How Beliefs about Climate Change Adapt? A Natural Experiment with Evidence on Excess Sensitivity to a Weather Event

Abstract

A prerequisite for adapting decisions to a new environment is the belief that the environment has changed. Agricultural field crop and grass-based cattle production involve long-term investments, including land conversion, buildings, drainage infrastructure, and crop-specific skill acquisition. Agricultural practices evolve to match the prevailing climate, so climate change will have major effects on the sector and timely adaptation is important for an efficient, economically sustainable production base. For a drought-prone region with variable weather and continental climate extremes, this chapter considers how a drought that occurred between two surveys of the same landowners affected responses to queries on viewpoints regarding changing weather patterns. Although drought is quite typical for the region and a single drought period is unlikely to be informative regarding climate change, we find that climate change beliefs were quite sensitive to the degree of drought experienced. The findings suggest that climate change perceptions are likely unstable, implying the need for caution when enacting intended to foster changing perspectives.

1 Introduction

Weather outcomes and the underlying climate enter many of the most important agricultural decisions. Despite the development of various agricultural technologies to cope with climate risk, climate remains a great influence on crop yields, and so on farmers' profits. For example, in 2019 heavy rainfall and flooding events prevented U.S. farmers from planting crops on more than 14 million acres in a timely manner (USDA, 2019). As a result, farmers are well-motivated to seek a better understanding of changes in weather patterns relevant to them so as to mitigate damage (e.g., Abendroth et al., 2020). In the process, they encounter various forms of information where for our purposes we classify weather/climate information used to make production decisions into i) subjective climate information based on first-hand experiences and feelings, and ii) objective data as might best be measured by official statistical sources.

These two forms of information receive different weights in decision-making while the processes involved in assimilating subjectively obtained climate information can lead to bias.

Individuals tend to base decisions on their perceptions (subjective information) as distinct from objective data (Akerlof and Dickens, 1982). Furthermore, statistical information is often recontextualized by decision makers based upon their own experiences (Marx et al., 2007). Therefore, how actual data affect human perceptions should be taken into consideration when analyzing farmer behavior and adaptation to climate. Support for climate policies is related to individual perceptions about climate change (Leiserowitz, 2006). Knowing the relationship between projected future climate and a farmer's viewpoint on climate change will allow policymakers to set the appropriate scope of and targets for climate change adaptation and mitigation policy as they seek to engage farmers.

In this chapter, we investigate the relation between human perception and weather events. Specifically, we focus on how beliefs about climate change adapt after experiencing an extreme weather event. We will examine objective statistical data by considering the weather history in our study area so as to understand respondents' previous experiences. We will also examine subjective, first-hand data, obtained from surveys conducted before and after a particular extreme weather event. Then, using Difference-in-Difference (DID) analysis, we analyze how perceptions about climate change shifted after experiencing the extreme weather event. The results will allow us to infer the relation between extreme weather event and human perception.

This chapter makes the following contributions to the literature. First, to our knowledge, no previous research regarding weather perceptions has used farmer panel data that was collected both i) before and ii) after an extreme weather event. The vast majority of relevant existing inquiries have used cross-sectional data that were only collected after an extreme weather event's occurrence (Spence et al., 2011; Haden et al., 2012; Niles et al., 2013). Second, previous studies on the topic have focused principally on personal experiences among the general public (Joireman et al., 2010; Li et al., 2011; Goebbert et al., 2012; Myers et al., 2013; Shao, 2016; Howe et al., 2019; Gärtner and Schoen, 2021). Only a few have focused on professionals whose business choices and performance outcomes are weather sensitive (Carlton et al., 2016). Our study subjects are farmers whose decisions are influenced by weather and, often, whose family livelihood depends on harvests that are dictated by weather. Experienced professionals have been found to make more rational decisions than people who are less experienced in the decision-making contexts at hand, likely because experiences admit a better understanding of the subject and deeper appreciation of related consequences (List 2004; List and Haigh 2009). Third, this study is distinguished from previous studies in that the survey was conducted without using the term “climate change”. Opinion on climate change can be heavily influenced by political and cultural background (McCright and Dunlap, 2011; Egan and Mullin, 2012; Myers et al., 2013; Yazar et al., 2021). Therefore, to prevent any possible bias the term “climate change” might evoke, our survey questions directly asked about changes in weather patterns. Finally, our most general contribution to the literature regards information on the stability and sensitivity of beliefs. We provide evidence that climate domain beliefs, at least regarding drought, may be excessively sensitive to recent events. Such sensitivity has important policy implications.

The remainder of this chapter is organized as follows. In the next section, we review existing literatures on how beliefs about climate change, and more generally beliefs about stochastic laws, change. We then describe our data and study area and follow up with a description of approaches to data analysis and methodologies used. After presenting the estimation results, we conclude with a brief discussion.

2 Literature Review

How we learn is determined in part by what is to be learned. Some information can be established deterministically by a controlled experiment designed and implemented by an experimenter so that learning can take place discretely over time. This is not the case when what is to be learned regards a distribution shift. Then repeated experiments are required in order to settle on the truth. Climate change refers to a change in climate at a location that occurs over many years and then persists for decades or longer (IPCC, 2021). Climate itself is an intricate assembly of stochastic events where climate change can be viewed as a re-weighting on event probabilities for a location as well as the emergence of weather events new to the location. Therefore, climate change can only be experienced by samples with timing determined by nature (Swim et al., 2011). Furthermore, personal perceptions about climate change are relatively unique as each individual has different preferences and circumstances, and may feel the impacts of climate change differently (Van Der Linden, 2014).

