* \\ \omega[U(\bar{y} - c - \underline{D})] + (1 - \omega)[U(\underline{y} - c)] & \text{if } \hat{\omega} \geq \omega^* \end{cases} \quad (11)$$

The farmer still decides not to adapt if $\hat{\omega} < \omega^*$ and to adapt if $\hat{\omega} \geq \omega^*$, but in Equation 11 the expected utility are expressed as a function of true objective probability.

An additional feature of the adaptation decision-making process of the farmers involves the accuracy of beliefs defined as ν . Farmers with less accurate priors would tend to have lower expected utility if differences in expected utility are higher for lower values of accuracy. The difference in expected utility, $\mathbb{E}U(\omega) - \mathbb{E}U(\hat{\omega}) \geq 0$, is computed from Equations 10 and 11, as in Giné et al. (2015). From this result, it is derived the following implication stated as a proposition.

Proposition 7 The more inaccurate the farmer is (i.e. the larger the difference between subjective probability $\hat{\omega}$ and objective probability ω), the lower the expected utility. Formally,

$$\frac{\partial [\mathbb{E}U(\omega) - \mathbb{E}U(\hat{\omega})]}{\partial \nu} \geq 0 \quad (12)$$

where $\nu = |\hat{\omega} - \omega|$ is the proxy for accuracy defined above. In other words, under the assumption that $\omega > \omega^*$ (and $\hat{\omega} < \omega^* < \omega$)⁸, farmers are more likely not to put in place an adaptation strategy when they should have adapted in order to maximize their expected utility. It follows that the probability of taking optimal choice a^* and adapt is (weakly) increasing with accuracy of beliefs.

5 Empirical Approach

The main econometric model is based on a fixed-effects linear probability model implemented in a panel framework. The choice of a linear probability model over a logit/probit is justified by the use of fixed effects in the empirical analysis. If the fixed effects included in the model were perfectly predicting the outcome variable, then the estimation with a logit would exclude the observations for which the model perfectly predicts the outcome and thus the estimation would provide the same estimates as a conditional logit. Moreover, in a fixed effects logit estimator, the maximum likelihood estimation of the coefficients in the model would not be consistent because of the incidental parameters problem (Neyman & Scott, 1948). This problem is substantial, in particular for small T, as it is the case in this study: Hsiao (2014) found that, for $T = 2$, the

⁸Throughout the theoretical model, it was considered the case where the prior was satisfying $\hat{\omega} < \omega$, whereas in the opposite case $\hat{\omega} \geq \omega$, it would automatically follow that $\Omega \geq 0$ and a farmer would always decide to adapt. Since the literature has provided empirical evidence of maladaptation and insufficient degree of adaptation to climate change (Burke & Emerick, 2016; Lobell, 2014), the case of inaccuracy stemming from over-estimation of the probability of a negative weather shock is discarded here.

bias in the maximum likelihood estimation is 100 percent.

5.1 First-Step: Subjective Perceptions

Baseline Estimating Equation

In the first-step of the empirical analysis, the aim is to test the theoretical propositions 1, 2, 3 and 4 and by estimating a fixed-effects panel regression whose econometric specification adopts as outcome variable the subjective perception of climate change ω_{iut} for the head of household i in union u in year of interview t . In order to estimate a causal link between weather and subjective perceptions, I follow the approach by Deschênes and Greenstone (2007), who suggest that weather variations can identify the impact of climate change. Equation 13 provides a standard formulation of the model

$$\omega_{iut} = \alpha_i + \alpha_u + \alpha_t + X'_{iut}\beta + \sum_k \gamma_k f_k(\mathbf{W}_{kut}) + u_{iut} \quad (13)$$

where ω_{iut} is the subjective perception of a change in a climate feature for the head of the household i in union u in year t . X_{iut} is a set of observable determinants of subjective perceptions at individual level, some of which are time-varying. The equation includes a full set of union fixed effects, α_u in order to absorb all unobserved union-specific time invariant determinants of the outcome variable. The equation also includes individual fixed effects α_i to control for potential unobserved time-invariant heterogeneity at the individual level and finally includes year fixed effects α_t , to control for unobserved shocks common to all individuals in a given year. The coefficient of interest is vector γ_k , associated to weather variable k , whose appropriate functional form $f(\cdot)$ is specified depending on the proposition to be tested. Standard errors are clustered at the household-level to account for correlation and heteroskedasticity within households.

Identification Strategy

The validity of the estimate of the impact of climate change based on Equation 13 relies on the assumption that its estimation will produce unbiased estimates of the γ vector. Formally, the consistency of each of the γ_k requires $E[f_k(\mathbf{W}_{kut})u_{iut} | \mathbf{X}_{iut}, \alpha_i, \alpha_u, \alpha_t] = 0$. By conditioning on the union and year fixed effects, the γ_k 's are identified from union-specific deviations in weather around the union average, once controlling for shocks common to all unions in a given year. This variation is presumed to be orthogonal to unobserved determinants of subjective perceptions, allaying potential omitted variables bias problems that could threaten the identification strategy. A shortcoming of this approach explained by Deschênes and Greenstone (2007) is that all the fixed effects are likely to magnify the importance of misspecification arising from measurement error, that generally attenuates the estimated parameters.

Linear and non-linear weather effects

The first specification aims at testing the linear and non-linear weather effects on subjective perceptions stated in Proposition 1. Non-linear effects are addressed by including the quadratic term (Schlenker & Roberts, 2009) and the inclusion of the standard deviation of temperature and precipitations is justified in order to infer whether changes in variability shape the awareness of climate change, given that agriculture heavily relies on the seasonality of the rainfalls and regularity of certain temperatures (Auffhammer & Carleton, 2018).

$$\omega_{iut} = \gamma_1 T_{ut} + \gamma_2 T_{ut}^2 + \gamma_3 \sigma_{ut}^T + \delta_1 R_{ut} + \delta_2 R_{ut}^2 + \delta_3 \sigma_{ut}^R + X'_{iut} \beta + \alpha_i + \alpha_u + \alpha_t + u_{iut} \quad (14)$$

where ω_{iut} is the subjective perception of a change in a climate feature. T_{ut} is the average temperature in union u at time t in the previous 5, 10 or 20 years, R_{ut} is the average precipitation in union u at time t in its previous 5, 10 or 20 years. The specification controls for a set of socio-demographic characteristics at the household level, X_{iut} , including age, sex, literacy of the head of the household, whether the head of the household is self-employed in farming activities, household size and whether the household receives information/advice from extension agents.

Growing Seasonal Effects

The second specification is formulated in order to test Proposition 2, according to which farmers' subjective perceptions to climate change are shaped heterogeneously by different historical climatic changes in the different growing seasons in Bangladesh. Studying the differences in the effects by growing seasons is becoming a standard approach in agricultural economics in developing countries (Auffhammer & Carleton, 2018; Deschênes & Greenstone, 2007). The estimated equation writes as follows:

$$\omega_{iut} = \sum_j \gamma_j T_{ut}^j + \sum_j \delta_j R_{ut}^j + \sum_j \theta_j \sigma_{ut}^{Tj} + \sum_j \zeta_j \sigma_{ut}^{Rj} + X'_{iut} \beta + \alpha_i + \alpha_u + \alpha_t + u_{iut} \quad (15)$$

where T_{ut}^j is a vector of seasonal ($j \in \{Kharif\ 1, Kharif\ 2, Rabi\}$) average temperature in union u at time t and R_{ut}^j is a vector of seasonal ($j \in \{Kharif\ 1, Kharif\ 2, Rabi\}$) cumulative precipitation in union u at time t . The specification can also be refined by matching each farmer to the growing season of reference defined as the growing season in which the household grows its main crop. The specification and the results of the refined approach are reported in the Appendix A.3.

Weather Anomalies Effects

The following specification aims at testing Proposition 3, according to which gradual and long-term

changes in climate do not shape farmers' subjective perceptions, but rather weather anomalies do. This hypothesis finds its basis on psychological literature (Druckman & Shafraneck, 2017; Joireman et al., 2010). Following Nicholson (1993) and Marchiori et al. (2012), anomalies are initially built as in Equation 1 both for precipitations and temperatures. The econometric specification writes as follows:

$$\omega_{iut} = \sum_k \gamma_k \text{Anomaly}_{ut}^k + X'_{iut} \beta + \alpha_i + \alpha_u + \alpha_t + u_{iut} \quad (16)$$

where Anomaly_{ut}^k measures the anomalies for $k \in \{\text{temperatures; precipitations}\}$ in union u in year t .

Extreme events and natural disasters

In order to test the implications of Proposition 4, according to which the frequency of extreme events and natural disasters shapes the subjective perceptions of these events, the econometric specification is designed as follows:

$$\omega_{iut} = \sum_j \gamma_j T_{ut}^j + \sum_j \delta_j R_{ut}^j + D'_{dt} \theta_D + X'_{iut} \beta + \alpha_i + \alpha_u + \alpha_d + \alpha_t + u_{iut} \quad (17)$$

where gradual long-term historical seasonal changes are now included as control, where T_{ut}^j is a vector of seasonal ($j \in \{\text{kharif 1, kharif 2, rabi}\}$) average temperature in union u in the 5-year period preceding the survey year t and R_{ut}^j is a vector of seasonal ($j \in \{\text{kharif 1, kharif 2, rabi}\}$) cumulative precipitation in union u in the 5-year period preceding the survey year t . The coefficients of interest are θ_D , where $D \in \{\text{Cold waves; Drought; Flood; Precipitation}\}$, which is the number of these extreme events and natural disasters occurred in the five-year period preceding the first round of the survey and between the two rounds in district d .

5.1.1 Confirmation Bias: An Instrumental Variable Approach

In order to test Proposition 5, on the hypothesis that farmers are subject to confirmation bias, I design a new econometric specification that adopts as outcome variable the self-reported number of weather events WE , where $WE \in \{D, F, R\}$, respectively the number of droughts, floods and changes in rainfall patterns that have adversely affected the household in the five-year period preceding the first wave and between the two survey rounds (so that the measure is round-specific). The main explanatory variable is the subjective perception ω^{WE} of a change in a climatic characteristic. The new empirical approach writes as follows:

$$WE_{iut} = \gamma \omega_{iut}^{WE} + X'_{iut} \beta + \alpha_i + \alpha_u + \alpha_t + u_{iut} \quad (18)$$

where WE_{iut} is the self-reported number of a weather event ($WE \in \{D, F, R\}$) that has negatively affected household i in union u . As discussed in Section 4, there is a two-way interaction effect between beliefs and

self-reported evidence, stemming from confirmation bias. An individual subject to confirmation bias would tend to overweight evidence that confirms her prior beliefs and reporting it in a selective manner. For this reason, Equation 18 might be subject to simultaneity bias and the estimates of the effect of perception on self-reported evidence may be upwardly biased.

In order to tackle the issue of endogeneity, a 2SLS approach is adopted by introducing an instrumental variable, namely a measure of historical objective weather. This variable would comply with the two restrictions that make valid an instrumental variable. First, the variables are relevant because it is sensible to expect a correlation between historical meteorological data and the perception of weather events, as documented and supported by the first propositions in the theoretical section. Second, these variables are expected to satisfy the exclusion restriction by entering in the function that determines individuals' memory of past weather events only through the subjective perception of these events. The validity of the instrument and the identifying assumption is thoroughly discussed below. The 2SLS approach has a first stage that mainly consists in the baseline econometric specification in Equation 13 as follows:

$$\omega_{iut}^{WE} = \pi \text{Objective Weather}_{iut} + X'_{iut}\beta + \alpha_i + \alpha_u + \alpha_t + \varepsilon_{iut} \quad (19)$$

and the second stage specified as follows:

$$WE_{iut} = \gamma \hat{\omega}_{iut}^{WE} + X'_{iut}\beta + \alpha_i + \alpha_u + \alpha_t + u_{iut} \quad (20)$$

where instrumenting the subjective perception of a weather event using the historical meteorological variables washes out the potential simultaneity bias and the concern about endogeneity. This allows to test Proposition 5 on farmers' confirmation bias in an empirically valid specification and to identify the effect of subjective perceptions on self-reported experiences of weather events as presence of a confirmation bias if the coefficient γ is positive and statistically significant.

Instrument Validity and Identifying Assumption

The nature of the variables in the empirical specification and the questions in the survey make the setting of testing confirmation bias particularly suitable for the use of an instrumental variable approach. Subjective perception of climatic change is subject to simultaneity bias and cognitive biases, that threaten the identification of its effect on individual's memory of past weather events. The use of past historical records of weather events as instrument would help strengthening the causality argument under the exclusion restriction that historical weather events do not affect self-reported evidence directly or via other channels besides beliefs. One potential concern with the specific instrument proposed here is that variation in the instrument has an additional indirect effect on self-reported evidence through the omitted variable of subjective well-being. According to the literature on climate effects on self-reported life satisfaction (Maddison & Rehdanz, 2011),

the 2SLS estimates might underestimate the effect of the bias stemming from perceptions on self-reported evidence. This could happen since weather has an effect on mood (Cunningham, 1979) which could in turn affect memory of past weather events (Forgas, Goldenberg, & Unkelbach, 2009) and thus threaten the exclusion restriction because of an omitted variable bias. Nevertheless, studies with a similar econometric specification as in this paper (Feddersen, Metcalfe, & Wooden, 2016) do not detect a relationship between climate and self-reported life satisfaction when using an individual fixed effects specification and they show that the effect of climate on self-reported life satisfaction is close to zero. These results in the literature allay the potential concern on the validity of the instrument.

Another potential concern about the exclusion restriction is that historical meteorological data affect the individual's memory of past weather events through the adaptation undertaken in past periods. This concern would arise if past weather affects past actions, which would in turn impose historical restraints on current actions. In order to allay the potential concern on the validity of the instrument, the econometric specification includes a long history of transient shocks that would reduce the bias introduced by historical restraints (Lemoine, 2018).

5.2 Second-Step: Behavioral Response

5.2.1 Do beliefs affect behavior?

In the theoretical framework in Section 4.2, the hypothesis is that if subjective probabilities deviate from objective probabilities, then increases in the subjective probability of the realization of the state s are associated with a higher probability of making the optimal decision that maximizes the utility. In the case of realization of the state $s_t = 1$, the optimal decision that maximizes the utility is to undertake an adaptation strategy, $a_t^* = 1$. If this was not the decision taken, this would lead to a lower contemporaneous utility. I posit that by controlling for the objective probabilities of a shock, represented by the coefficient of variation in temperature and precipitation, and for contemporaneous and historical weather shocks, the first moment of the weather distribution, I can identify the causal effect of subjective probability of climate change on the implementation of adaptation strategies.

The following econometric specification aims to directly explore the testable implications of the theory presented in Section 4.2:

$$a_{iut} = \zeta_{perc} \text{Perception}_{iut} + \gamma_1 f(w_{ut}) + \gamma_2 f(w_{ut-\tau}) + \zeta_2 CV_{ut}^R + \zeta_3 CV_{ut}^T + \theta_D D_{dt} + X'_{iut} \beta + \alpha_i + \alpha_u + \alpha_d + \alpha_t + u_{iut} \quad (21)$$

where a_{iut} is an indicator variable that indicates whether the household has implemented an on-farm adaptation strategy to climate change (changes in crop variety, increases in irrigation rate, changes in planting dates, increases in fertilizer rate). A function of contemporaneous weather variables $f(w_{ut})$ and a function of historical weather variables $f(w_{ut-\tau})$ are included in the specification. These variables are included in

order to control for the direct and indirect impact that historical and current weather can have on the probability of implementing an adaptation strategy and on shaping subjective perceptions of climate change through realised shocks (Alem & Colmer, 2018). For a similar reason, extreme events and natural disasters ($D \in \{\text{Droughts; Floods}\}$) are also included in the specification, in order to control for shocks that are beyond the level of rainfall and temperature experienced, whereas accounting for the first-moment relationship between weather and adaptation decision might not be sufficient to isolate the effect of subjective and objective risk.