No consensus has yet emerged about whether a relationship exists between an extreme weather experience and perceptions about climate change. Many scholars have identified evidence that experiencing extreme weather events affects one's perception about climate change (Weber, 2013). However, not all studies agree that people change their perceptions after experiencing extreme weather events or how perceptions change. Whitmarsh (2008) has argued that there is no difference in responses to climate change between those who do and do not experience extreme floods. Brulle et al. (2012) found that none among high temperature, extreme precipitation, and drought had a significant effect on public concerns about climate change. On the other hand, Spence et al. (2011) examined the linkage between flooding experience and perceptions about climate change to infer that experiencing a flood does promote both concern about and actions to mitigate climate change. In an analysis that connected the U.S. National Oceanic and Atmospheric Administration (NOAA) storm events database with public opinion surveys, Konisky et al. (2015) found a positive relationship between an experience of extreme weather events and expressions of concern about climate change. Working with U.S. crop loss data and survey information about federal farm advisor viewpoints, Niles et al. (2019) demonstrated that experiencing extreme drought alters perceptions about weather variability as distinct from perceptions about climate change.

While the relationship between experiencing extreme weather events and climate change perceptions remains unclear, no literature has considered subject prior experiences when analyzing the relation between extreme weather experiences and climate change perceptions. Individuals perceive events based on their experience and personal values (Lazarus 1984; Loewenstein et al. 2001). Individuals who have frequently experienced certain weather events can increase their knowledge about these events and adapt their decisions on how to respond (Hansson et al., 1982). As climate change is a progressive process of adjustments in average weather patterns over a long time period, in order to examine how extreme weather events affect climate change perceptions it is important to control for a respondent's entire prior weather event experiences.

Belief formation regarding climate change is an important strand in the larger literature on belief updating, a literature that a brief review cannot possibly do justice to (Benjamin, 2019). Shiller (1981) and also De Bondt and Thaler (1985) have, for example, demonstrated that beliefs about future stock returns are excessively sensitive to information and may even respond to information of no relevance for stock returns. In addition to the novel challenge these observations pose for the efficient market hypothesis (Fama, 1970) and for neoclassical economics more generally, this finding is remarkable in the behavioral economics possibilities that it has posed and in making connections with disparate literatures. Among these are connections with experimental psychology and psychology more generally.

The earliest experiments on Bayesian updating were conducted by Ward Edwards and colleagues (Edwards and Phillips, 1968), who demonstrated conservatism in updating prior information and also the underweighting of prior beliefs (Benjamin, 2019; Kahneman and Tversky, 1973). This corpus also showed that more recent events are given extra weight in belief updates (Pitz and Reinhold, 1968; Grether, 1992; Benjamin, 2019), i.e., there are recency effects. Recency effects have long been detected in laboratory settings (Broadbent and Broadbent, 1981). They are also known to be present in learning to manage finances (Agarwal et al., 2008) and popular assessments of performance (Page and Page, 2010). Perhaps the most relevant work on how weather events affect beliefs about climate change is due to Deryungina (2013), who used Gallup Poll surveys in the United States over the years 2003-2010. She found little evidence of recency effects and substantial evidence in favor of Bayesian updating.

3 Data

In this section we introduce the data used in our analysis. As we are interested in the relationship between human perceptions and actual weather events, these data consist of two sets. One includes responses to two surveys that were conducted in 2015 and 2018. This set provides us with perceptions about climate change as well as respondent and farm characteristics. The other set contains objective official weather data as provided by the U.S. Drought Monitor (2021). The sets are linked by respondent location of residence information. Details on each data set are provided in separate subsections below.

3.1. Survey Data

Two surveys were conducted in 2015 and 2018 as part of a larger endeavor to understand land use adaptation and climate change. The first was conducted before a drought, and indeed before any reasonable indicators became available that a drought would occur in two years. In 2017 a drought hit North Dakota, South Dakota, and Montana, decreasing agricultural production, and resulting over one billion dollars in economic losses (Hoell et al., 2019). The drought, which occurred unexpectedly during the rainy season (Otkin et al., 2017), commenced in mid-May and spread through the Northern Great Plains until July 25th. The drought separated farmers into groups according to drought severity incidents in their locality, as measured objectively by government agencies through well-established procedures. The event provides a natural economic experiment in that it is a randomized treatment (Dunning, 2012).

Our study includes 20 counties in North Dakota and 37 counties in South Dakota, all east of the Missouri River (Figure 1). In each county, the majority of all farmland acres are under cultivated annual crops. The survey targeted farm operators who operated more than 100 acres and had recently raised at least some wheat, corn, soybeans, or grass/hay. The survey sample was purchased from a farm sampling frame provided by Survey Sampling International (now, after company rebranding, Dynata, self-claimed to be "the world's largest first-party data company, with a global reach of nearly 70 million consumers and business professionals"). Sample selection was proportional by county so that more farmers were included from counties with comparatively more eligible farms. All survey mailing and data coding were handled by the Iowa State University Survey Research Center. The survey has been reported elsewhere where further details are available in Wang et al. (2017) and Wimberly et al. (2017), where studies examined issues related to land use change.

Figure 2 describes the timeline for our belief adaptation natural experiment. For the first survey (Survey #1), conducted in 2015, 3,000 surveys were mailed and 1,026 completed surveys were returned (34.2% response rate). The drought, which we consider to be nature's treatment, arrived two years later. In 2018, a follow-up survey (Survey #2) was conducted for the 884 respondents who had completed the 2015 survey and were less than 70 years old at the time of the 2018 survey. We received 517 surveys back, a 61.9% response rate. Among Survey #2 responses, 506 were sufficiently complete for inclusion in our analysis. Figure 1 shows the number of sufficiently complete responses for both surveys across the counties studied.

For weather pattern perceptions about drought, the respondents were asked to indicate 'less', 'same', or 'more' compared to the past 10 years. In addition, we collected respondent demographics, farm business characteristics such as whether they applied no-till cropping or used tile drainage, as well as land ownership status and soil characteristics including slope and Land Capability Classes (LCC). LCC classification partitions land into eight categories based on soil and land attributes (Helms, 1992). Variable descriptions and summary statistics are presented in Table

1.

Table 1 Variable Descriptions and Summary Statistics

Variable	Description	Mean (Std. Dev.)	Min	Max
drou15	Drought pattern perception in 2015. Less drought (=1); Same (=2); More drought (=3) compared to the past 10 years.	1.89 (0.70)	1	3
drou18	Drought pattern perception in 2018. Less drought (=1); Same (=2); More drought (=3) compared to the past 10 years.	2.16 (0.74)	1	3
Birth year	Birth year	1960 (9.93)	1929	1992
Education	Highest education level completed. Less than high school (1); high school (2); some college/technical school (3); 4-year college degree (4); Advanced degree (5)	3.04 (0.84)	1	5
Earn	Level of annual gross farm/ranch sales: <$50K (1); $50K-$99.9K (2); $100K-$249.9K (3); $250K-$499.9K (4); $500K-$999.9K (5); $1 million+ (6)	3.91 (1.31)	1	6
Ownership	Land ownership status. Own all acres farmed (1); own most acres farmed, renting the remainder (2); own and rent roughly equal number of farmland acres (3); rent most acres farmed, owning the remainder (4); rent all acres farmed (5)	2.79 (1.16)	1	5
No-till	=1 if adopted or increased use of no-till between 2005 and 2015; = 0 otherwise.	0.51 (0.50)	0	1
Drainage	=1 if adopted or increased drainage on cropland acres between 2005 and 2015; = 0 otherwise.	0.23 (0.42)	0	1
LCC4	Percentage of soils with Land Capability Classification (LCC) less than or equal to IV within 1 mile radius	95.41 (11.44)	0.02	100
Slope	Percentage of soils with slope less than or equal to 4 within 1 mile radius.	48.52 (36.73)	0	100
Latitude	Latitude of respondent's location	45.29 (1.31)	42.91	47.83
Longitude	Longitude of respondent's location	-98.00 (1.07)	-100.78	-96.47

Given non-responses (38.1%) in the second survey, representativeness and sample selection issues are concerns. Table 2 compares responses given in the repeated samples with those given by subjects who took part only in Survey #1. Significant differences in mean drought pattern perceptions and farm ownership become apparent. Respondents who answered the follow up survey in 2018 were more likely to own a comparatively higher percentage of farmland. The farm ownership variable is 0.17 lower in the repeated group. Also, when compared with those who completed Survey #1 only, Survey #2 respondents reported on average 0.38 units lower perceived changes in drought. This difference leads us to conjecture that there may be a selection bias. Except for these differences, the repeated group and the non-repeated group show no significant difference.

Table 2 2015 Summary Statistics for Survey #1 Responses, broken down by those who answered both surveys and those who answered only Survey #1

	Repeated, (Answered both surveys)		Non-repeated, (i.e., answered Survey #1 only)	
	Mean	Std. Dev.	Mean	Std. Dev.
Drou15 ***	1.89	0.70	2.27	1.15
Drought Severity	1.07	0.91	1.14	0.95
Age	3.03	0.85	2.98	0.94
Education	3.04	0.84	2.99	0.88
Annual income	3.91	1.31	3.82	1.39
Farm ownership **	2.79	1.16	2.96	1.23
LCC4	95.41	11.44	95.98	10.44
Slope	48.52	36.73	49.18	3841
Drainage	0.23	0.42	0.21	0.41
No-till	0.51	0.50	0.51	0.50

*,**,*** indicates mean difference is significant at 10%, 5%, 1% levels, respectively.

3.2. Drought Data

As the survey data only provide us with how respondents perceived weather, we also need an objective weather metric to compare with. For this purpose, the Drought Index (DI) from the U.S. Drought Monitor (USDM) as recorded on July 25th from the years 2000 through 2017 was collected. We choose the drought condition on July 25th 2017 because the drought was most widespread during that week. The USDM is reported weekly and its values are temporally stable, but to confirm robustness we also considered data recorded on July 18th and August 1st. The magnitude of drought effect[1] is smaller with these alternative dates as the drought was most common in the week of July 25th 2017 but they had no material effect on our results. The data range 2000-2017 was chosen because DI data are available since 2000 while 2017 represents the extent of data available to the 2018 survey respondents.

The index DI is produced jointly by the National Drought Mitigation Center (NDMC) at the University of Nebraska-Lincoln, NOAA, and the U.S. Department of Agriculture (USDA) using satellite-based assessments and climatological indices such as the Palmer Drought Severity Index and the Keech-Byram Drought Index for fire (U.S. Drought Monitor, 2021). This index identifies drought severity under four categories as described in Table 3. Unlike other index such as the Palmer Drought Severity Index or the Standardized Precipitation Index, DI is not a statistical model. DI aggregates a variety of contributory factors, including soil moisture, hydrological inputs, climatological inputs as well as local data such as grazing conditions or information about how drought is affecting people, to ensure index robustness and suitability for monitoring impact on agriculture (Svoboda et al., 2002). The severity of drought experienced by each respondent was assumed to be that for the farm address as collated with DI spatial maps.

Table 3 Description of Drought Monitor Index

Drought Category	Description of the Category (U.S. Drought Monitor, 2012)	N[1)]
None	-	13
D0	Abnormally dry: when going into drought, short-term dryness slows growth of crops/pastures and when going out of drought, there are some lingering water deficits.	150
D1	Moderate drought: some damage to crop/pastures, some developing water shortages.	196
D2	Severe drought: crop/pasture losses are likely, water shortages are common.	108
D3	Extreme drought: major crop/pasture losses, widespread water shortages.	39
D4	Exceptional drought: are exceptional and widespread crop/pasture losses and shortages of water creating water emergencies.	0

1) N represents the number of respondents who answered survey in both 2015 and 2018. Total N = 506.

[1] We applied Difference-in-difference analysis with the data 1 week before July 25th and 1 week after July 25th and both results show that the drought changed people's perceptions toward that there were more droughts.

We form H, for history, as our historical drought indicator by using 18 years (2000-2017) of drought data to arrive at the unconditional probability of experiencing any level of drought at a given location on July 25th as

$$H \equiv \Pr(\text{Drought } 07/25) = \frac{\text{Years among 2000-'17 in which drought occurred on } 07/25}{18}. \quad (1)$$

Historical data, not reported due to space constraints, show that droughts are comparatively less frequent in North Dakota.