The equation includes a set of household-level controls that is now extended. Besides socio-demographic characteristics already included in the specification of subjective perceptions, such as age, sex, literacy of the head of the household, whether the head of the household is self-employed in farming activities and household size, the equation includes economic and agricultural characteristics that can have an impact on the adaptation decision-making process of the household (Eskander et al., 2016). Controls included are a proxy for credit constraint (defined as log one plus unpaid loans of the household), an indicator variable for the ownership of a tractor, an indicator variable for the ownership of other agricultural assets and an indicator on whether the household receives information on agricultural extension from formal sources, defined as television, newspapers and radio. The additional household characteristics included as controls could shed light on interesting mechanisms in the adaptation decision-making process. For example, the coefficient associated to receiving formal information (defined as receiving information from TV, radio or newspaper) might play a role when studying adaptation strategies. In fact, farmers could extract knowledge from this formal channel that can help them make a more informed choice in the adaptation decision-making process (Aker, 2011). The credit constraint is expected to have a negative impact on the adaptive capacities of an household, in particular, when households adapt by changing crop variety or using more fertilizer, that usually would imply making further use of the borrowing market. On the other hand, credit constraints should not have an impact on adaptation strategies as changes in planting dates. The ownership of a tractor and of other agricultural assets are expected to have a positive effect on adaptation by changes in crop variety, reflecting the household's ability to invest and the importance of agriculture (Abid et al., 2015).

The econometric specification also includes a full-set of individual, union, district and year fixed effects $\{\alpha_i; \alpha_u; \alpha_d; \alpha_t\}$, in order to wash out all the potential unobserved heterogeneity at any of these levels. Standard errors are clustered at the household-level to account for correlation and heteroskedasticity within households.

The coefficients of interest in Equation 21 are ζ_s , that proxy for subjective and objective climate change risk. Objective uncertainty is modelled as in Alem and Colmer (2018) by the coefficient of variation. The novelty stands in the introduction of such a coefficient also for temperature measures, as adaptation strategies such as changes in planting dates can be driven by uncertainty in temperatures. This is also because there is a high degree of correlation between atmospheric parameters and the integration of temperature variables should strip away as much residual variation as possible, allaying any first-order concerns (Auffhammer

et al., 2013). The coefficient of variation is measured as the standard deviation divided by the mean in the five-year period preceding the first wave of the survey and between the two waves of the survey to ensure that variation is round-specific. Subjective uncertainty is defined by the vector $Perception_{iut}$, that is modelled as the outcome variable in the first-step, i.e., an indicator variable for each of the features of climate in which individual i has perceived a change. Given that the focus is on a specific subset of on-farm adaptation strategies (change in crop variety, more irrigation, change in planting dates and higher rate of fertilizer), the five subjective perceptions included in the specification should not all have a statistically significant impact on the implementation of adaptation strategies, but the effect of subjective perceptions on adaptation strategies should be limited to perceived increases in droughts, changes in rainfall patterns and decreases in precipitation (Gorst et al., 2018). Equation 21 tests empirically Proposition 6 by positing that the probability of adapting should be weakly increasing in the subjective probability $\hat{\omega}$ of changes in rainfall patterns, decreases in precipitation and increases in droughts.

This empirical setting has a direct correspondence with the theoretical framework developed in Section 4, in particular Equation 9, under the assumption that there is a mapping between weather and adaptation strategies, such that

$$U(a_{it}) = \underbrace{\sum_{\tau=1}^{t-1} \beta^\tau u(\text{weather}_{it-\tau})}_{\text{historical weather}} + \underbrace{\beta^t u(\text{weather}_{it})}_{\text{contemporaneous weather}} + \hat{\mathbb{E}} \left[\underbrace{\sum_{\tau=t+1}^T \beta^\tau u(\text{weather}_{it+\tau|s_t})}_{\mathbb{E}(\text{future weather})} \right] \quad (22)$$

where, by controlling for historical and contemporaneous effects of weather, the effect of subjective and objective probabilities of future weather events on the adaptation decision-making process through anticipatory utility can be discerned. Figure A3 illustrates the main relationships identified in the empirical approach for the determinants of the present actions at time t , i.e., the implementation of adaptation strategies. Present actions depend on future, present and past weather, where the potential bias introduced by historical restraints is ruled out by using a history of transient shocks (Lemoine, 2018).

5.2.2 Accuracy

The proxy for accuracy in the theoretical model is $\nu = |\hat{\omega} - \omega|$. In the spirit of Giné et al. (2015), the accuracy of beliefs in the data is measured by computing a chi-square statistic. This is the accepted test for differences between two binned distributions from two data sets. Let O_k be the observed value of number of weather event k reported from historical meteorological data in the last 5 years. Let E_k be the number of weather events self-reported by the head of the household in the survey. These two values enter in the chi square computation respectively as the number of events observed and the number expected according to some known distribution. Following Flannery, Press, Teukolsky, and Vetterling (1992), because of the binned nature of the two data sets, the denominator is normalized as the sum of O_k and E_k rather than the average. Each term in a chi-square sum is supposed to approximate the square of a normally distributed

quantity with unit variance and the variance of the difference of two normal quantities is the sum of their individual variances. The chi-square statistic writes

$$\chi_c^2 = \sum_k \frac{(O_k - E_k)^2}{O_k + E_k} \quad (23)$$

where c are the degrees of freedom, equal to the number of bins k , (the type of weather events), since the sum of the O_k 's is not necessarily equal to the sum of E_k 's. This approach allows to consider the chi-square statistic as a measure of association in a contingency table analysis of two data sets, that are assumed to be taken from the same unknown distribution.

The econometric specification that tests empirically Proposition 7 writes as follows:

$$a_{iut} = \zeta_\chi \chi_{idt}^2 + \gamma_1 f(w_{ut}) + \gamma_2 f(w_{ut-\tau}) + X'_{iut} \beta + \alpha_i + \alpha_u + \alpha_d + \alpha_t + u_{iut} \quad (24)$$

The more accurate the farmer, the more likely that she undertakes an adaptation strategy. In other words, the probability of adapting is weakly increasing in the accuracy. This means that ζ_χ should be negative, since higher χ_{idt}^2 values are associated with larger differences between the prior subjective and historical distribution of weather events and natural disasters.

6 Results

This section presents the main results. Section 6.1 shows some of the most interesting results of the theoretical propositions on the heterogeneous impact of historical climatic changes by growing seasons, the effect of weather anomalies and natural disasters and an empirical test of the confirmation bias. Section 6.2 shows the results of the estimation of the effect of beliefs and accuracy of beliefs on the implementation of adaptation strategies. Section 6.3 summarizes the robustness checks conducted, that are described in detail in the Appendix.

6.1 Heterogeneous impact of weather events on subjective perceptions

The empirical results of Proposition 1 testing whether historical weather has an impact on subjective perceptions are reported in the Appendix to save space (see Table A4). In a nutshell, results seem to confirm the validity of Proposition 1, according to which farmers' subjective perceptions of climate change are driven by historical weather, concluding that the longer the time dimension considered for historical meteorological changes, the higher the explanatory power of weather on perceptions.

Table 7 displays the estimation results for the specification in Equation 15 that empirically tests the implications of Proposition 2. Average temperature, total precipitation and their standard deviation are included in the specification for each of the growing seasons in Bangladesh. This specification aims at concluding whether experienced weather in the year of interview affects heterogeneously farmers' perceptions

depending on the growing season in which variations occur. Overall, there is enough heterogeneity in the effect across growing seasons on subjective perceptions. For example, increases in total precipitations affect the probability of perceiving increases in flood in different ways depending on the growing season in which they occur: an increase in the precipitation in the pre-monsoon season, *Kharif 1*, decreases the probability of perceiving an increase in floods (column (1)), but it increases the probability of perceiving an increase in the variability of rainfalls (column (4)). A potential explanation for this result is that one would tend to expect higher levels of rainfall in the monsoon season, therefore increases in precipitations during this season affect negatively the perception of increases in floods. This is confirmed by the fact that the coefficient associated to precipitation in the monsoon season, *Kharif 2*, is not statistically significant in the specification using perceived erratic rainfalls as outcome variable. Curiously, the coefficients associated to average temperatures in pre-monsoon and monsoon seasons are negative and statistically significant in the specification concerning a perceived increase in droughts (column (2)) and an increase in the average temperature in the winter season, *Rabi*, is associated with an increase in the probability of perceiving an increase in cold (column (3)). There is another counterintuitive result in the specification of subjective perceived increases in erratic rainfall (column (4)), in which the coefficients of the standard deviations of precipitations in each growing season are negatively associated with perceived increases in erratic rainfall and, similarly, increases in precipitation in the winter season is positively associated with perceived decreases in precipitations (column (5)). Overall, farmers' subjective perceptions of climate change seem to be heterogeneously shaped by climatic changes by growing seasons and the results confirm Proposition 2. However, some results might seem quite counterintuitive, calling for more work on cognitive biases and farmers' misperceptions. Results might also suggest that the integration of other measures of historical weather as explanatory variables could be adequate. In particular, the standardized precipitation evapotranspiration index (SPEI) for drought assessment (Miah, Abdullah, & Jeong, 2017) or an actual measure of flood exposure (Guiteras, Jina, & Mobarak, 2015) may be more powerful predictors for subjective perceptions of droughts and floods.

Table 7: Growing Season Climatic Changes and Subjective Perceptions

	Dependent Variable: <i>Subjective Perception</i>				
	(1) Increase Flood	(2) Increase Drought	(3) Increase Cold	(4) Erratic Rainfalls	(5) Decrease Precipitations
Total prec in Kharif 1	-0.00129*** (0.000360)	0.000124 (0.000362)	-0.000644* (0.000355)	0.00184*** (0.000386)	0.000321 (0.000387)
Total prec in Kharif 2	0.000441 (0.000269)	-0.000586** (0.000294)	0.000194 (0.000310)	0.000434 (0.000317)	0.000262 (0.000300)
Total prec in Rabi	-0.00758* (0.00399)	0.00256 (0.00427)	0.00354 (0.00461)	-0.00263 (0.00532)	0.0146*** (0.00490)
SD prec in Kharif 1	0.00308*** (0.000986)	-0.000597 (0.000983)	0.00149 (0.000913)	-0.00353*** (0.00106)	-0.00156* (0.000928)
SD prec in Kharif 2	-0.00142* (0.000790)	0.000117 (0.000913)	-0.000972 (0.000877)	-0.00381*** (0.00110)	0.000649 (0.000919)
SD prec in Rabi	0.0245*** (0.00854)	0.00497 (0.00888)	-0.00973 (0.00919)	-0.00802 (0.00980)	-0.0297*** (0.00915)
Avg temp in Kharif 1	0.0206 (0.138)	-0.312** (0.131)	-0.277** (0.129)	0.510*** (0.135)	-0.243 (0.149)
Avg temp in Kharif 2	1.250** (0.627)	-1.011* (0.600)	-0.603 (0.573)	-0.776 (0.605)	-1.165** (0.582)
Avg temp in Rabi	-0.175 (0.361)	0.486 (0.384)	0.672* (0.374)	0.512 (0.440)	0.654 (0.444)
SD temp in Kharif 1	-0.287*** (0.0875)	0.264*** (0.0871)	-0.124 (0.0976)	0.193* (0.103)	0.0928 (0.0990)
SD temp in Kharif 2	-0.487* (0.279)	-0.144 (0.276)	0.0280 (0.269)	0.543* (0.301)	0.0472 (0.294)
SD temp in Rabi	0.105 (0.384)	-0.743* (0.419)	0.215 (0.457)	0.969* (0.521)	-0.257 (0.461)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1428	1428	1428	1428	1428
adj. <i>R</i> ²	0.074	0.458	0.056	0.325	0.438

Notes: Clustered-robust standard errors at household-level. Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8 displays the estimation results for the econometric specifications in Equation 16 that aimed at testing Proposition 3, formulated on the basis of the psychological literature (Druckman & Shafraneck, 2017; Joireman et al., 2010). Anomalies for temperature and precipitation are built in such a way that they capture deviations in the weather from the norm. Results, however, seem not to provide empirical evidence for this hypothesis. For example, counterintuitively, a one standard deviation increase in precipitation leads to a 13.7 percentage points decrease in the probability of perceiving an increase in floods (column (1)). Similarly, a one standard deviation increase in precipitation is associated with a 11.9 percentage points decrease in the probability of perceiving an increase in cold (column (3)). Likewise, a one standard deviation increase in precipitation is associated with a 13.3 percentage points increase in the probability of perceiving a decrease in precipitations and a one standard deviation increase in temperature is associated with a 17.4 p.p. increase in the probability of perceiving a decrease in precipitations (column (5)). Keeping in mind that the specification is a linear probability model and therefore predicted values of the outcome variables are not bounded within the probability interval between 0 and 1, and coefficients are the marginal effects, the magnitude of these effects is considerably large, despite being counterintuitive. A refinement of the construction of the measures

of anomalies is built following Coniglio and Pesce (2015) and results are displayed in the Appendix in Table A17 to save space. In particular, it is interesting the bidirectional effect of the two precipitation anomalies on the subjective perception of more erratic rainfalls (column (4)): positive precipitation anomalies have a positive and statistically significant coefficient, whereas negative precipitation anomalies have a negative and statistically significant coefficient, suggesting that farmers are more oriented to perceive a change in rainfall variability with an increase in anomalies related to abundant rainfalls. Moreover, as one would expect, positive anomalies of temperature have a negative and statistically significant effect on the perceived increase in cold (column (3)), whereas it is more surprising a similar coefficient associated to positive temperature anomalies and negative precipitation anomalies in the specification that considers subjective perceptions of an increase in droughts (column (2)). Overall, it seems that distinguishing between anomalies above or below one standard deviation from the long-term mean contributes to better characterize the effect of anomalies on subjective perceptions.

Table 8: Subjective Perceptions and Anomalies à la Marchiori, Maystadt, and Schumacher (2012)

	Dependent Variable: <i>Subjective Perception</i>				
	(1)	(2)	(3)	(4)	(5)
	Increase Flood	Increase Drought	Increase Cold	Erratic Rainfalls	Decrease Precipitations
Temperature Anomaly	-0.0253 (0.0440)	-0.00865 (0.0457)	0.0734 (0.0482)	-0.0240 (0.0561)	0.174*** (0.0469)
Precipitation Anomaly	-0.137** (0.0659)	0.0478 (0.0687)	-0.119* (0.0617)	0.0161 (0.0870)	0.133* (0.0746)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1428	1428	1428	1428	1428
adj. <i>R</i> ²	0.011	0.448	0.087	0.253	0.420

Notes: Clustered-robust standard errors at household-level. Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9 displays the estimates of the specification that tests Proposition 4 about the effect of extreme events and natural disasters on subjective perceptions. The econometric specification is reported in Equation 17. Controlling for historical gradual weather changes, the coefficients of interest are those associated with the number of cold waves, droughts, floods and precipitation events as reported by the EM-DAT in the five-year period preceding the first round of interview and between the two rounds. Overall, the estimates seem to be aligned with the logical hypotheses and results seem to be coherent, confirming Proposition 4. The extreme weather event that appears to have a statistically significant effect across different subjective perceptions is drought. In particular, drought events tend to decrease the probability of perceiving an increase in flood and increase the probability in perceiving increases in droughts, in erratic rainfalls and in decreases in precipitations. Interestingly, an increase in the number of cold waves events is negatively associated with the subjective perception of increases in cold (column (3)) and also with perceived increases in erratic rainfall (column (4)). Flood events have a negative and statistically significant effect on perceived increases in droughts (column (2)) and on perceived decreases in precipitations (column (5)).

Table 9: Subjective Perceptions and Extreme Weather Events

	Dependent Variable: <i>Subjective Perception</i>				
	(1) Increase Flood	(2) Increase Drought	(3) Increase Cold	(4) Erratic Rainfalls	(5) Decrease Precipitations
Cold Waves	0.0139 (0.0270)	-0.0365 (0.0290)	-0.0663** (0.0318)	-0.0921*** (0.0351)	0.0169 (0.0297)
Droughts	-0.226** (0.0888)	0.188** (0.0776)	-0.132 (0.0955)	0.212** (0.0995)	0.146* (0.0836)
Floods	-0.00110 (0.0221)	-0.0943*** (0.0207)	0.00701 (0.0252)	-0.0380 (0.0251)	-0.0417* (0.0252)
Precipitations	0.0208 (0.0168)	-0.0241 (0.0188)	-0.00510 (0.0187)	-0.0153 (0.0212)	-0.0213 (0.0190)
Weather Controls	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1428	1428	1428	1428	1428
adj. <i>R</i> ²	0.024	0.463	0.044	0.272	0.417

Notes: Clustered-robust standard errors at household-level. Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Weather Controls: Average temperature and precipitation in Kharif 1, Kharif 2 and Rabi in 5-year period before first round of the survey and in the period between the first and second round. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Besides the explanatory power that controls such as age, literacy, extension advices are documented to have on farmers' subjective perceptions of climate change (Deressa et al., 2011), the inclusion of socio-economic characteristics in all the results displayed so far is also motivated by the contribution of these variables to the adjusted R^2 of the specifications. In fact, specifications that include only historical weather and fixed effects have lower predictive power compared to the same specifications with historical weather, fixed effects and socio-economic controls⁹. For this reason, a thorough analysis on the factors that shape subjective perceptions of climate change should also include individual socio-economic covariates when assessing the effect of personally experienced climate change and weather anomalies (Weber, 2016).

Confirmation Bias

Table 10 displays the OLS estimates of the specification in Equation 18, that tests Proposition 5, on farmers being subject to confirmation bias. The estimates of the three variables of subjective perceptions reveal that there is a positive relationship between the subjective perception of a change in a climatic characteristic and the self-reported number of weather events experienced by the household¹⁰. The results seem to follow the logical intuition and provide evidence for the presence of confirmation bias in perception of extreme events such as floods and droughts (column (1) and (2)).

⁹The adjusted R^2 is systematically higher in the specifications including also socio-economic controls by around 5 p.p. on average. This value is pulled downwards because of the recurring systematically low explanatory power of the specifications on subjective perceptions of increases in floods and in cold, which could be motivated by the low rate of perception of such events (see Table 3) among farmers that might generate more noise from measurement error or misestimations.

¹⁰Specifications including subjective perception of increase in cold and subjective perception of decrease in precipitation are excluded since in the survey farmers are not asked to self-report the number of cold waves or decreases in precipitation experienced.

Table 10: Confirmation Bias: OLS Estimates

	Dependent Variable: <i>Self-Reported Evidence</i>		
	(1) Flood	(2) Drought	(3) Erratic Rain
Perception	0.316*** (0.111)	0.220** (0.0868)	0.0574 (0.0512)
Household Controls	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
adj. R^2	0.129	0.034	0.064
Dep Var Mean	0.402	0.378	0.060
Dep Var SD	0.922	0.778	0.439
N	1428	1428	1428

Notes: Clustered-robust standard errors at household-level. Household Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Weather Controls: Historical Average of temperature and precipitation in the 20-year period preceding the interview. Each column reports the estimate for the coefficient associated to the subjective perception of a change in the occurrence of a climatic characteristics, i.e., subjective perception of an increase in floods, in droughts and of more erratic rainfall. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The use of subjective perceptions as explanatory variables makes the specification potentially subject to simultaneity bias, which may threaten the identification of their effect. As discussed in Section 5 historical weather is therefore used as instrumental variable in order to identify the causal effect of subjective perceptions on self-reported experiences of weather events and provide more robust evidence of the presence of confirmation bias. Table 11 reports the 2SLS estimates of the specification in Equation 20 and the first-stage estimates that use as instrument the historical weather variables. Starting from the first stage, the relationship between historical average precipitation and subjective perceptions is negative and statistically significant, except for the case of subjective perceptions of erratic rainfall where the coefficient associated to the instrument is positive and statistically significant. The KP F-stat for weak instruments is above conventional levels for all specifications, even though some caution is needed when interpreting the results in column (2) where the F-stat is closer to the critical level of acceptance.

2SLS estimates confirm OLS results and indicate the existence of a positive relationship between subjective perceptions and self-reported evidence even when controlling for historical transient shocks, in order to rule out the potential bias stemming from historical restraints (Lemoine, 2018). Farmers seem to be subject to confirmation bias, with a statistically significant coefficient associated to the subjective perception of an increase in droughts and in erratic rainfalls (columns (2) and (3)).

Table 11: Confirmation Bias: 2SLS Estimates

Dependent Variable: <i>Self-Reported Evidence</i>			
	(1) Flood	(2) Drought	(3) Erratic Rain
Perception	0.478 (1.082)	4.722** (2.347)	0.767* (0.414)
K-P F-stat	9.138	7.616	9.727
SW F-stat	9.14	7.62	9.73
Household Controls	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
<i>First-Stage Estimates for Perception</i>			
Objective Weather	-0.00734*** (0.00243)	-0.00148** (0.000689)	0.00884*** (0.00283)
Household Controls	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
<i>N</i>	1428	1428	1428

Notes: Clustered-robust standard errors at household-level. Household Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Weather Controls: Historical Average of temperature and precipitation in the 20-year period preceding the interview. Each column reports the estimate for the coefficient associated to the subjective perception of a change in the occurrence of a climatic characteristics, i.e., subjective perception of an increase in floods, in droughts and of more erratic rainfall. The historical average precipitation in the 5-year period preceding the first round and between the two waves of the survey is used as an instrument. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.2 Beliefs, Accuracy and Behavioral Response

This section reports the results of the empirical testing of the theoretical propositions concerning the behavioral response of farmers to changes in subjective probabilities and in their accuracy of beliefs. The estimates for the baseline econometric specification in Equation 21 are displayed in Table A20 to save space and are summarized here, before showing and discussing the main results based on growing season variability in Table 12.

The coefficients of interest are those related to subjective and objective probabilities for an individual. The theoretical model predicts that if the subjective probability of realization of weather events does not coincide with the objective true probability, the decision made by the farmer on adapting depends on the subjective perception of climate change, such that the subjective belief has a direct effect on the probability of adapting. The effect of self-reported subjective perceptions can be interpreted under the assumption that measurement-error problems are not dominant, and potential cognitive problems leading to measurement problem would not produce bias since the appropriate controls (i.e. year- and individual-specific dummies) are included (Bertrand & Mullainathan, 2001). By controlling for historical and contemporaneous rainfall and temperature and for the occurrence of natural disasters and extreme events, any residual variation in rainfall and temperature variability captures the direct effects of objective probabilities on the implementation of adaptation strategies.

Since the implementation of one of the four adaptation strategies considered is not mutually exclusive, it is not possible to implement a multinomial logit estimation, unless all potential mixes of adaptation strategies were also considered. The coefficients associated to subjective perceptions are aligned with the theoretical predictions and of sizeable magnitude. In Table A20 as expected, the coefficient associated to the subjective perception of increases in floods is not statistically significant in three out of the four specifications and has a positive and statistically significant effect on the probability of changing planting dates as adaptation strategy. Since the focus is on on-farm adaptation strategies, higher perception of flood events should not have effects on the implementation of such adaptation strategies, whereas the literature (Gray & Mueller, 2012; Guiteras, 2009) agrees that more effective adaptation strategies to flooding would be migration or the construction of diversion ditches. A subjectively perceived increase in droughts is associated with an increase in the probability of changing planting dates and using more fertilizer, *ceteris paribus*. Similarly, farmers who perceive erratic rainfall are more prone to change crop variety (column (1)), increase the rate of irrigation (column (2)) and change planting dates (column (3)). Finally, a subjectively perceived decrease in precipitation is positively associated with an increase in irrigation rate (column (2)) and in fertilizer rate (column (4)). Overall, it seems that subjective perceptions on changes in rainfall patterns are a powerful predictor of the implementation of on-farm adaptation strategies, supporting the hypothesis that changes in patterns of weather variables, besides levels, should be taken into account (Maddison, 2007).

The results show that, when accounting for the variation in probability of adapting associated with historical weather effects, there is not substantial residual variation captured by the proxy for objective

uncertainty. The coefficients associated to the temperature and rainfall variability are both significant at conventional levels only in the case of adapting by changing planting dates and with opposite direction: temperature variability has a positive coefficient, whereas precipitation variability has a negative coefficient. Rainfall variability is also significant when considering adaptation by changes in crop variety and increases in the rate of fertilizer, respectively with a positive and negative effect. The latter case might be explained by the fact that water and fertilizers are complements and an increase in precipitation variability, with more risk in not getting enough water or getting too much, could decrease the probability of adapting by using more fertilizer.

Table 12 displays the estimates for the refined econometric specification in Equation 21 that differentiates the coefficients of variation of temperature and precipitation by growing seasons. This empirical analysis is novel and, based on the results in Section 6.1, variability by growing season can have an important role in the adaptation decision-making process. Moreover, the use of growing seasons for the objective measures of variability increases the overall explanatory power of the estimations. The theoretical model predicts that the subjective probabilities of realization should have a direct effect on the probability of adapting, if they do not coincide with the true probability by growing season. The coefficients associated to subjective probabilities are still significant at conventional levels and maintain the same directions and similar magnitudes across the four different specifications. When statistically significant, the effect of subjective probabilities on the implementation of adaptation strategies is always positive and has an average magnitude of around 13 p.p. across the specifications. Objective temperature and precipitation variability by growing season have heterogeneous effects in direction and magnitude on the probabilities of implementing any of the adaptation strategies considered. For example, increases in the temperature variability in the pre-monsoon season *Kharif 1* lead to decreases in the probability of increasing the rate of fertilizer (column (4)). Increases in the temperature variability in the monsoon season *Kharif 2* have a negative and statistically significant effect on the probability of changing crop variety (column (1)), increasing the rate of irrigation (column (2)) and changing planting dates (column (3)). A similar results holds for increases in the temperature variability in the winter season *Rabi*. Precipitation variability in *Rabi* has a positive and statistically significant effect on changes in crop variety, increases in the rate of irrigation and changes in planting dates. Likewise, precipitation variability in *Kharif 2* has a positive and statistically significant effect on changes in crop variety. Overall, the positive relationship between precipitation variability and implementation of adaptation strategies seems to confirm the theoretical hypothesis and to show a tendency to adjust the cropping calendar in order to synchronize crop planting and the growing period with changes in rainfall patterns, change crop variety for example towards more drought-tolerant and resistant to erratic rainfall varieties and to optimize water-use efficiency by increasing the rate of irrigation. The agricultural data in BCCAS preclude further investigation based on the specific crop in each season in order to distinguish the cropping season in which the newly adopted crop grows or whether changes in planting dates entail earlier or later shifts in the growing seasons of reference. This is left for future research.

Table 12: Adaptation Strategies and Variations by Growing Season

	Dependent Variable: <i>Adaptation Strategy</i>			
	(1) Crop Variety	(2) More Irrigation	(3) Planting Dates	(4) More Fertilizer
Subj. Increase Flood	-0.0107 (0.0491)	-0.0424 (0.0471)	0.120** (0.0527)	0.0715 (0.0537)
Subj. Increase Drought	-0.0711 (0.0461)	0.0649 (0.0420)	0.109** (0.0499)	0.133*** (0.0513)
Subj. Increase Cold	0.0330 (0.0458)	0.0135 (0.0416)	-0.0529 (0.0522)	-0.0651 (0.0465)
Subj. Erratic Rainfall	0.135*** (0.0407)	0.163*** (0.0374)	0.126*** (0.0454)	0.0513 (0.0459)
Subj. Decrease Precipitation	-0.00105 (0.0481)	0.113*** (0.0410)	-0.0295 (0.0480)	0.121*** (0.0462)
CV Temperature Kharif 1	-26.64 (28.58)	-7.274 (24.57)	-22.71 (30.60)	-55.75* (28.58)
CV Temperature Kharif 2	-134.7*** (33.93)	-55.08* (31.27)	-77.00** (35.92)	15.32 (37.07)
CV Temperature Rabi	-72.61* (39.47)	-90.89*** (29.55)	54.63 (40.24)	-28.96 (37.46)
CV Precipitation Kharif 1	-1.822 (1.449)	-5.182*** (1.223)	-2.669* (1.398)	-2.531* (1.407)
CV Precipitation Kharif 2	3.926*** (1.305)	0.267 (1.016)	-0.799 (1.432)	-2.103 (1.477)
CV Precipitation Rabi	1.740* (0.910)	1.784** (0.837)	3.823*** (0.978)	-0.163 (1.067)
Receive Formal Information	-0.00197 (0.0538)	-0.0151 (0.0462)	0.185*** (0.0578)	-0.0580 (0.0524)
Log Unpaid Debt	-0.0216*** (0.00669)	-0.00904 (0.00641)	0.0130* (0.00729)	-0.00199 (0.00733)
Tractor Ownership	0.619*** (0.225)	0.195 (0.161)	-0.0973 (0.217)	0.297 (0.223)
Other Agricultural Assets Ownership	0.113** (0.0470)	-0.00139 (0.0503)	-0.0709 (0.0587)	0.0297 (0.0585)
Historical Weather Controls	Yes	Yes	Yes	Yes
Current Weather Controls	Yes	Yes	Yes	Yes
Disaster Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
<i>N</i>	1428	1428	1428	1428
adj. <i>R</i> ²	0.285	0.411	0.130	0.131

Notes: Clustered-robust standard errors at household-level. Household Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Historical Weather Controls: Average temperature and average total precipitation over the past 20-year period. Current Weather Controls: Average temperature and average total precipitation in growing seasons of reference in year of interview and in previous year. Disaster Controls: Number of drought and flood events. Fixed Effects: Household, Union, District, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Finally, I test Proposition 7 of the model: inaccuracy on subjective probabilities increases the scope for mistakes in the optimal decision to adapt. In other words, inaccurate farmers, who have larger differences between the prior subjective and historical distribution of weather events and natural disasters, are more likely not to implement adaptation strategies. Table 13 displays the estimation results for the econometric specification in 24. The regressor of interest is χ^2 , the chi-square statistic computed according to the formula in Equation 23 for head of household i in district d in year of interview t . Lower accuracy in beliefs (i.e. an increase in χ^2) results in a lower probability of adapting by changing crop variety (column (1)). Similarly, more inaccurate farmers are less likely to change planting dates or increase the rate of fertilizer, although the coefficient is not statistically significant. The specification controls for the same set of household characteristics and historical and contemporaneous weather as in Equation 21 whose coefficients are omitted for the sake of brevity.

The coefficients associated to the additional household-level controls seem to support the hypotheses formulated in Section 5 on their direction and statistical significance both in Tables 12 and 13. The ownership of agricultural assets and tractors makes farmers more likely to adapt by changing crop variety compared to changing planting dates, whereas farmers with credit constraint seem to be more likely to adapt by changing planting dates. A final remark concerns agricultural extension services. Even when including in the specification a more precise type of agricultural extension service such as the formal information from TV, newspapers and radio, the coefficient associated is statistically significant and positive only for adaptation by changes in planting dates. This might suggest that current agricultural extension services may not be as effective as they could be (Duflo, Kremer, & Robinson, 2011). An improvement of such services could help to educate farmers on the different characteristics of the natural events and how to cope with them through different adaptation strategies.

6.3 Robustness Checks

In this section, I summarize the additional exercises performed to probe the robustness of the findings, which are described in more detail and presented extensively in Appendix A.3 and A.4. First, I match each household with the growing season in which the main crop is grown and verify that the main results of the effect of weather on subjective perceptions is robust to the focus on the growing season in which the household grows its main crop. Results are displayed in Table A5 and test the robustness of Propositions 1 and 2. Changes in standard deviation of temperature seem to be a persistent driver of subjective perceptions, whereas changes in average temperature and total precipitation do not have a significant effect on any subjective perception except for the counterintuitive positive effect on the subjective perception of a decrease in precipitations, as already found in Table 7. Further robustness checks test that short-term (1- and 5-year differences) and long-term (10- and 20-year differences) deviations in seasonal cumulative precipitation and average temperature shape farmers' subjective perceptions. The specification and the results are reported in the Appendix (Tables A6, A7, A8 and A9). Specifications are also refined by matching each household with the short-term and

Table 13: Accuracy and Adaptation Strategies

	Dependent Variable: <i>Adaptation Strategy</i>			
	(1) Crop Variety	(2) More Irrigation	(3) Planting Dates	(4) More Fertilizer
χ^2	-0.0190** (0.00790)	0.00510 (0.00753)	-0.00488 (0.00909)	-0.00155 (0.00866)
Receive Formal Information	-0.0107 (0.0528)	-0.00723 (0.0474)	0.167*** (0.0602)	-0.0410 (0.0532)
Log Unpaid Debt	-0.0245*** (0.00657)	-0.0127* (0.00670)	0.0137* (0.00743)	-0.00394 (0.00726)
Tractor Ownership	0.722*** (0.226)	0.170 (0.153)	-0.119 (0.228)	0.234 (0.211)
Other Agricultural Assets Ownership	0.104** (0.0466)	0.0200 (0.0517)	-0.0688 (0.0596)	0.0482 (0.0603)
Historical Weather Controls	Yes	Yes	Yes	Yes
Current Weather Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428
adj. R^2	0.240	0.347	0.065	0.115

Notes: Clustered-robust standard errors at household-level. Household Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Historical Weather Controls: Average temperature and average total precipitation over the past 20-year period. Current Weather Controls: Average temperature and average total precipitation in growing seasons of reference in year of interview and in previous year. Fixed Effects: Household, Union, District, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

long-term deviations in average temperature and cumulative precipitations in the growing season in which the main crop is grown (Tables [A10](#), [A11](#), [A12](#) and [A13](#)). An additional robustness test entails the use of different time horizons in the assessment of the heterogeneous effect of temperature and precipitations on subjective perceptions by growing season. Tables [A14](#), [A15](#) and [A16](#) report the estimates using respectively a 5-, 10- and 20-year time dimension.