4 Study Area, Drought History and Hypothesis Development

The study area is part of the Prairie Pothole region in the Dakotas where corn, soybeans, and wheat are currently the dominant cropland uses. Wheat is grown throughout the area, being most prevalent toward the north and west. Corn is dominant in the region's southern and eastern parts while soybean is most widely planted in the north (Alemu et al., 2020). The region's agriculture is susceptible to drought damage because all crops, but especially corn, require water throughout growth in order to mature. This region has experienced significant land use changes in the last two decades or so, as documented by several studies (e.g., Wimberly et al., 2013). While crop prices and improved crop yields have been identified as the main drivers of the conversion of grassland to cropland in this region, climate and weather factors have also been proposed as an important driver (e.g., Rashford et al., 2016). Thus, understanding climate change patterns and farmers' perceptions of these patterns will help better design policies intended to address grassland loss in the region.

Due to complex interactions among three air masses; Continental Polar, Maritime Tropical, and Maritime Polar (Ahrens, 2007), this region experiences inherently high weather variability as well as comparatively extreme precipitation and temperature events within and between years (Conant et al., 2018). The majority of total annual precipitation occurs during spring months (April to June) but interannual variability in springtime precipitation is large (Knapp and Smith, 2001). A time series presentation of DI measurements broken down by severity level but averaged over all areas in the two states is provided in Figure 3. It can be seen that droughts are common in the region, and also that a severe drought occurred in 2012 for an extended period of time.

Figure 4 describes the study area's 1-year Standardized Precipitation Index (SPI; McKee et al., 1993) by state. SPI is an index based on the distribution of precipitation over a recent time window. It is formed from dividing the difference between precipitation and mean precipitation for a specified time divided by the standard deviation, where mean and standard deviation are determined from the climatological record. A larger value indicates a more severe condition. Generally, 3-, 6-, 12-, 24- and 48-month time windows SPI values are used depending on research purposes. SPI with shorter time windows describe short-term precipitation patterns and these are appropriate precipitation indices for monsoon regions where conditions are generally wet during a given period. Longer timescale SPI reflect long-term precipitation patterns and tends toward zero unless there is a distinctive dry or wet trend. Also, while the USDM Drought Index became available in 2000 SPI has been is available since 1980.

We think the one-year SPI is most appropriate for studying historical weather patterns. A positive (respectively, negative) SPI value on a date indicates that precipitation on this date exceeds (is less than) average precipitation over the given time scale. According to SPI conventions, a drought occurs whenever the SPI value is below -1.0. Figure 4 illustrates extensive historical inter-annual fluctuation in precipitation, showing that the region has been prone to recurring droughts. In the region's meteorological records most droughts have lasted less than one year but every few decades prolonged drought periods (the 1930s Dust Bowl, 1955-1960, and 1988-1990) also occur (Jencso et al., 2019). In general, Northern Plains region droughts lasting 3-5 months occur approximately once every 5 years and droughts lasting 6-8 months occur approximately once every 10 years (NIDIS/NOAA, 2018).

When we look at the historical DI, according to Eqn. (1) the average probability of experiencing a drought on July 25th during 2000-2017 was 0.35 across all respondents and the average severity level on July 25th during 2000-2017 was 0.72 with range between 0.17 and 2. Figures 5 describes the actual drought severity on July 25th 2017 with average drought severity on July 25th each year during 2000-2017. The drought on July 25th 2017 is presented in shaded area and the darker shade represents more severe drought. The drought severity in 2017 was highest in the west. The dots in gray-scale describe the average severity level during 2000-2017 and darker the dot, more severe the drought. When we compare the historical average with the July 25th 2017 severity level the Spearman correlation coefficient is 0.229 (p=0.000), also indicating recurring droughts in the region. Thus, our main hypothesis is that the 2017 drought should not have been a surprise.

5 Methods

5.1 Conceptual Considerations

The information content of the 2017 drought should of course depend very much on a location's drought history. In what follows we take the standard approach to understand information updating, namely Bayesian analysis (Stone, 2013). We denote the 2017 drought event by I_{2017} and signify prior perceptions by $\Pr(M_t)$ where t=2015 or 2018, where M_t represents the survey respondent's subjective assessment at time t, that droughts are becoming more common. The complementary expressed subjective probability, i.e., that they are not becoming more common, is given as $\Pr(NM_t) = 1 - \Pr(M_t)$. From Bayes' theorem, when $\Pr(M_{2018})$ represents a respondent's 2018 survey posterior probability then

$$\Pr(M_{2018} \text{ and } I_{2017}) \equiv \overbrace{\Pr(M_{2018} \mid I_{2017})}^{\substack{\text{Posterior}\\ \text{given event } I_{2017}}} \times \Pr(I_{2017}) \equiv \overbrace{\Pr(I_{2017} \mid M_{2018})}^{\substack{\text{Update given}\\ \text{event } I_{2017}}} \times \frac{\Pr(M_{2018})}{\Pr(M_{2015})} \times \overbrace{\Pr(M_{2015})}^{\text{Prior}}. \tag{2}$$

so that

$$\frac{\Pr(M_{2018} \mid I_{2017})}{\Pr(M_{2015})} \equiv \frac{\Pr(M_{2018})}{\Pr(M_{2015})} \times \frac{\Pr(I_{2017} \mid M_{2018})}{\Pr(I_{2017})}. \tag{3}$$

If the unconditional probabilities are the same, i.e., $\Pr(M_{2018}) = \Pr(M_{2015})$, then we may write the equation as

$$\frac{\Pr(M_{2018} \mid I_{2017})}{\Pr(M_{2015})} \equiv \frac{\Pr(I_{2017} \mid M_{2018})}{\Pr(I_{2017})}. \tag{4}$$

as the relative drought-conditioned probability update regarding future droughtiness. The left-hand side in (4) determines how the drought event shapes beliefs about climate while the right-hand side characterizes how beliefs about climate shape drought probabilities. If the drought is not a surprising event then $\Pr(M_{2018} \mid I_{2017}) / \Pr(M_{2015}) \approx 1$ so that the extent to which $\Pr(M_{2015}) / \Pr(M_{2018} \mid I_{2017})$ is less than one measures surprise. Baldi and Itti (2009) use this conditioning observation to characterize surprise (or Wow) as, in our terminology,

$$W(I_{2017}, M) = -\ln\left(\frac{\Pr(M_{2018} \mid I_{2017})}{\Pr(M_{2015})}\right). \tag{5}$$