The robustness of Proposition 3 is tested by refining the definition of temperature and precipitation anomalies as in Coniglio and Pesce ([2015](#)). Results are reported in Table [A17](#).

Robustness checks on the validity of Proposition 5, concerning the presence of confirmation bias, are also conducted. In particular, the econometric specification considers as outcome variable the difference between the number of self-reported flood and drought events by the household and the historical objective number of these events occurred in the same time frame in the district of the household as reported by the EM-DAT database^{[11](#)}. OLS and 2SLS estimates are displayed in Tables [A18](#) and [A19](#), confirming that farmers are subject to confirmation bias when reporting droughts events.

In the attempt to identify the causal effect of subjective probabilities on adaptation strategy, I define the main regressor of interest in other alternative manners. The first one builds a vector Perceptions_{iut} , that is an unweighted average of the five indicator variables about subjective perception of climate change used

¹¹The focus is only on these two weather events since these events are the only both reported in the survey and in the EM-DAT database.

separately in Equation [21](#) so that Perceptions $\in \{0, 0.2, 0.4, 0.6, 0.8, 1\}$, for individual i in union u in year of interview t . Results are displayed in Panel A in Table [A21](#). The coefficient associated to the vector of perceptions is positive and statistically significant at any conventional level for all four specifications. For example, an increase by one unit in the vector of perceptions (meaning that a farmer perceives all five features of climate change) results in a 22.1 p.p. increase in the probability of changing crop variety, *ceteris paribus* (column (1)). These results can be interpreted under the assumption that all five features of climatic changes go in the same direction of a intensifying climate change (therefore a higher value corresponds to a farmer with more accurate subjective probabilities) and that the function of the vector Perceptions is linear.

An additional robustness test is conducted by creating an index of subjective perception as a result of a principal component analysis on the five subjective perceptions of an individual. The Perception index extracted is the first principal component that explains the largest amount of the variation of the data and it is normalized and centered at 0 with standard deviation of 1. Panel B in Table [A21](#) displays the estimates. The coefficient associated with the Perception Index is positive across the four specifications and statistically significant in four cases. For example, a one standard deviation increase in the perception index results in a 14 p.p. increase in the probability of increasing the rate of irrigation (column (2)) and in a 11 p.p. increase in the probability of increasing the rate of fertilizer, *ceteris paribus* (column (4)). Overall, these results show that the direction and magnitude of the effect of subjective perceptions on adaptation strategies is robust to alternative manners of aggregating subjective perceptions.

Finally, all estimates of the specifications that include weather variables computed through the interpolation of geographical coordinates are robust when extending the bounding distances to 30 and 40 km.

7 Limitations

This section discusses potential concerns and limitations of the empirical specification adopted in the paper. First and foremost, the main concern regards the problem of migration as adaptation in this context. As specified several times throughout the paper, the focus of this study is on-farm adaptation strategies implemented in the two rounds of the household survey. Nevertheless, a very small percentage of interviewed households in the first wave (around 1.8%) could not be reinterviewed because they migrated. The survey does not provide additional information on the reason of migration and the fact that migrated households do not belong all to the same union or geographical close unions might support the hypothesis that the driver of the migration choice was not a common negative economic shock or a natural disaster in a specific geographical area. If the share of households migrated between the first and second wave was non-random, the estimation presented above would suffer from selection bias (Heckman, [1979](#)). In this regard, a distribution by union and agroecological zone of the households interviewed, as compared to the original one (Figure [1](#)) was presented in Figure [A1](#). Moreover, additional evidence that allays the concern of potential bias is reported in Tables [A2](#) and [A3](#), respectively the full sample counterpart of Tables [3](#) and [5](#). It is possible to

infer that both on subjective perceptions and adaptation there are not substantial differences between the estimation sample and the full sample.

The use of subjective data as dependent variable, as done in the first step of the empirical analysis, might cast some doubts. In fact, the measurement error in reported perceptions might be correlated with a set of characteristics and behaviors that cannot be observed (Bertrand & Mullainathan, 2001). This would severely bias estimates if the measurement error is correlated with the explanatory variables. The problem of unobserved heterogeneity that could lead to spurious regressions is addressed in the empirical specifications by using individual fixed effects, under the assumption that the dependent variable is linear and potential measurement errors are time invariant and thus washed out by individual fixed effects (Senik, 2005).

On a brighter side, subjective data can be useful as explanatory variables and can be good predictors (Bertrand & Mullainathan, 2001). For this reason, the inclusion of them in the empirical analysis of the adaptation decision-making process would add explanatory power to the specification. In particular, the use that has been done in this paper of subjective data is aligned with what is suggested by the literature. Subjective variables are in fact useful for explaining differences in behavior across individuals.

A critique that might be raised against the empirical specification adopted is whether the adaptive capacity of an agent is determined by past weather. At the basis of this hypothesis, there is the concern raised by Lemoine (2018), according to whom past weather affects past actions, that impose historical restraints on current actions. The sign of the bias would depend on the relationship between actions. If actions are intertemporal complements, high past actions would justify higher present actions, whereas if they were intertemporal substitutes, high past actions would justify lower present actions. Using a long history of transient shocks reduces the bias introduced by historical restraints, which would then allow the estimator to recover the effects of climate on actions.

8 Conclusion

In this paper, I present a model of subjective perceptions and adaptation strategies in response to climatic changes. I assess the accuracy of beliefs by comparing subjective probabilities to historical data and objective probabilities and find considerable heterogeneity in beliefs and accuracy. A number of propositions has been stated from the theoretical framework in order to be tested empirically. I apply panel fixed effects strategies to investigate three main hypotheses in the context of rural households of Bangladesh. First, I find that farmers' subjective perceptions of climate change are affected heterogeneously by historical objective weather. Changes in precipitations and temperature patterns have different effects on subjective perceptions by growing season and drought and flood events drive considerably subjective perceptions of these events. Second, farmers are subject to confirmation bias, the tendency to overweight evidence that confirms own beliefs, in particular when reporting droughts. Finally, farmers' subjective probabilities of climatic changes are a powerful predictor of behavioural responses through adaptation strategies, even when controlling for

objective probabilities in weather, measured using the coefficient of variation. Moreover, the accuracy of farmers explains differences in the adaptation decision-making process. Inaccurate farmers appear to be more likely not to adapt by changing crop variety and thus make suboptimal decisions, which could, in turn, lower their yields and profits.

The analysis of farmers' subjective perceptions of climatic changes and implementation of on-farm adaptation strategies can considerably contribute to the design of adequate policies for agricultural security. Policies directed to informational and communication campaigns seem to be potential solutions to raise the awareness of climatic changes that could foster the implementation of adaptation strategies.

A number of potential avenues are left open for future research. The theoretical model implemented in this paper could be further expanded by relaxing the assumption that farmers form priors on the damage caused by the negative shock and perfectly estimate it. A wedge in the estimation of the damage by the farmer and by a foresighted planner could be introduced. On the empirical side, future research should focus on the use of finer and more frequent weather data, in order to precisely estimate the reaction of subjective perceptions and agricultural adaptation decisions to weather shocks occurring in different moments of the growing season. Additional follow-up rounds of the household survey would allow to test the hypotheses formulated here on a longer time dimension by adopting other estimation methods such as a long differences approach (Burke & Emerick, 2016) which would better capture climate change. Information on the intensive margin of the adaptation strategies, namely the intensity of the change in use of inputs or specific changes in crop variety would also allow to refine the analysis and enrich it with useful information for future policy recommendations.

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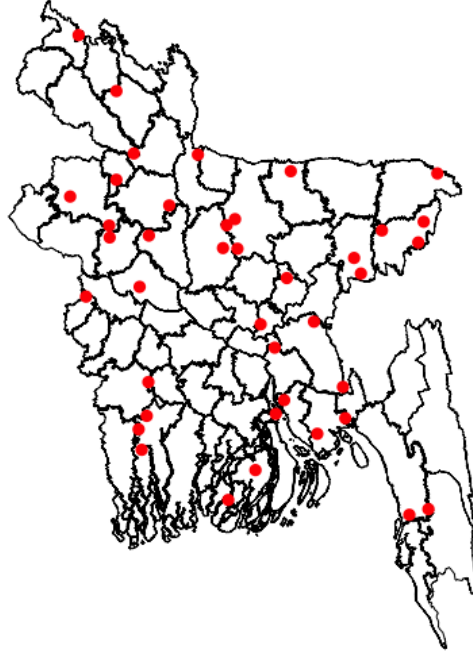
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A Appendix

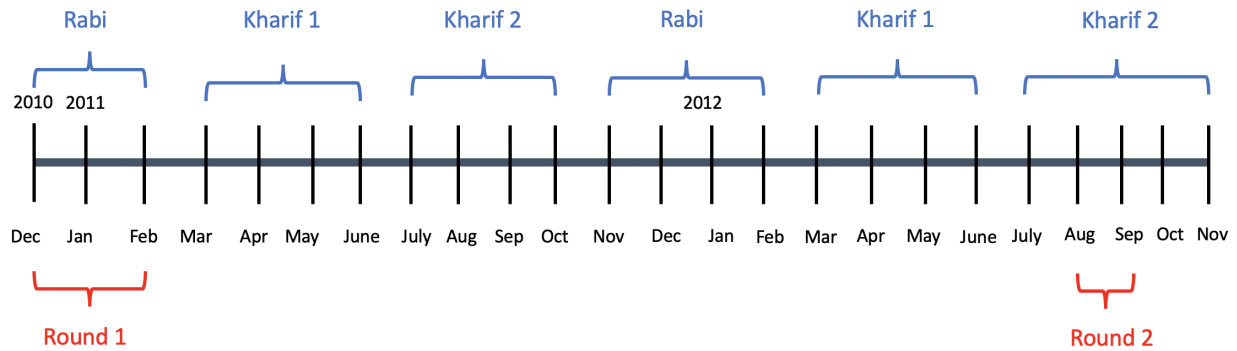
A.1 Survey Characteristics

Figure A1: Map of Bangladesh with Survey Unions Centroids



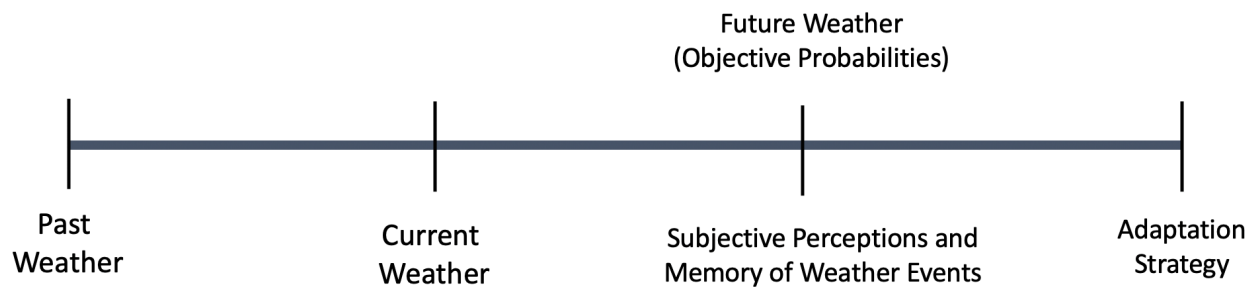
Source: Author's computation, BCCAS union centroids data.

Figure A2: Timeline of Survey and Growing Seasons



Source: Author's computation.

Figure A3: Timeline of the determinants of adaptation



Note: Adapted from Lemoine (2018).

Table A1: 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 A2: Summary statistics on subjective perceptions of climate change by survey wave in full sample

	N	Mean	SD
2011			
Perceived any changes in climate over the last 20 years	800	0.67	0.47
Perceived an increase in floods	800	0.11	0.32
Perceived an increase in droughts	800	0.26	0.44
Perceived an increase in cold	800	0.19	0.40
Perceived an increase in unseasoned/erratic rain	800	0.26	0.44
Perceived a decrease in precipitations	800	0.23	0.42
2012			
Perceived any changes in climate over the last 20 years	800	0.96	0.19
Perceived an increase in floods	800	0.18	0.38
Perceived an increase in droughts	800	0.92	0.27
Perceived an increase in cold	800	0.13	0.33
Perceived an increase in unseasoned/erratic rain	800	0.86	0.35
Perceived a decrease in precipitations	800	0.87	0.33
Total			
Perceived any changes in climate over the last 20 years	1600	0.82	0.39
Perceived an increase in floods	1600	0.14	0.35
Perceived more hot during hot season (Drought)	1600	0.59	0.49
Perceived an increase in cold	1600	0.16	0.37
Perceived an increase in unseasoned/erratic rain	1600	0.56	0.50
Perceived a decrease in precipitations	1600	0.55	0.50
Observations	1600		

Notes: A farmer is considered to have perceived a change in climate over the 20-year period preceding the year of the interview if she has answered "Yes" to at least one of the question on perceptions below.

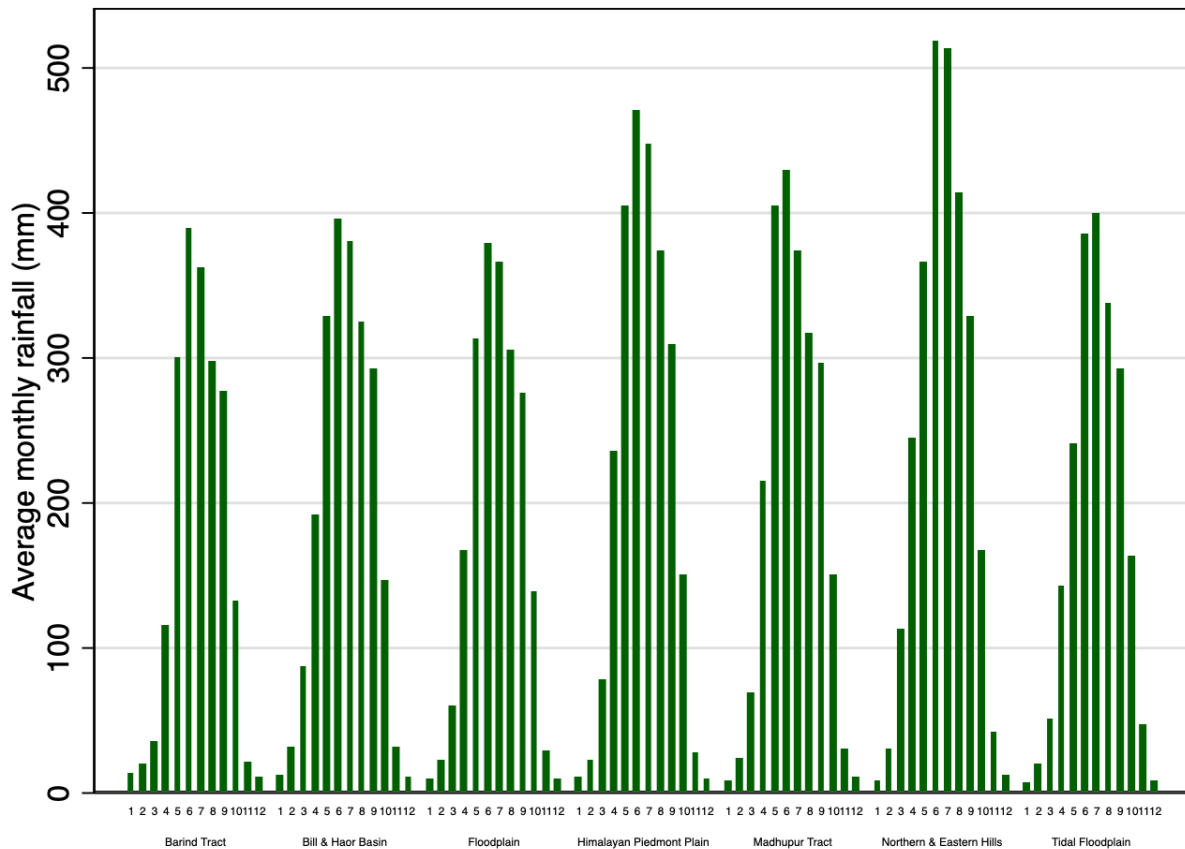
Table A3: Summary Statistics on On-Farm Adaptation Strategies by survey wave in full sample

	Mean		SD	
	2011	2012	2011	2012
Implemented on-farm adaptation strategy	.88	.89	.325	.37
Change crop variety	.581	.714	.494	.469
Irrigated more	.576	.534	.494	.499
Change planting dates	.382	.313	.486	.464
Higher rate of fertilizer application	.555	.68	.497	.467

Notes: A household is considered to have implemented an on-farm adaptation strategy if it has answered "Yes" to at least one of the strategies in the table. N = 1600 (800 households interviewed by survey round).

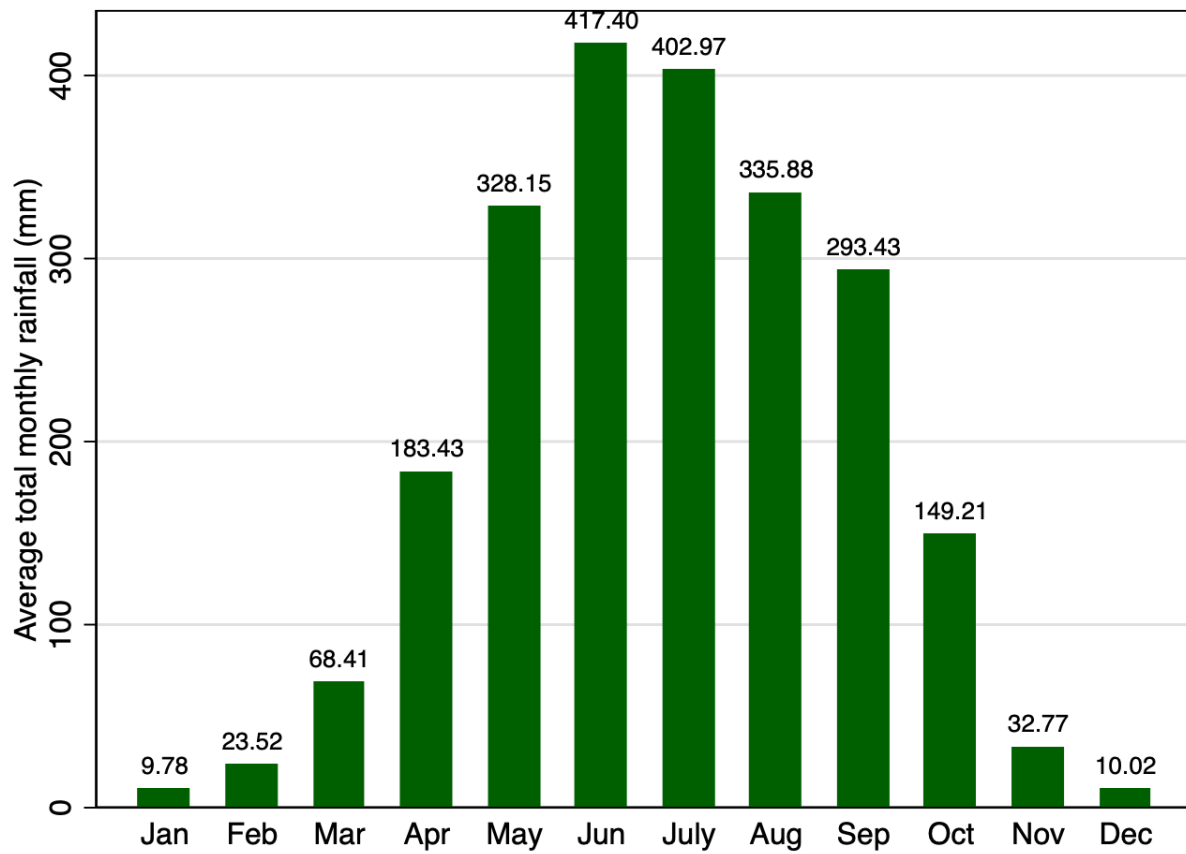
A.2 Bangladesh Climate

Figure A4: Monthly average rainfall by Agroecological Zone



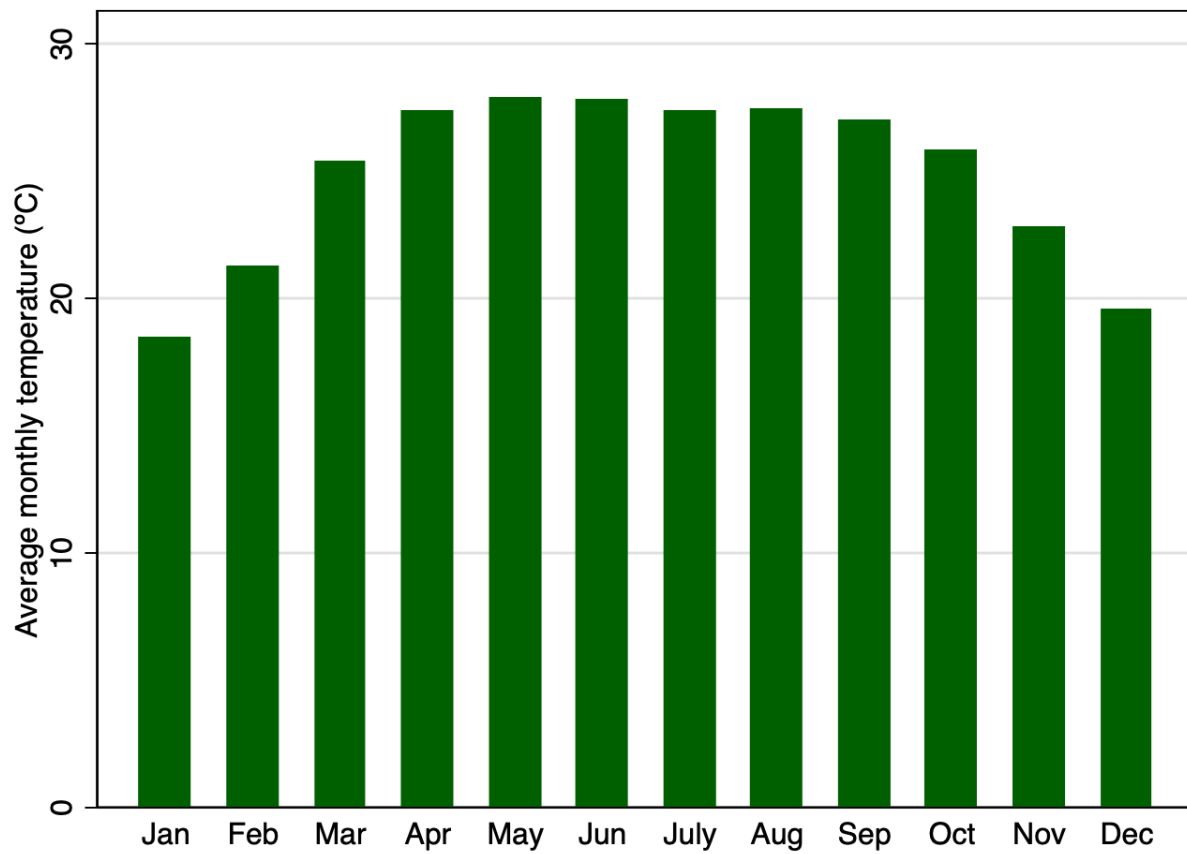
Source: Author's computation, ERA5-Land monthly data 1981-2012.

Figure A5: Monthly average rainfall 1981-2012



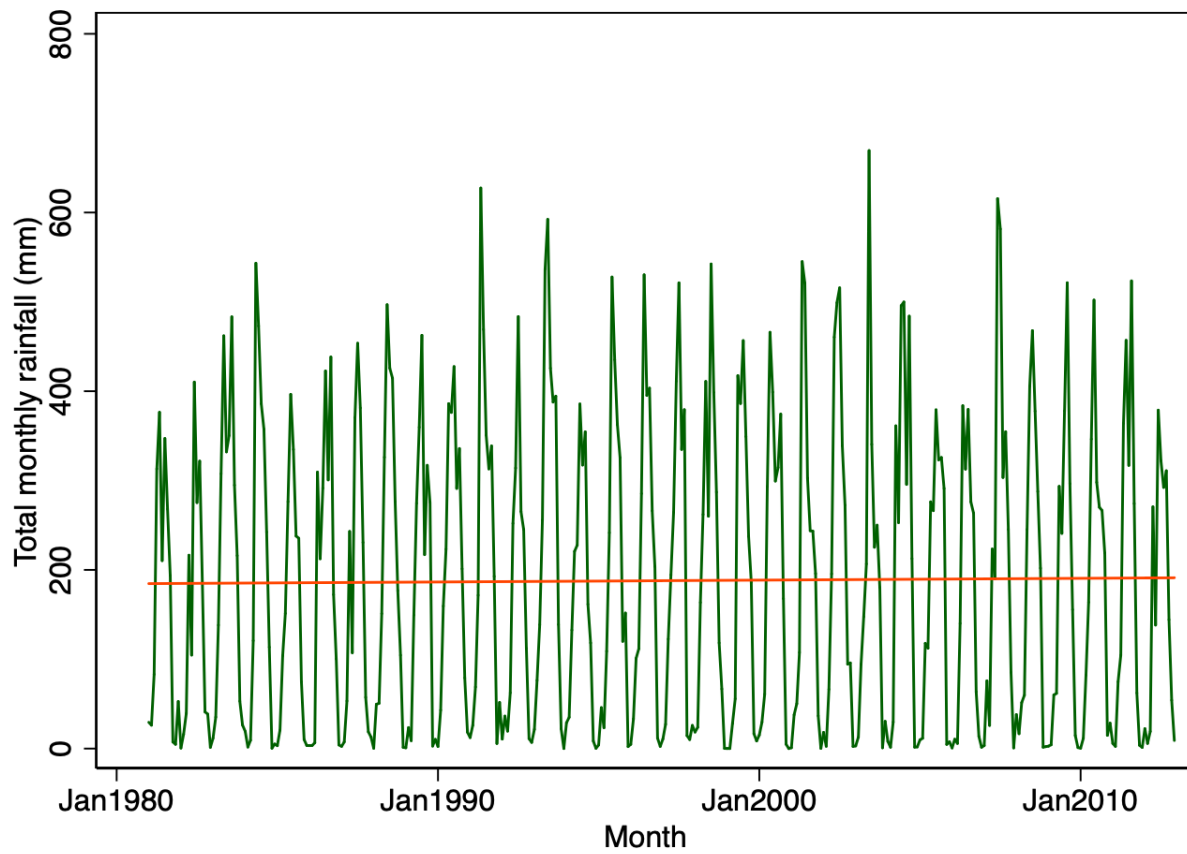
Source: Author's computation, ERA5-Land monthly data 1981-2012.

Figure A6: Monthly average temperature 1981-2012



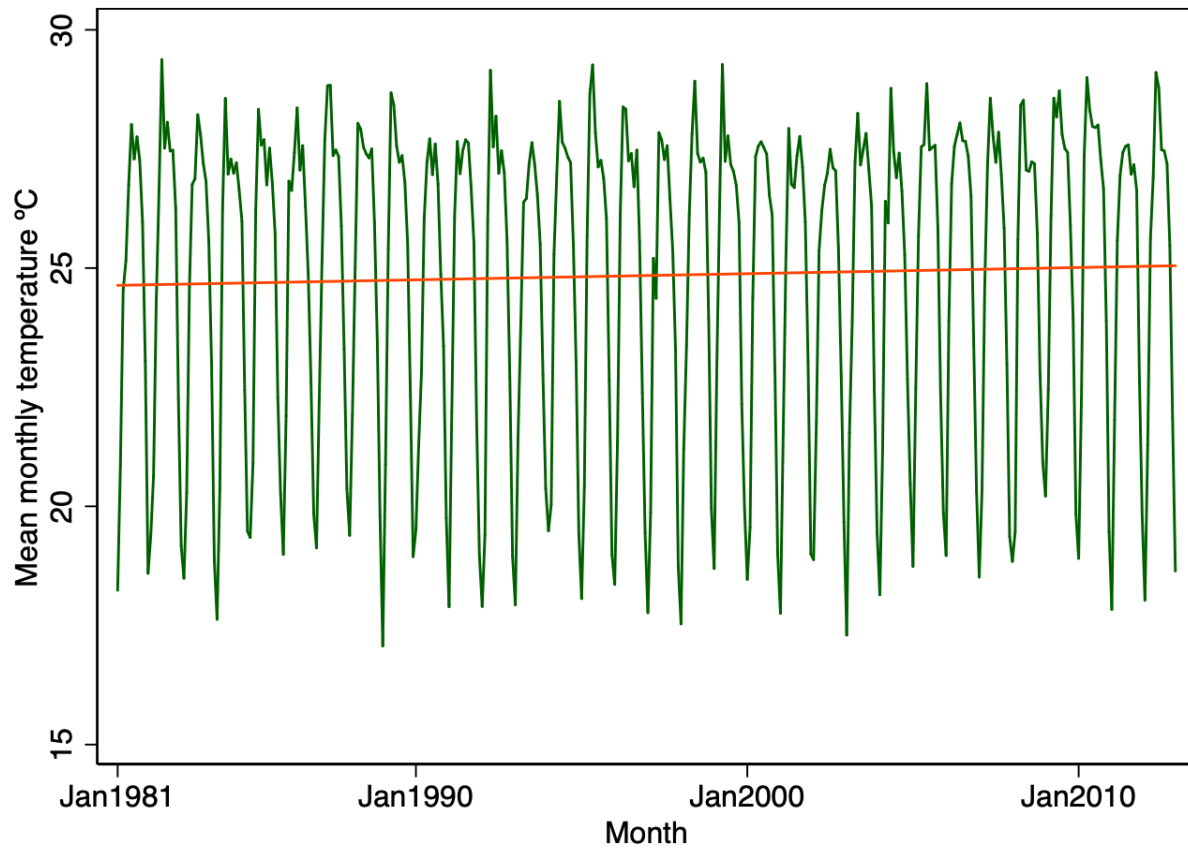
Source: Author's computation, ERA5-Land monthly data 1981-2012.