We write $S_u(k, D_i) \in [0,1]$ as the share of respondents in 2017 drought zone D_i who take the view in year $u \in \{2015, 2018\}$ that drought is becoming $k \in K \equiv \{\text{Less, Same, More}\}$ likely. We follow Baldi and Itti in using the entropy form to characterize zone-specific ex-ante average surprise as

$$W(D_i) = -\sum_{k \in K} S_{2015}(k, D_i) \ln\left(\frac{S_{2018}(k, D_i)}{S_{2015}(k, D_i)}\right), (6)$$

where no surprise can be depicted by $S_{2018}(k, D_i) = S_{2015}(k, D_i)\ \forall k \in K$ so that $W(D_i) = 0$, the statistic's least value. Using our data, we test our main hypothesis that average surprise is zero. Given that surprise is registered, alternative reasonable hypotheses are that surprise should increase with drought severity, i.e., $W(D_{i+1}) \geq W(D_i)\ \forall i \in \{0,1,2,3\}$, and that the drought was more of a surprise for North Dakota than for South Dakota.

5.2 Empirical Analysis

With the intent to further our understanding of how drought affects climate change perception, the methods used are of two types. The first involves descriptive statistics, including intertemporal comparisons of cumulative distributions, and comparisons among means. The second general approach is DID analysis. This analysis allows us to measure the treatment effect by examining differences between the average change over time for a treatment group, who experienced the drought on July 25th 2017, and the average change over time for a control group, who did not experienced any drought on July 25th 2017.

Two identifying assumptions should be satisfied in order to apply DID analysis (Angrist and Pischke, 2009). The treatment should be mean-independent with respect to the error term. In other words, there should not be any unobserved variables that affect both the farmers' perception and the severity of the drought that a farmer experiences. Because ours is a natural experiment and farmers had no control over which drought they experienced, this assumption is not violated. The second assumption generally referred to as 'parallel trends', is that the background trend over time should be the same across the treatment and control groups. A commonly used method to verify this second assumption is visual inspection, i.e., comparing plots for the treatment and control groups. A statistical test of the parallel trend assumption can be made by including a time regressor in the model to control for trends (Card and Krueger, 2000; Hastings, 2004; Besley and Burgess, 2004). However, as our data consists of only two periods we can apply neither visual inspection nor time lags to validate this assumption. We assume that the parallel trends assumption holds. We consider this a reasonable assumption because our treatment is randomized by nature, and so is likely exogenous to respondent's characteristics (Cunningham, 2021).

DID analysis allows us to measure the treatment effect by examining differences between estimated coefficients for the treatment group and those for the control group. Our DID model is specified as

$$\text{Perception}_{i,t} = \alpha_0 + \alpha_1 \text{Dtime} + \beta * \text{Tr} + \gamma * \text{Dtime} * \text{Tr} + \sum_i \lambda_i x_i + \varepsilon_{i,t}, \quad (7)$$

where Dtime (0 = pre-treatment, 1 = post-treatment) and Tr (1 = Experienced drought, 0 = Did not experienced drought) are dummy variables and $\varepsilon_{i,t}$ is the error term. The variables denoted by x_i are controls such as respondent demographics. The interaction term Dtime*Tr is our primary object of interest. The interaction term coefficient should capture changes in respondent perceptions between surveys.

When viewed collectively, prior drought history in the region (figures 3 and 4), the 2017 drought map (Figure 5), and Spearman correlations suggest that farmers in the region are well-accustomed to drought. For this reason, we frame our hypothesize as $\gamma = 0$ because farmers who experienced drought in 2017 should not alter their climate change perception as a result of the drought event.

6 Results

In this section, we first examine intertemporal cumulative distributions and compare how responses changed over the two surveys. Then we calculate how much of a surprise the drought was to the respondents based on the Baldi and Itti (2009) entropy metric. Lastly, effects of the drought on perceptions are estimated using DID analysis, as the entropy analysis only tells us whether there was a significant shift in perceptions, not the direction of the shift.

6.1 Temporal Changes in Perception Responses

In this sub-section, we use intertemporal cumulative distributions to examine how the perceptions shifted over the two surveys. Then we calculate the measure of surprise. This analysis allows us to ascertain whether prior perceptions about weather held constant or changed after experiencing drought.

Figure 6 shows the cumulative percentage of views expressed in 2018 conditional on views expressed in 2015. From the graph, respondents who expressed the view in 2015 that there were more droughts are also more likely to indicate in the 2018 survey that there were more droughts. Similarly, respondents with the view in 2015 that there were fewer droughts are also more likely to provide this answer in the 2018 survey. Figure 7 focuses on those who answered that there were more droughts in 2018 and decomposes respondents by the severity of drought incurred in 2017. The figure shows that for D1, D2, and D3 level droughts the percentage of the respondents who held that there had been more droughts increased between surveys. Among those who had experienced D0 level drought the percentage decreased slightly. When we look at how individual views changed between the two surveys, see Figure 8, a distinctive pattern emerges. Respondents who experienced the D0 level drought changed their views toward more droughtiness (from “Less” to “Same” or “More” in union with from “Same” to “More”) was smaller than the proportion who changed their views toward less drought (from “More” to “Same” or “Less” in union with from “Same” to “Less”). However, for drought levels D1, D2, and D3 the fraction shift was reversed. Noteworthy is that the difference, ‘change toward more drought’ less ‘change toward less drought’, increases with the 2017 drought severity level, being -2% for D0, 27% for D1, 30% for D2, and 54% for D3.

The shifts in perception can be measured by how surprised the respondents were when they experienced the 2017 drought. According to Table 4, the average surprise increases with drought severity when the respondents experienced the drought in 2017. Not experiencing any drought was also a surprise and was more surprising than the level D2 drought. Comparing states, the drought was more surprising in North Dakota. In short, the 2017 drought was a surprise to the respondents and shifted drought pattern perceptions.