Figure A7: Monthly standard deviation rainfall 1981-2012



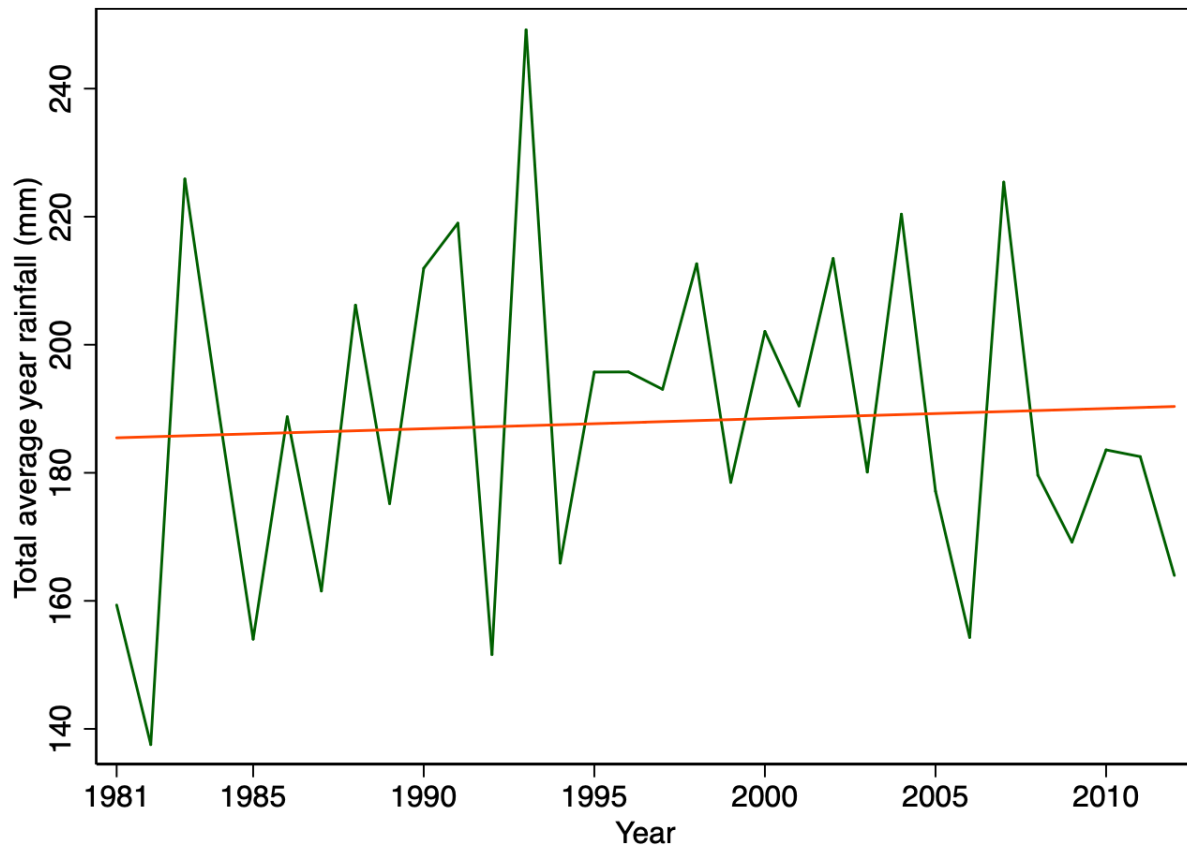
Source: Author's computation, ERA5-Land monthly data 1981-2012.

Figure A8: Monthly average temperature 1981-2012



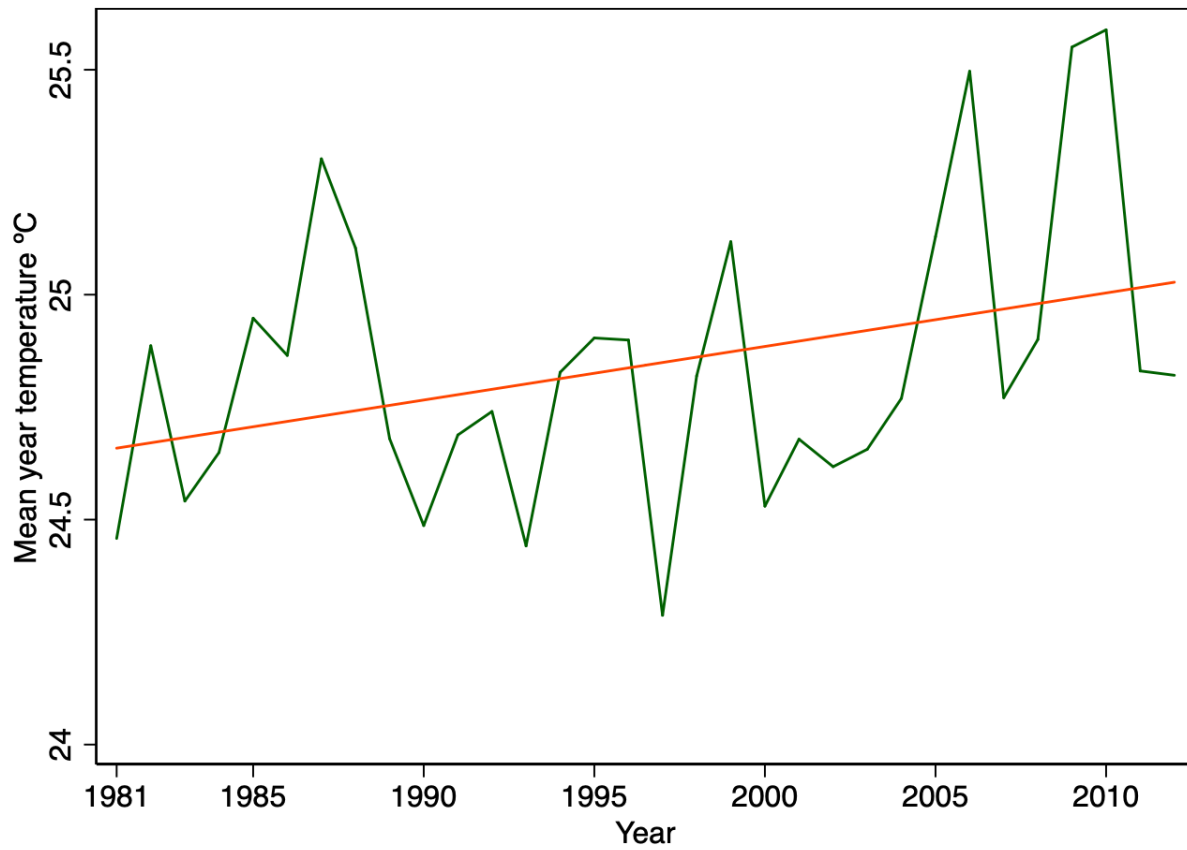
Source: Author's computation, ERA5-Land monthly data 1981-2012.

Figure A9: Yearly standard deviation rainfall 1981-2012



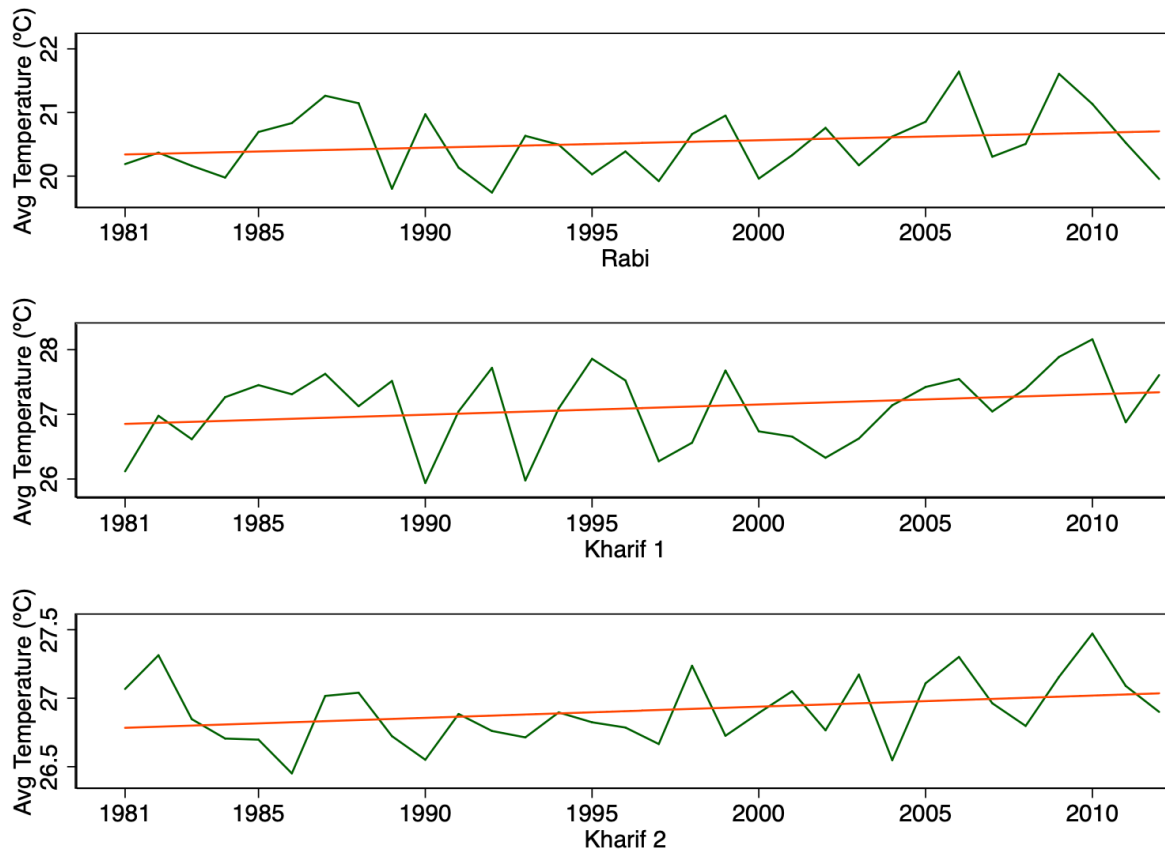
Source: Author's computation, ERA5-Land monthly data 1981-2012.

Figure A10: Yearly average temperature 1981-2012



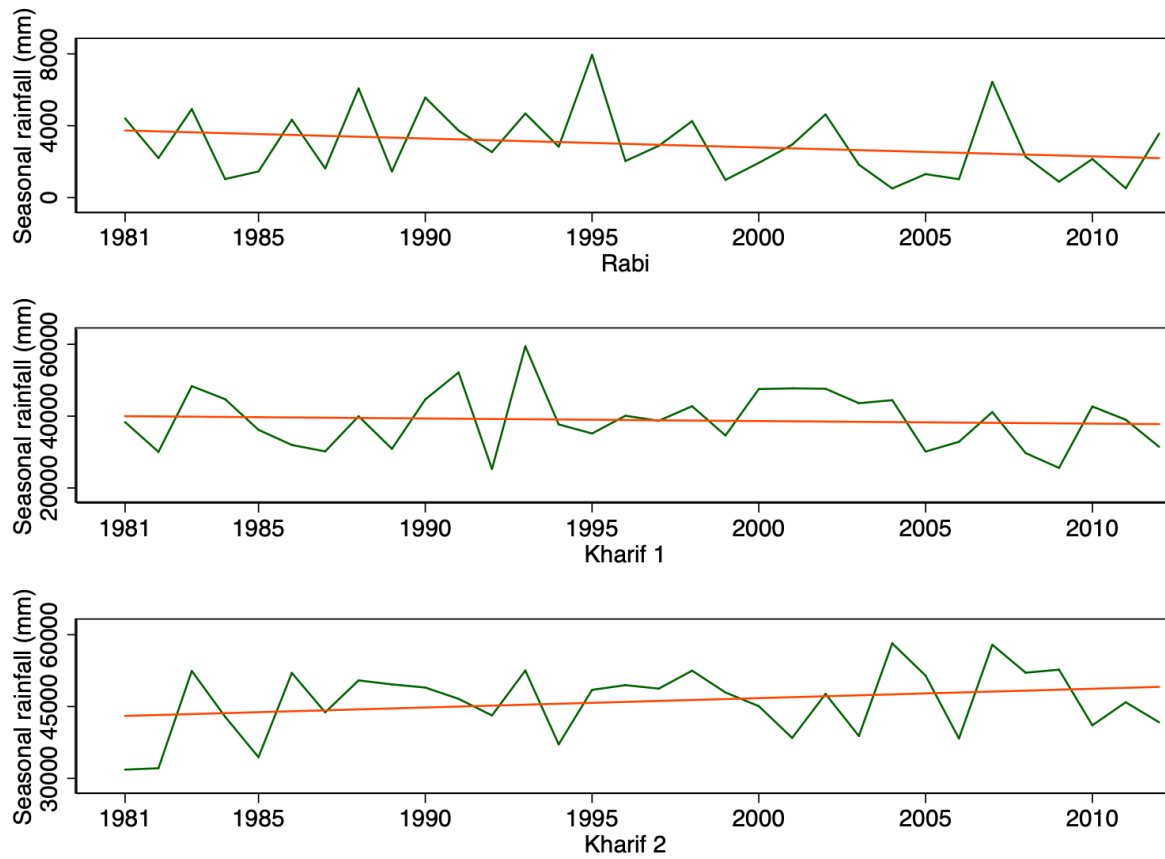
Source: Author's computation, ERA5-Land monthly data 1981-2012.

Figure A11: Growing Season Average temperature 1981-2012



Source: Author's computation, ERA5-Land monthly data 1981-2012. Rabi season is the winter growing season including months of November, December, January and February. Kharif 1 season is the pre-monsoon growing season including months of March, April, May and June. Kharif 2 season is the monsoon growing season including months of July, August, September and October.

Figure A12: Growing Season Cumulative Precipitation 1981-2012



Source: Author's computation, ERA5-Land monthly data 1981-2012. Rabi season is the winter growing season including months of November, December, January and February. Kharif 1 season is the pre-monsoon growing season including months of March, April, May and June. Kharif 2 season is the monsoon growing season including months of July, August, September and October.

A.3 Subjective Perceptions

Does historical weather affect perceptions?

Table A4 displays the estimation results for the baseline econometric specification in Equation 14. Each column reports the estimates for the subjective perception of each of the climatic features of interest. Panel A, B and C display the coefficients associated to the historical weather variables for temperature and precipitation respectively in the 5-year, 10-year and 20-year period preceding the survey. All models control for household, union and year of interview fixed effects and a set of control variables. It is interesting that a higher number of historical temperature and precipitation coefficients tend to gain statistical significance when a longer time period is considered. Concerning the subjective perception of an increase in flood, there is a positive and statistically significant effect of the average temperature in the previous 20 years whose total effect can be represented by an inverse U-shaped relationship because of the negative and statistically significant coefficient associated to its quadratic term. Despite the fact that this is not the most intuitive result, since the subjective perception of an increase in floods includes a perception of more water falling from the mountains, more water from the mountains might be explained by higher temperatures rather than by changes in precipitations. Concerning subjective perceptions of increases in droughts and in colds, the most interesting result is the persistence of the positive and statistically significant coefficient associated to standard deviation of temperature in previous 10 and 20 years for subjective increases in droughts and negative and statistically significant in previous 10 and 20 years for subjective increases in cold. Subjective increases in droughts include in the questionnaire the perception of more hot during hot season, that could be represented by shifts in the variability of temperature in the period considered. The standard deviation of precipitation has a positive and statistically significant coefficient in the regression using as outcome variable the perceived increase in variability of rainfalls when considering the 5-year and 20-year period preceding the interview. Finally, as expected, an increase in the average precipitations in any of the three time dimensions considered is associated with a decrease in the probability for an individual of perceiving a decrease in precipitations.