Table 4 Share of Drought Pattern Perception and the Measure of Surprise by Their Drought Experience in 2017 and State

Drought experience	Year	Drought pattern perception			Wow
		Less	Same	More	
No drought	2015	18%	45%	36%	0.30
	2018	36%	55%	9%	
D0	2015	30%	47%	23%	0.003

	2018	31%	49%	20%	
D1	2015	32%	50%	18%	0.16
	2018	18%	39%	43%	
D2	2015	23%	51%	26%	0.18
	2018	7%	45%	48%	
D3	2015	43%	54%	3%	0.54
	2018	16%	38%	46%	
State	Year	Less	Same	More	Wow
North Dakota	2015	40%	49%	12%	0.15
	2018	21%	46%	33%	
South Dakota	2015	25%	50%	25%	0.05
	2018	19%	42%	39%	

6.2 Effect of the Drought on the Farmer's Perception

Table 5 provides the DID estimates. The dependent variable is a perception about drought, and treatment is whether the respondents experienced any level of drought in 2017. Respondents who experienced no drought are considered to be untreated. Control variables include farmer demographics, farm characteristics, and the probability of drought. The coefficient for the interaction term Dtime*Tr, generated by multiplying the drought experience and time dummy variables, is 0.530 and is statistically significant (p=0.000). It is larger than zero, indicating that the 2017 drought shifted perceptions toward there being more droughts. This is a large shift as the perception index has range [1, 3].

Table 5 DID Analysis on the Perception of Drought Pattern

Variable	Coefficient (Std. Err.)
Dtime (=1 if after 2017 drought)	-0.073 (0.085)
Tr (=1 if experienced drought)	-0.071 (0.081)
Dtime*Tr	0.530^{***} (0.101)

Birth year	0.009*** (0.003)
Education	0.054* (0.028)
Income	-0.060*** (0.019)
Ownership	0.052*** (0.020)
Crop ratio	-0.028 (0.101)
Probability of drought	0.906*** (0.253)
LCC4	0.003* (0.002)
Slope	0.001 (0.001)
Drainage	0.007 (0.064)
No-till	0.051 (0.049)
Constant	-17.079*** (4.907)

*,**,*** indicates significance at 10%, 5%, 1% levels, respectively.

7 Assessment and concluding remarks

Figures 3 and 4 show that the 2017 drought was less severe than the one that occurred three years before the first survey. The 2017 drought lasted for three months and only the one-year SPI for the north central region in South Dakota went below -1. By contrast, the 2012 drought lasted for a year and was much more severe than the 2017 drought. Between 1980 and 2017, SPI fell to -1 or lower on more than 10 occasions. These past events show that the 2017 drought should not have been a surprisingly severe event for farmers in the area. Yet respondents were surprised.

A single survey comparison cannot allow for distinctions to be made between a shift in opinions that is fundamentally unstable and one that, although perhaps similar to prior shifts, turns out to be permanent. An approach other than ours, probably using regular polling, would be needed to better understand opinion stability. In any case, surveys alone will not convey how and why opinions harden. Information is likely not the only, or even dominant, factor in determining viewpoints because a taste for conformity arising from fear or to gain acceptance or to internalize dissonant pressures (Kelman, 1958) may also matter as may the tangibility of the weather event at issue (Asch, 1951).

A matter that remains unclear is whether the sensitivity of climate change perceptions to weather events can facilitate the management of climate change, including consent to policy adjustments. For better or worse, public and private responses that are conditioned on weather events will generate a more receptive citizenry so long as policies are put into effect quickly. However, those that take longer to implement or modify may miss the moment. The wisdom of policy enactment based on ephemeral, although genuine, support is another matter.

References

Abendroth, L. J., Miguez, F. E., Castellano, M. J., Carter, P. R., Messina, C. D., et al. (2021) Lengthening of maize maturity time is not a widespread climate change adaptation strategy in the US Midwest. *Global Change Biology*, 27(11), 2426-2440.

Agarwal, S., J. C. Driscoll, X. Gabaix, and D. Laibson. (2008) Learning in the Credit Card Market. National Bureau of Economic Research Working Paper 13822, February, Cambridge MA.

Ahrens C. D. (2007) *Meteorology today: an introduction to weather, climate, and the environment*, 8th edn. Thompson, Brooks/Cole.

Akerlof, G. A. and Dickens, W. T. (1982) The economic consequences of cognitive dissonance. *The American Economic Review*, 72(3), 307-319.

Alemu, W. G., Henebry, G. M., and Melesse, A. M. (2020) Land Cover and Land Use Change in the US Prairie Pothole Region Using the USDA Cropland Data Layer, *Land*, *9*(5), 166.

Angrist, J. D., and J.S. Pischke. (2009) *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press, Princeton NJ.

Asch, S. E. (1955) Opinions and Social Pressure. *Scientific American*, 193(5), 31-35.

Baldi, P. and L. Itti. (2009) Bayesian surprise attracts human attention. *Vision Research*, 49, 1295-1306.

Benjamin, D. J. (2019) Errors in probabilistic reasoning and judgment biases. In: B. Douglas Bernheim, S. DellaVigna, D. Laibson, (Eds.), *Handbook of Behavioral Economics – Foundations and Applications, Volume 2*, Ch. 2, pp. 69-186. Elsevier.

Besley, T. and Burgess, R. (2004) Can labor regulation hinder economic performance? Evidence from India. *Quarterly Journal of Economics*, 119(1), 91-134.

Broadbent, D. E. and M. H. P. Broadbent. (1981) Recency Events in Visual Memory. *Quarterly Journal of Experimental Psychology*, 33(1), 1-15.

Brulle, R. J., Carmichael, J., and Jenkins, J. C. (2012) Shifting Public Opinion on Climate Change: An Empirical Assessment of Factors Influencing Concern over Climate Change in the U.S., 2002-2010. *Climatic Change*, 114(2), 169-188.

Card, D. and Krueger, A. B. (2000) Minimum wages and employment: a case study of the fast-food industry in New Jersey and Pennsylvania: reply. *American Economic Review 90*(5), 1397-1420.

Carlton, J. S., Mase, A. S., Knutson, C. L., Lemos, M. C., Haigh, T., et al. (2016) The Effects of Extreme Drought on Climate Change Beliefs, Risk Perceptions, and Adaptation Attitudes. *Climatic Change*, 135(2), 211-226.

Conant, R. T., Kluck, D., Anderson, M., Badger, A., Boustead, B. M., et al. (2018) Northern Great Plains. In *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II* [Reidmiller, D.R., C.W. Avery, D.R. Easterling, K.E. Kunkel, K. L. M., Lewis, T. K. Maycock, & B. C. Stewart (eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 941-986. Accessed June 2019, doi: 10.7930/NCA4.2018.CH22.

Cunningham, S. (2021) *Causal inference*. Yale University Press.

De Bondt, W. F. M. and R. Thaler. (1985) Does the Stock Market Overreact? *Journal of Finance*, 40(3), 793-805.

Deryungina, T. (2013) How do People Update? The Effects of Local Weather Fluctuations on Beliefs about Global Warming. *Climatic Change*, 118, 397-416.

Dunning, T. (2012) *Natural Experiments in the Social Sciences: A Design-Based Approach.* Cambridge University Press.

Edwards, W. and Phillips. L. D. (1968) Man as transducer for probabilities in Bayesian command and control systems. In: B. Kleinmuntz, (Ed.), *Human Judgements and Optimality*, pp. 360-401. Wiley, New York.

Egan, P. J. and M. Mullin. (2012) Turning Personal Experience into Political Americans' Perceptions about Global Warming. *Journal of Politics*, 74(3), 796-809.

Fama, E. F. (1970) Efficient Capital Markets: A Review of Theory and Empirical Work. *Journal of Finance,* 25(2), 383-417.

Gärtner, L. and H. Schoen. (2021) Experiencing climate change: revisiting the role of local weather in affecting climate change awareness and related policy preferences. *Climatic Change,* 167(3), 1-20.

Goebbert, K., Jenkins-Smith, H. C., Klockow, K., Nowlin, M. C., and Silva, C. L. (2012) Weather, Climate, and Worldviews: The Sources and Consequences of Public Perceptions of Changes in Local Weather Patterns. *Weather, Climate, and Society,* 4(2), 132-144.

Grether, D. M. (1992) Testing Bayes' Rule and the Representativeness Heuristic: Some Experimental Evidence. *Journal of Economic Behavior and Organization*, 17(1), 31-57.

Haden, V. R., Niles, M. T., Lubell, M., Perlman, J., and Jackson, L. E. (2012) Global and Local Concerns: What Attitudes and Beliefs Motivate Farmers to Mitigate and Adapt to Climate Change? *PLoS ONE,* 7(12).

Hansson, R. O., Noulles, D., and Bellovich, S. J. (1982) Knowledge, warning, and stress: A study of comparative roles in an urban floodplain. *Environment and Behavior,* 14(2), 171-185.

Hastings, J. S. (2004) Vertical relationships and competition in retail gasoline markets: Empirical evidence from contract changes in Southern California. *American Economic Review,* 94(1), 317-328.

Helms, D. (1992) *The Development of the Land Capability Classification. In Readings in the History of the Soil Conservation Service*, Soil Conservation Service, Washington DC.

Hoell, A., Perlwitz, J., and Eischeid, J. (2019) The Causes, Predictability, and Historical Context of the 2017 U.S. Northern Great Plains Drought. NOAA National Integrated Drought Information System. https://repository.library.noaa.gov/view/noaa/23003

Howe, P. D., Marlon, J. R., Mildenberger, M., and Shield, B. S. (2019) How will climate change shape climate opinion? *Environmental Research Letters*, 14(11), 113001.

IPCC, 2021: Annex VII: Glossary [Matthews, J. B. R., J. S. Fuglestvedt, V. Masson-Delmotte, V. Möller, C. Méndez, R. van Diemen, A. Reisinger, S. Semenov (ed.)]. In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [MassonDelmotte, V., P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu and B. Zhou (eds.)]. Cambridge University Press. In Press.

Jencso, K., Parker, B., Downey, M., Hadwen, T., Howell, A., et al. (2019) Flash Drought: Lessons Learned from the 2017 Drought Across the U.S. Northern Plains and Canadian Prairies. NOAA National Integrated Drought Information System.

Joireman, J., Barnes, H., and Duell, B. (2010) Effect of Outdoor Temperature , Heat Primes and Anchoring on Belief in Global Warming. *Journal of Environmental Psychology,* 30(4), 358-367.

Kahneman, D. and Tversky, A. (1973) On the Psychology of Prediction. *Psychological Review*, 80(4), 237-251.