Table A4: Baseline Specification - Weather and Subjective Perceptions of Climate Change

	Dependent Variable: <i>Subjective Perception</i>				
	(1)	(2)	(3)	(4)	(5)
	Increase Flood	Increase Drought	Increase Cold	Erratic Rainfalls	Decrease Precipitations
<i>Panel A</i>					
Avg prec in prev 5 years	-0.0314 (0.0262)	0.0433* (0.0248)	-0.0359 (0.0239)	0.0131 (0.0284)	-0.0576** (0.0281)
Avg temp in prev 5 years	-25.36 (37.30)	46.58 (33.59)	41.88 (36.19)	50.73 (36.78)	106.6*** (37.55)
Avg prec ² in prev 5 years	0.0000154 (0.0000419)	-0.0000423 (0.0000396)	0.0000238 (0.0000398)	-0.0000228 (0.0000440)	0.000101** (0.0000435)
Avg temp ² in prev 5 years	0.497 (0.746)	-0.914 (0.671)	-0.863 (0.721)	-0.988 (0.731)	-2.183*** (0.749)
SD prec in prev 5 years	0.00139 (0.00428)	-0.00623 (0.00517)	0.0165*** (0.00499)	0.0200*** (0.00608)	0.0144*** (0.00520)
SD temp in prev 5 years	-1.539 (1.156)	0.497 (1.103)	0.580 (1.050)	6.030*** (1.321)	3.383*** (1.210)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.006	0.450	0.041	0.308	0.420
<i>Panel B</i>					
Avg prec in prev 10 years	-0.0532 (0.0496)	0.00892 (0.0487)	-0.0547 (0.0499)	-0.00548 (0.0557)	-0.187*** (0.0510)
Avg temp in prev 10 years	64.40 (52.51)	-7.548 (45.22)	29.54 (46.19)	-330.1*** (54.34)	38.54 (48.59)
Avg prec ² in prev 10 years	0.000160* (0.0000922)	0.0000226 (0.0000884)	0.00000873 (0.0000969)	-0.000181* (0.0000990)	0.000214** (0.000100)
Avg temp ² in prev 10 years	-1.297 (1.017)	0.0906 (0.882)	-0.595 (0.903)	6.435*** (1.056)	-0.806 (0.947)
SD prec in prev 10 years	-0.0206 (0.0150)	-0.0216* (0.0131)	0.0313*** (0.0110)	0.00312 (0.0160)	0.0594*** (0.0128)
SD temp in prev 10 years	-2.113 (1.404)	2.507** (1.247)	-2.108* (1.156)	5.049*** (1.392)	0.271 (1.295)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.012	0.450	0.037	0.290	0.427
<i>Panel C</i>					
Avg prec in prev 20 years	-0.260** (0.104)	0.120 (0.0938)	-0.219** (0.0943)	0.213** (0.0978)	-0.0558 (0.102)
Avg temp in prev 20 years	229.0*** (83.86)	119.8 (77.66)	-111.4 (74.22)	-232.9** (95.74)	-214.9*** (78.43)
Avg prec ² in prev 20 years	0.000707*** (0.000220)	-0.000247 (0.000186)	0.0000181 (0.000149)	-0.000515*** (0.000192)	-0.000260 (0.000189)
Avg temp ² in prev 20 years	-4.988*** (1.680)	-2.237 (1.549)	1.841 (1.469)	5.649*** (1.897)	4.160*** (1.570)
SD prec in prev 20 years	-0.133*** (0.0439)	-0.0189 (0.0400)	0.121*** (0.0380)	0.106** (0.0528)	0.151*** (0.0430)
SD temp in prev 20 years	-5.217* (2.740)	5.754* (3.008)	-12.26*** (3.281)	5.600 (3.879)	1.038 (3.392)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.045	0.450	0.054	0.305	0.421
N	1428	1428	1428	1428	1428

Notes: Clustered-robust standard errors at household-level. Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Growing season of reference

Given that in the first wave the BCCAS collects information on agriculture plot utilization in the previous production year (from December 2009 to December 2010), I compute the proportion of the production of each crop for each household weighted by the amount of production, in order to identify the main crop for each household. In this manner, it is possible to identify the growing season of interest for each household, may it be *Kharif 1*, *Kharif 2* or *Rabi*, defined as the growing season in which the main crop of the household grows. Unfortunately, such methodology cannot be implemented in the second wave, due to limited data. Therefore, I use questions from the module investigating adaptation strategy, in particular questions asking whether they have changed crop type or planted earlier or later in a given growing season. If the farmer states a change to a particular crop type in a different growing season than the reference one in the previous wave, I assign to the household a new growing season. Likewise, if the farmer states to be planting earlier or later in a growing season which is not the same as the one of its main crop in the previous wave, I assign to the household such growing season. The estimating equation writes as follows:

$$\omega_{iut} = \gamma_1 T_{ut}^{GS} + \gamma_2 \sigma_{ut}^{T,GS} + \delta_1 R_{ut}^{GS} + \delta_2 \sigma_{ut}^{R,GS} + X'_{iut} \beta + \alpha_i + \alpha_u + \alpha_t + u_{iut} \quad (25)$$

Results are displayed below in Table [A5](#).

Table A5: Subjective Perceptions of Climate Change and Changes in Growing Season of Reference

	(1)	(2)	(3)	(4)	(5)
	Increase Flood	Increase Drought	Increase Cold	Erratic Rainfalls	Decrease Precipitations
GS Total prec	-0.0000845 (0.000118)	-0.00000626 (0.000100)	0.0000723 (0.0000901)	-0.0000155 (0.000113)	0.000257*** (0.0000903)
GS Avg temp	0.0161 (0.0167)	0.00552 (0.0156)	-0.00334 (0.0159)	-0.0117 (0.0183)	0.0122 (0.0141)
GS SD prec	-0.000425 (0.000399)	0.000412 (0.000444)	-0.0000457 (0.000389)	0.000691 (0.000526)	-0.000456 (0.000368)
GS SD temp	-0.0933*** (0.0321)	0.00296 (0.0330)	0.0564** (0.0261)	0.0887** (0.0395)	0.0922*** (0.0305)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1428	1428	1428	1428	1428
adj. <i>R</i> ²	0.004	0.448	0.031	0.257	0.417

Notes: Clustered-robust standard errors at household-level. Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Short- and long-term deviations by growing season

The following specifications test whether short-term (1- and 5-year differences) and long-term (10- and 20-year differences) deviations in seasonal cumulative precipitation and average temperature shape farmers' subjective perceptions.

$$\omega_{iut} = \sum_j \gamma_j \Delta_1 T_{ut}^j + \sum_j \delta_j \Delta_1 R_{ut}^j + X'_{iut} \beta + \alpha_i + \alpha_u + \alpha_t + u_{iut} \quad (26)$$

where $\Delta_1 T_{ut}^j$ is a vector of seasonal ($j \in \{\text{Kharif 1, Kharif 2, Rabi}\}$) 1-year difference in average temperature in union u at time t and R_{ut}^j is a vector of seasonal ($j \in \{\text{Kharif 1, Kharif 2, Rabi}\}$) 1-year difference cumulative precipitation in union u at time t .

Similarly, the specification can adopt a longer time horizon, computing 5-, 10- and 20- year differences.

$$\omega_{iut} = \sum_j \gamma_j \Delta_5 T_{ut}^j + \sum_j \delta_j \Delta_5 R_{ut}^j + X'_{iut} \beta + \alpha_i + \alpha_u + \alpha_t + u_{iut} \quad (27)$$

$$\omega_{iut} = \sum_j \gamma_j \Delta_{10} T_{ut}^j + \sum_j \delta_j \Delta_{10} R_{ut}^j + X'_{iut} \beta + \alpha_i + \alpha_u + \alpha_t + u_{iut} \quad (28)$$

$$\omega_{iut} = \sum_j \gamma_j \Delta_{20} T_{ut}^j + \sum_j \delta_j \Delta_{20} R_{ut}^j + X'_{iut} \beta + \alpha_i + \alpha_u + \alpha_t + u_{iut} \quad (29)$$

Tables [A6](#), [A7](#), [A8](#) and [A9](#) display the results.

Table A6: Panel Regression Subjective Perceptions of Climate Change using Difference in Weather Variables of 1 years

	(1)	(2)	(3)	(4)	(5)
	Increase Flood	Increase Drought	Increase Cold	Erratic Rainfalls	Decrease Precipitations
Δ_1 temp Kharif 1	-0.0265 (0.0371)	-0.0528 (0.0375)	-0.0963** (0.0387)	0.194*** (0.0391)	-0.0292 (0.0417)
Δ_1 temp Kharif 2	0.610*** (0.190)	-0.259 (0.210)	0.00677 (0.220)	-0.140 (0.254)	-0.398* (0.236)
Δ_1 temp Rabi	0.0443 (0.122)	0.0651 (0.133)	0.207 (0.133)	-0.0260 (0.145)	0.0948 (0.151)
Δ_1 prec Kharif 1	-0.0000331 (0.0000630)	-0.0000525 (0.0000680)	-0.0000236 (0.0000653)	0.000327*** (0.0000700)	-0.0000737 (0.0000718)
Δ_1 prec Kharif 2	0.0000509 (0.0000843)	-0.0000144 (0.0000969)	-0.0000173 (0.0000947)	-0.000243** (0.000108)	0.000204** (0.000103)
Δ_1 prec Rabi	0.000714 (0.00110)	-0.000287 (0.00117)	0.00110 (0.00116)	0.0000252 (0.00136)	0.00118 (0.00145)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428
adj. R^2	0.021	0.448	0.041	0.277	0.424

Notes: Clustered-robust standard errors at household-level. Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7: Panel Regression Subjective Perceptions of Climate Change using Difference in Weather Variables of 5 years

	(1)	(2)	(3)	(4)	(5)
	Increase Flood	Increase Drought	Increase Cold	Erratic Rainfalls	Decrease Precipitations
Δ_5 temp Kharif 1	-0.0254 (0.0719)	-0.0885 (0.0851)	0.0147 (0.0927)	0.416*** (0.102)	0.140 (0.0882)
Δ_5 temp Kharif 2	0.880*** (0.206)	-0.0407 (0.201)	0.227 (0.205)	-0.807*** (0.232)	-0.424** (0.211)
Δ_5 temp Rabi	-0.382*** (0.107)	0.165 (0.110)	-0.0351 (0.115)	0.309** (0.129)	0.231** (0.115)
Δ_5 prec Kharif 1	-0.000514*** (0.000139)	-0.0000853 (0.000124)	0.0000949 (0.000113)	0.000754*** (0.000135)	0.000251** (0.000115)
Δ_5 prec Kharif 2	-0.0000307 (0.000151)	-0.0000158 (0.000162)	0.000143 (0.000149)	0.000124 (0.000193)	0.000347** (0.000174)
Δ_5 prec Rabi	0.00177** (0.000883)	0.000536 (0.000812)	-0.000990 (0.000825)	-0.00170* (0.000885)	-0.0000398 (0.000847)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428
adj. R^2	0.035	0.451	0.034	0.293	0.421

Notes: Clustered-robust standard errors at household-level. Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8: Panel Regression Subjective Perceptions of Climate Change using Difference in Weather Variables of 10 years

	(1) Increase Flood	(2) Increase Drought	(3) Increase Cold	(4) Erratic Rainfalls	(5) Decrease Precipitations
Δ_{10} temp Kharif 1	0.102* (0.0571)	-0.0573 (0.0613)	-0.215*** (0.0624)	-0.401*** (0.0682)	-0.175*** (0.0613)
Δ_{10} temp Kharif 2	-0.150 (0.154)	-0.124 (0.171)	0.506*** (0.164)	-0.00220 (0.175)	0.515*** (0.158)
Δ_{10} temp Rabi	0.128 (0.160)	-0.199 (0.189)	0.569*** (0.192)	0.394* (0.217)	0.179 (0.201)
Δ_{10} prec Kharif 1	0.000294** (0.000115)	-0.000143 (0.000112)	-0.000222** (0.000107)	-0.000692*** (0.000122)	-0.000436*** (0.000112)
Δ_{10} prec Kharif 2	-0.000395*** (0.000131)	-0.0000902 (0.000135)	0.000181 (0.000131)	0.000490*** (0.000147)	0.000717*** (0.000133)
Δ_{10} prec Rabi	0.000820 (0.000725)	0.000817 (0.000543)	-0.000239 (0.000523)	-0.000444 (0.000538)	-0.00117** (0.000533)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428
adj. R^2	0.019	0.454	0.053	0.305	0.440

Notes: Clustered-robust standard errors at household-level. Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9: Panel Regression Subjective Perceptions of Climate Change using Difference in Weather Variables of 20 years

	(1) Increase Flood	(2) Increase Drought	(3) Increase Cold	(4) Erratic Rainfalls	(5) Decrease Precipitations
Δ_{20} temp Kharif 1	0.0578 (0.0632)	-0.166** (0.0651)	-0.256*** (0.0692)	0.172** (0.0713)	-0.200*** (0.0695)
Δ_{20} temp Kharif 2	1.200*** (0.291)	-0.525* (0.281)	-0.198 (0.280)	-1.054*** (0.332)	-1.059*** (0.283)
Δ_{20} temp Rabi	-0.247 (0.198)	0.167 (0.203)	-0.0545 (0.211)	-0.357 (0.227)	0.0512 (0.211)
Δ_{20} prec Kharif 1	-0.0000941* (0.0000544)	-0.0000554 (0.0000529)	-0.0000538 (0.0000551)	0.000367*** (0.0000562)	0.00000427 (0.0000532)
Δ_{20} prec Kharif 2	0.000399*** (0.000138)	-0.000217 (0.000137)	-0.000196 (0.000132)	-0.00108*** (0.000143)	-0.000253* (0.000142)
Δ_{20} prec Rabi	-0.000714 (0.000773)	0.000394 (0.000778)	-0.000293 (0.000825)	-0.00258*** (0.000836)	0.000412 (0.000812)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428
adj. R^2	0.027	0.452	0.052	0.327	0.423

Notes: Clustered-robust standard errors at household-level. Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Short- and long-term deviations in the growing season of reference for the household

The following specifications test whether short-term (1- and 5-year differences) and long-term (10- and 20-year differences) deviations in cumulative precipitation and average temperature in the growing season in which the household grows its main crop shape farmers' subjective perceptions.

$$\omega_{iut} = \gamma_1 \Delta_1 T_{ut}^{GS} + \delta_1 \Delta_1 R_{ut}^{GS} + X'_{iut} \beta + \alpha_i + \alpha_u + \alpha_t + u_{iut} \quad (30)$$

$$\omega_{iut} = \gamma_1 \Delta_5 T_{ut}^{GS} + \delta_1 \Delta_5 R_{ut}^{GS} + X'_{iut} \beta + \alpha_i + \alpha_u + \alpha_t + u_{iut} \quad (31)$$

$$\omega_{iut} = \gamma_1 \Delta_{10} T_{ut}^{GS} + \delta_1 \Delta_{10} R_{ut}^{GS} + X'_{iut} \beta + \alpha_i + \alpha_u + \alpha_t + u_{iut} \quad (32)$$

$$\omega_{iut} = \gamma_1 \Delta_{20} T_{ut}^{GS} + \delta_1 \Delta_{20} R_{ut}^{GS} + X'_{iut} \beta + \alpha_i + \alpha_u + \alpha_t + u_{iut} \quad (33)$$

Tables [A10](#), [A11](#), [A12](#) and [A13](#) display the results of the estimated equations above.

Table A10: Panel Regression Subjective Perceptions of Climate Change using Difference in Weather Variables in Growing Season of 1 year

	(1)	(2)	(3)	(4)	(5)
	Increase Flood	Increase Drought	Increase Cold	Erratic Rainfalls	Decrease Precipitations
Δ_1 temp GS	-0.0377 (0.0241)	0.0170 (0.0257)	-0.0142 (0.0226)	0.0729*** (0.0272)	0.0697*** (0.0266)
Δ_1 prec GS	-0.000119* (0.0000619)	0.0000794 (0.0000554)	0.0000391 (0.0000351)	0.000108* (0.0000580)	0.0000998** (0.0000431)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428
adj. R^2	0.013	0.449	0.031	0.260	0.412

Notes: Clustered-robust standard errors at household-level. Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A11: Panel Regression Subjective Perceptions of Climate Change using Difference in Weather Variables in Growing Season of 5 years

	(1) Increase Flood	(2) Increase Drought	(3) Increase Cold	(4) Erratic Rainfalls	(5) Decrease Precipitations
Δ_5 temp GS	-0.0504 (0.0405)	0.0645 (0.0409)	0.000948 (0.0359)	0.0613 (0.0436)	0.121*** (0.0413)
Δ_5 prec GS	0.0000314 (0.0000732)	0.0000660 (0.0000712)	-0.0000409 (0.0000707)	0.00000459 (0.0000862)	-0.000128* (0.0000756)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428
adj. R^2	0.010	0.450	0.030	0.254	0.414

Notes: Clustered-robust standard errors at household-level. Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A12: Panel Regression Subjective Perceptions of Climate Change using Difference in Weather Variables in Growing Season of 10 years

	(1) Increase Flood	(2) Increase Drought	(3) Increase Cold	(4) Erratic Rainfalls	(5) Decrease Precipitations
Δ_{10} temp GS	-0.0534* (0.0320)	0.00779 (0.0329)	0.0294 (0.0299)	0.0670* (0.0388)	0.127*** (0.0358)
Δ_{10} prec GS	-0.000159* (0.0000958)	0.000149 (0.0000927)	-0.0000416 (0.0000917)	0.000237** (0.000116)	0.000175* (0.0000963)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428
adj. R^2	0.011	0.450	0.031	0.259	0.416

Notes: Clustered-robust standard errors at household-level. Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A13: Panel Regression Subjective Perceptions of Climate Change using Difference in Weather Variables in Growing Season of 20 years

	(1) Increase Flood	(2) Increase Drought	(3) Increase Cold	(4) Erratic Rainfalls	(5) Decrease Precipitations
Δ_{20} temp GS	0.0138 (0.0356)	0.0297 (0.0363)	-0.0327 (0.0368)	0.00155 (0.0413)	-0.0564 (0.0370)
Δ_{20} prec GS	-0.0000686 (0.0000637)	0.0000732 (0.0000540)	0.0000243 (0.0000419)	0.0000234 (0.0000548)	0.0000352 (0.0000479)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428

Notes: Clustered-robust standard errors at household-level. Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Climatic Changes by Growing Season

The following specification adopts the same strategy as in Equation [15](#). It distinguishes the effects of climate change on subjective perceptions by growing season and uses average temperature and precipitation in the 5-, 10- and 20-year period preceding the year of interview.

$$\omega_{iut} = \sum_j \gamma_j \bar{T}_{ut}^j + \sum_j \delta_j \bar{R}_{ut}^j + X'_{iut} \beta + \alpha_i + \alpha_u + \alpha_t + u_{iut} \quad (34)$$

Table [A14](#) displays the estimates using average temperature and precipitations in the 5-year period preceding the interview by growing season.

Table A14: Panel Regression Subjective Perceptions of Climate Change in 5-year Growing Seasons

	(1) Increase Flood	(2) Increase Drought	(3) Increase Cold	(4) Erratic Rainfalls	(5) Decrease Precipitations
Avg temp in Kharif 1 last 5y	-1.080* (0.617)	1.244* (0.664)	-1.094 (0.702)	-0.543 (0.844)	-0.307 (0.701)
Avg temp in Kharif 2 last 5y	3.925* (2.035)	-2.394 (2.213)	0.507 (2.430)	2.028 (2.703)	-1.365 (2.360)
Avg temp in Rabi last 5y	0.156 (0.904)	-2.071** (0.802)	0.234 (0.822)	1.105 (0.955)	-0.0312 (0.878)
Avg prec in Kharif 1 last 5y	-0.00155 (0.00140)	0.000812 (0.00152)	0.000446 (0.00154)	-0.00167 (0.00165)	0.00171 (0.00171)
Avg prec in Kharif 2 last 5y	0.00129 (0.00151)	-0.00269 (0.00164)	0.0000597 (0.00164)	0.00488** (0.00191)	-0.000460 (0.00165)
Avg prec in Rabi last 5y	-0.00178 (0.0112)	-0.0147 (0.0116)	0.00784 (0.0117)	-0.000754 (0.0146)	0.0226* (0.0126)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1428	1428	1428	1428	1428
adj. <i>R</i> ²	0.009	0.453	0.039	0.263	0.417

Notes: Clustered-robust standard errors at household-level. Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table [A15](#) displays the estimation results for the econometric specifications that uses average temperature and precipitation in the 10-year period preceding the interview. Overall, this table corroborates the previous analysis, that empirically validates Proposition 2, according to which historical changes by growing seasons have heterogeneous impacts on subjective perceptions of climate change. An increase in precipitation in the pre-monsoon season *Kharif 1* is associated with a decrease in the probability of perceiving increases in floods and an increase in the probability of perceiving erratic rainfall and, counterintuitively, in the probability of perceiving a decrease in precipitations. Additional evidence that corroborates the hypothesis of the heterogeneous impacts of precipitations by growing season is provided in the specifications that use as outcome variable perceived increases in erratic rainfall (column (4)) and decreases in precipitations (column (5)). In fact, in these specifications, the coefficient associated to average precipitations in *Kharif 1* is positive and statistically significant and the coefficient associated to average precipitations in *Rabi* is negative (though not statistically significant at conventional levels in column (5)). Increases in precipitations in the monsoon season *Kharif 2* have a positive and statistically significant effect on the perception of erratic rainfall and a

negative and statistically significant effect on the perception of decreases in precipitations.

Table A15: 10-year Growing Seasons Climatic Changes and Subjective Perceptions

	Dependent Variable: <i>Subjective Perception</i>				
	(1) Increase Flood	(2) Increase Drought	(3) Increase Cold	(4) Erratic Rainfalls	(5) Decrease Precipitations
Avg temp in Kharif 1 last 10y	-1.262 (0.814)	1.289 (0.856)	-0.584 (0.882)	3.304*** (0.982)	2.224*** (0.827)
Avg temp in Kharif 2 last 10y	-2.303 (6.909)	-3.246 (7.722)	-4.064 (7.932)	29.10*** (9.009)	-9.898 (7.378)
Avg temp in Rabi last 10y	0.395 (1.186)	-2.439** (1.080)	-0.765 (0.966)	1.553 (1.326)	-2.703** (1.113)
Avg prec in Kharif 1 last 10y	-0.00337*** (0.00108)	-0.000748 (0.001000)	0.000942 (0.000816)	0.00478*** (0.001000)	0.00202** (0.000959)
Avg prec in Kharif 2 last 10y	0.00335 (0.00302)	-0.00320 (0.00363)	-0.00749** (0.00363)	0.00700* (0.00396)	-0.0137*** (0.00359)
Avg prec in Rabi last 10y	-0.00279 (0.0161)	-0.0356** (0.0160)	0.00383 (0.0153)	-0.0438** (0.0186)	-0.00229 (0.0169)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1428	1428	1428	1428	1428
adj. <i>R</i> ²	0.023	0.452	0.041	0.324	0.432

Notes: Clustered-robust standard errors at household-level. Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A16 shows the results for the econometric specification in Equation 34 that uses average temperature and precipitations in the 20-year period preceding the interview by growing season.

Table A16: Panel Regression Subjective Perceptions of Climate Change in 20-year Growing Seasons

	(1) Increase Flood	(2) Increase Drought	(3) Increase Cold	(4) Erratic Rainfalls	(5) Decrease Precipitations
Avg temp in Kharif 1 last 20y	-4.059 (3.178)	3.410 (3.250)	-5.719 (3.673)	8.703** (3.535)	7.854** (3.594)
Avg temp in Kharif 2 last 20y	14.18 (8.868)	3.402 (9.153)	2.017 (9.880)	-21.67** (9.354)	5.816 (9.971)
Avg temp in Rabi last 20y	9.869*** (3.715)	-2.695 (3.909)	4.049 (4.129)	3.531 (4.328)	-5.107 (4.239)
Avg prec in Kharif 1 last 20y	-0.00199 (0.00180)	0.000499 (0.00188)	-0.00296 (0.00200)	-0.00500** (0.00207)	0.00153 (0.00191)
Avg prec in Kharif 2 last 20y	-0.0171*** (0.00465)	0.00228 (0.00429)	0.00464 (0.00384)	0.0192*** (0.00469)	0.0188*** (0.00465)
Avg prec in Rabi last 20y	0.0368** (0.0181)	-0.0165 (0.0188)	0.0272 (0.0188)	0.00903 (0.0204)	-0.0366* (0.0205)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1428	1428	1428	1428	1428
adj. <i>R</i> ²	0.040	0.447	0.033	0.338	0.428

Notes: Clustered-robust standard errors at household-level. Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Temperature and Precipitation Anomalies

Equation 16 can also be refined by disentangling the effect of positive and negative anomalies in temperature and precipitation patterns, building the measures in the spirit of Coniglio and Pesce (2015) as in Equations 2 and 3. The estimated specification writes as follows:

$$\omega_{iut} = \sum_k \sum_{sign} \gamma_{k,sign} k_{(sign)anomalies, ut} + X'_{iut} \beta + \alpha_i + \alpha_u + \alpha_t + u_{iut} \quad (35)$$

where $k \in \{\text{temperature; precipitation}\}$ and $sign \in \{-; +\}$ denote the four parameters of interest.

Results are displayed in in Table A17. They provide evidence of the negative effects of scarce rainfall (negative precipitation anomalies) on perceived increases in floods and positive effects associated with both positive and negative anomalies of temperatures. Differently from what expected, positive anomalies of temperature have a negative and statistically significant effect on the perceived increase in droughts (column (2)). On the other hand, coherently, there is evidence of a negative effect on perceived increase in cold associated with positive anomalies of temperatures (column (3)) and an opposite sign for anomalies related to abundant and scarce rainfall - respectively positive and negative - on the perceived variability of rainfall (column (4)). Temperature and precipitation anomalies seem not to have a significant effect on perceived decreases in precipitations (column (5)), where this result might be interpreted against the validity of Proposition 3.

Table A17: Subjective Perceptions and Anomalies à la Coniglio and Pesce (2015)

	Dependent Variable: <i>Subjective Perception</i>				
	(1) Increase Flood	(2) Increase Drought	(3) Increase Cold	(4) Erratic Rain	(5) Decrease Precipitations
+ Temperature Anomalies	0.760*** (0.281)	-0.672** (0.290)	-0.797** (0.328)	-1.342*** (0.315)	-0.555 (0.359)
- Temperature Anomalies	0.262* (0.152)	-0.290* (0.156)	-0.256 (0.166)	-0.387** (0.168)	0.0272 (0.174)
+ Precipitation Anomalies	0.00300 (0.00205)	-0.00305 (0.00221)	-0.00350 (0.00247)	0.00787*** (0.00261)	-0.000792 (0.00255)
- Precipitation Anomalies	0.00301*** (0.00113)	-0.00304*** (0.00116)	-0.00158 (0.00127)	-0.00307** (0.00137)	-0.00148 (0.00135)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1428	1428	1428	1428	1428
adj. <i>R</i> ²	0.005	0.451	0.043	0.319	0.418

Notes: Clustered-robust standard errors at household-level. Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Fixed Effects: Household, Union, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Farmers' Accuracy and Confirmation Bias

Farmers' accuracy and presence of confirmation bias can also be tested by building the outcome variable as the difference between the self-reported number of weather events experienced by the household and the historical objective number of weather events occurred in the district of the household in the same time period¹². The outcome variable is built as follows:

$$\Delta WE = \text{self-reported number} - \text{objective number} \quad (36)$$

where $WE \in \{\text{Floods, Droughts}\}$ ¹³. The main regressor of interest is the subjective perception of an increase in the number of the weather event of interest in each specification reported in Table A18. Data do not allow to run two different regressions distinguishing between farmers that over-estimate and under-estimate the number of weather events (i.e., respectively $\Delta >$ and < 0), because there is not enough variability in the some of the estimation sub-samples. The econometric specification writes as follows

$$\Delta WE = \theta \omega_{iut}^{WE} + X'_{iut} \beta + W'_{ut} \gamma + \alpha_i + \alpha_u + \alpha_d + \alpha_t + u_{iut} \quad (37)$$

Table A18: Accuracy of Self-Reported Evidence and Subjective Perceptions

	(1) Floods	(2) Droughts
Perception	0.705*** (0.178)	0.213** (0.0903)
Household Controls	Yes	Yes
Weather Controls	Yes	Yes
Fixed Effects	Yes	Yes
Dep Var Mean	-0.331	0.293
Dep Var SD	1.413	0.844
N	1428	1428
adj. R^2	0.032	0.091

Notes: Each column reports the estimate for the coefficient associated to the subjective perception of a change in the occurrence of a climatic characteristics, i.e., subjective perception of an increase in floods and in droughts, respectively. Clustered-robust standard errors at household-level. Household Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Weather Controls: Average Temperature and Precipitation over the 20-year period preceding the interview. Fixed Effects: Household, Union, District, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

¹²Respectively, in the five-year period preceding the first round of the survey and between the two rounds.

¹³The focus is only on these two variables since these events are the only both reported in the survey and in the EM-DAT database, where the historical objective number of weather events is taken from.

When adopting a 2SLS approach similar to the one in Table [11](#), with the same first stage, the estimates are displayed in Table [A19](#). Similarly to what found in Table [11](#), 2SLS estimates confirm the OLS results and seem to provide evidence that farmers are subject to confirmation bias when asked to report the number of droughts events.

Table A19: Farmers' Accuracy: 2SLS Estimates

	(1)	(2)
	Floods	Droughts
Perception	0.581 (1.612)	3.220* (1.810)
Household Controls	Yes	Yes
Weather Controls	Yes	Yes
Fixed Effects	Yes	Yes
K-P F-stat	9.138	7.616
<i>N</i>	1428	1428

Notes: Each column reports the estimate for the coefficient associated to the subjective perception of a change in the occurrence of a climatic characteristics, i.e., subjective perception of an increase in floods and in droughts, respectively. Clustered-robust standard errors at household-level. Household Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Weather Controls: Average Temperature and Precipitation over the 20-year period preceding the interview. Fixed Effects: Household, Union, District, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.4 Adaptation Strategies

Table A20: Adaptation Strategies to Climate Change

	Dependent Variable: <i>Adaptation Strategy</i>			
	(1) Crop Variety	(2) More Irrigation	(3) Planting Dates	(4) More Fertilizer
Subj. Increase Flood	-0.0342 (0.0518)	-0.0479 (0.0476)	0.121** (0.0525)	0.0669 (0.0538)
Subj. Increase Drought	-0.0349 (0.0478)	0.0657 (0.0423)	0.100** (0.0506)	0.133** (0.0514)
Subj. Increase Cold	0.0365 (0.0474)	0.0133 (0.0421)	-0.0685 (0.0520)	-0.0637 (0.0467)
Subj. Erratic Rainfall	0.160*** (0.0406)	0.171*** (0.0374)	0.137*** (0.0442)	0.0700 (0.0442)
Subj. Decrease Precipitation	0.0139 (0.0502)	0.113*** (0.0416)	-0.0378 (0.0478)	0.127*** (0.0466)
CV Temperature	33.86 (27.60)	8.168 (18.62)	58.48** (29.25)	-19.99 (24.75)
CV Precipitation	2.109*** (0.448)	-0.363 (0.368)	-2.830*** (0.472)	-1.178*** (0.434)
Receive Formal Information	-0.0108 (0.0534)	-0.0232 (0.0460)	0.187*** (0.0580)	-0.0521 (0.0537)
Log Unpaid Debt	-0.0196*** (0.00691)	-0.0106 (0.00668)	0.0136* (0.00732)	-0.00475 (0.00734)
Tractor Ownership	0.646*** (0.179)	0.213 (0.175)	-0.104 (0.218)	0.334 (0.229)
Other Agricultural Assets Ownership	0.212*** (0.0480)	0.0824 (0.0524)	-0.0267 (0.0588)	0.0442 (0.0586)
Historical Weather Controls	Yes	Yes	Yes	Yes
Current Weather Controls	Yes	Yes	Yes	Yes
Disaster Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
<i>N</i>	1428	1428	1428	1428
adj. R^2	0.251	0.364	0.119	0.118

Notes: Clustered-robust standard errors at household-level. Household Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Historical Weather Controls: Average temperature and average total precipitation over the past 20-year period. Current Weather Controls: Average temperature and average total precipitation in growing seasons of reference in year of interview and in previous year. Disaster Controls: Number of drought and flood events. Fixed Effects: Household, Union, District, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A21: Adaptation Strategies to Climate Change and Perceptions Index

	Dependent Variable: <i>Adaptation Strategy</i>			
	(1) Crop Variety	(2) More Irrigation	(3) Planting Dates	(4) More Fertilizer
<i>Panel A</i>				
Perceptions	0.221* (0.118)	0.408*** (0.0987)	0.262** (0.115)	0.325*** (0.113)
CV Temperature	33.11 (27.53)	13.83 (18.55)	47.77* (28.82)	-17.61 (25.04)
CV Precipitation	2.387*** (0.439)	-0.240 (0.361)	-2.747*** (0.460)	-1.286*** (0.417)
Historical Weather Controls	Yes	Yes	Yes	Yes
Current Weather Controls	Yes	Yes	Yes	Yes
Natural Disaster Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
adj. R^2	0.152	0.369	0.092	0.118
Perceptions Mean	0.402	0.402	0.402	0.402
Perceptions SD	0.247	0.247	0.247	0.247
<i>Panel B</i>				
Perception Index	0.0633** (0.0281)	0.143*** (0.0237)	0.0597* (0.0304)	0.110*** (0.0278)
CV Temperature	33.63 (27.54)	9.544 (18.37)	51.48* (28.55)	-20.18 (24.35)
CV Precipitation	2.420*** (0.437)	-0.185 (0.358)	-2.706*** (0.461)	-1.241*** (0.416)
Historical Weather Controls	Yes	Yes	Yes	Yes
Current Weather Controls	Yes	Yes	Yes	Yes
Disaster Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
adj. R^2	0.152	0.385	0.091	0.127
Perception Index Mean	0	0	0	0
Perception Index SD	1	1	1	1
N	1428	1428	1428	1428

Notes: Clustered-robust standard errors at household-level. Household Controls: Age, Literacy, HoH self-employed in farming activities, HH receives information from extension agents, HH size. Historical Weather Controls: Average temperature and average total precipitation over the past 20-year period. Current Weather Controls: Average temperature and average total precipitation in growing seasons of reference in year of interview and in previous year. Disaster Controls: Number of drought and flood events. Fixed Effects: Household, Union, District, Year; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.