Kelman, H. C. (1958) Compliance, Identification, and Internalization: Three Processes of Attitude Change. *Journal of Conflict Resolution*, 2(1), 51-60.
Knapp, A. K., and Smith, M. D. (2001) Variation among biomes in temporal dynamics of aboveground primary production. *Science*, 291 (5503), 481-484.
Konisky, D. M., Hughes, L., and Kaylor, C. H. (2015) Extreme Weather Events and Climate Change Concern. *Climatic Change*, 134(4), 533-547.
Lazarus, R. S. (1984) On the primacy of cognition. *American Psychologist*, 39(2), 124–129. https://doi.org/10.1037/0003-066X.39.2.124
Leiserowitz, A. (2006) Climate change risk perception and policy preferences: The role of affect, imagery, and values. *Climatic Change*, 77, 45-72.
List, J.A. (2004) Neoclassical theory versus prospect theory: Evidence from the marketplace. *Econometrica*, 72(2), 615-625.
List, J.A. and Haigh, M.S. (2009) Investment under uncertainty: testing the options model with professional traders. *Review of Economics and Statistics*, 92(4), 974-984.
Li, Y., Johnson, E. J., and Zaval, L. (2011) Local Warming : Daily Temperature Change Influences Belief in Global Warming. *Psychological Science*, 22(4), 454-459.
Loewenstein, G. F., Weber, E. U., Hsee, C. K., and Welch, N. (2001) Risk as feelings. *Psychological bulletin*, 127(2), 267.
Marx, S. M., Weber, E. U., Orlove, B. S., Leiserowitz, A., Krantz, D. H. et al. (2007) Communication and Mental Processes: Experiential and Analytic Processing of Uncertain Climate Information. *Global Environmental Change*, 17(1), 47-58.
McCright, A. M. and Dunlap, R. E. (2011) Cool Dudes: The Denial of Climate Change among Conservative White Males in the United States. *Global Environmental Change*, 21(4), 1163-1172. http://dx.doi.org/10.1016/j.gloenvcha.2011.06.003.
McKee, T. B., Doesken, N. J., and Kleist, J. (1993) The relationship of drought frequency and duration to time scales. *Proceedings of the 8th Conference on Applied Climatology*, 17(22), 179-183.
Myers, T. A., Maibach, E. W., Roser-Renouf, C., Akerlof, K., and Leiserowitz, A. A. (2013) The Relationship between Personal Experience and Belief in the Reality of Global Warming. *Nature Climate Change*, 3(December), 343-347.
NIDIS/NOAA. 2018. *Historical Character of United States Northern Great Plains Drought*.
Niles, M. T., Lubell, M., and Haden, V. R. (2013) Perceptions and Responses to Climate Policy Risks among California Farmers. *Global Environmental Change*, 23(6), 1752-1760.
Niles, M. T., Wiener, S., Schattman, R. E., Roesch-McNally, G., and Reyes, J. (2019) Seeing Is Not Always Believing: Crop Loss and Climate Change Perceptions among Farm Advisors. *Environmental Research Letters*, 14(4), 044003.
Otkin, J. A., Svoboda, M., Hunt, E. D., Ford, T. W., Anderson, M. C., et al. (2017) Flash Droughts: A Review and Assessment of the Challenges Imposed by Rapid-Onset Droughts in the United States. *Bulletin of the American Meteorological Society*, 99, 911-919.
Page, L. and Page, K. (2010) Last Shall be First: A Field Study of Biases in Sequential Performance Evaluation on the Idol Series. *Journal of Economic Behavior and Organization*, 73(2), 186-198.
Pitz, G. F. and Reinhold, H. (1968) Payoff Effects in Sequential Decision-making. *Journal of Experimental Psychology*, 77(2), 249-257.
Rashford, B. S., Adams, R. M., Wu, J., Voldseth, R. A., Guntenspergen, G. R., et al. (2016).

Impacts of climate change on land-use and wetland productivity in the Prairie Pothole Region of North America. *Regional Environmental Change*, 16(2), 515-526.

Shao, W. (2016) Are Actual Weather and Perceived Weather the Same? Understanding Perceptions of Local Weather and Their Effects on Risk Perceptions of Global Warming. *Journal of Risk Research*, 19(6), 722-742. http://dx.doi.org/10.1080/13669877.2014.1003956.

Shiller, R. J. (1981) Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends? *American Economic Review*, 71(3), 421-436.

Spence, A., Poortinga, W., Butler, C., and Pidgeon, N. F. (2011) Perceptions of Climate Change and Willingness to Save Energy Related to Flood Experience. *Nature Climate Change*, 1(4), 46-49. http://dx.doi.org/10.1038/nclimate1059.

Stone, J. V. (2013) *Bayes' Rule: A Tutorial Introduction to Bayesian Analysis*. Sebtel Press.

Svoboda, M., Lecomte, D., Hayes, M., Heim, R., Gleason, K., et al. (2002) The Drought Monitor. *Bulletin of the American Meteorological Society*, 83(8), 1181-1190.

Swim, J., Clayton, S., Doherty, T., Gifford, R., Howard, G. et al. (2011) *Physiology and Global Climate Change: Addressing a Multi-Faceted Phenomenon and Set of Challenges. A Report by the American Psychological Association's Task Force on the Interface Between Psychology and Global Climate Change*. American Psychological Association, Washington.

USDA. 2019. 2019 acreage data as of August 1, 2019. Available at: https://www.fsa.usda.gov/news-room/efoia/electronic-reading-room/frequently-requested-information/crop-acreage-data/index (accessed 13 July 2022).

U.S. Drought Monitor. What is the USDM. Available at: https://droughtmonitor.unl.edu/About/WhatistheUSDM.aspx (accessed 22 May 2021).

USGCRP. 2014. Hatfield, J., G. Takle, R. Grotjahn, P. Holden, R. C. Izaurralde, T. Mader, E. Marshall, & D. Liverman, 2014: Ch. 6: Agriculture. Climate Change Impacts in the United States: The Third National Climate Assessment, J. M. Melillo, Terese (T.C.) Richmond, and G. W. Yohe, Eds., U.S. Global Change Research Program, 150-174.

Van Der Linden, S. (2014) On the Relationship between Personal Experience, Affect and Risk Perception: The Case of Climate Change. *European Journal of Social Psychology*, 44(5), 430-440.

Wang, T., Luri, M., Janssen, L., Hennessy, D. A., Feng, H., et al. (2017) Determinants of motives for land use decisions at the margins of the Corn Belt. *Ecological Economics*, 134, 227-237.

Weber, E. U. (2013) Seeing Is Believing. Nature Publishing Group 3(April), 1-2.

Whitmarsh, L. (2008) Are Flood Victims More Concerned about Climate Change than Other People? The Role of Direct Experience in Risk Perception and Behavioural Response. *Journal of Risk Research*, 11(3), 351-374.

Wimberly, M. C., Janssen, L. L., Hennessy, D. A., Luri, M., Chowdhury, N. M. et al. (2017) Cropland expansion and grassland loss in the eastern Dakotas: New insights from a farm-level survey. *Land Use Policy*, 63, 160-173.

Wright, C. K., & Wimberly, M. C. (2013). Recent land use change in the Western Corn Belt threatens grasslands and wetlands. *Proceedings of the National Academy of Sciences*, 110(10), 4134-4139.

Yazar, M., York, A., and Kyriakopoulos, G. (2021) Heat Exposure and the Climate Change Beliefs in a Desert City: The Case of Phoenix Metropolitan Area. *Urban Climate* 36(December 2020), 100769. https://doi.org/10.1016/j.uclim.2020.100769.