How Beliefs about Climate Change Adapt? An Assessment with a Natural Experiment

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How Beliefs about Climate Change Adapt?

An Assessment in Agricultural Production with a Natural Experiment

Abstract

Weather is one of the most important factors in agriculture. Farmers predict the weather and make choices to mitigate a potential damage and risk. However, weather may be perceived differently by each farmer and this perception may further influence their agricultural decision making. In this study, we used Difference-in-Differences analysis to examine the relationship between farmers' experience of drought and how their perception changes. By applying the drought that occurred in July 2017 as a natural experiment, survey data conducted on North and South Dakota farmers before and after the drought are used for analysis. The result shows that after experiencing drought, perception changed that there had been more drought in the Weather Unconcerned Class. The degree of change was greater as farmers experience more severe drought. On the other hand, no significant relationship was found between drought experience and perception change in the Weather Concerned Class. Regardless of whether the farmer belongs to the Weather Concerned Class or the Weather Unconcerned Class, the ranking of the importance of climate in agricultural decision was also not related to drought experience.

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, a warm winter in 2012 caused $220 million in losses of Michigan cherries (USGCRP, 2014) and in 2019 heavy rainfall and flooding prevented farmers from planting crops on more than 14 million acres (USDA, 2019). As a result, farmers try their best to predict climate change and mitigate the damage. In this process, they encounter various forms of information and for our purposes we can classify weather/climate information that is used to make production decisions into i) subjective climate information based on first-hand experiences and ii) objective data based on official sources. However, these two pieces of information do not always work at the same direction as subjectively obtained climate information can be biased. Statistical information is often recontextualized by the decision maker based upon their own experiences (Marx et al., 2007) and individuals tend to base decisions on their perceptions (subjective information) as distinct from objective data (Akerlof and Dickens, 1982). Therefore, how actual data affect human perceptions should be taken into consideration when analyzing farmer's behavior and adaptation to climate. Also, knowing the relationship between climate change and a farmer's perception allows policy makers to set appropriate scope of and targets for climate change adaptation and mitigation policy because support for climate policies is related to individual perceptions about climate change (Leiserowitz, 2006).

There is less consensus over whether or not a relationship exists between an experience of extreme weather and climate change perception. A large number of scholars have found evidence that experiencing extreme weather events affects one's perception about the climate change (Niles et al. 2019; Spence et al. 2011; Weber, 2013). Niles et al. (2019) demonstrated that experiencing extreme drought alters perceptions about weather variability. Spence et al. (2011) examined the linkage between flooding experience and perception of climate change. However, Whitmarsh (2008) argued that there is no difference between those who experienced extreme floods and those who did not in their responses to climate change. We focus on the hypotheses that recent personal experience of an extreme weather event will change perceptions about weather patterns and the importance of weather changes on their agricultural land use decision.

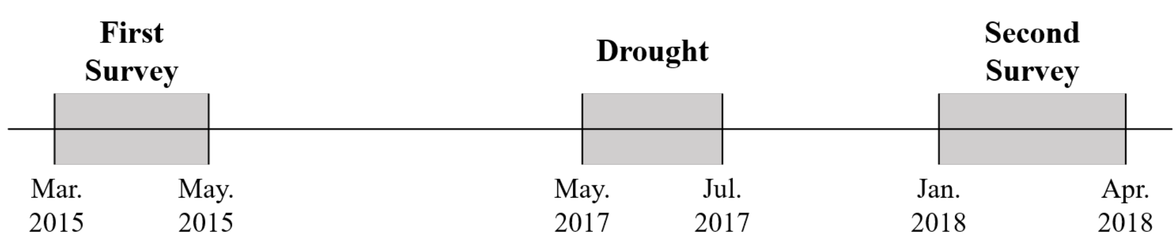
Previous studies on the topic have mainly focused on personal experiences among the general public (Joireman et al., 2010; Li et al., 2011; Goebbert et al., 2012; Myers et al., 2013; Shao, 2016). Only a few focused on professionals whose business choices and performance outcomes are weather sensitive (Carlton et al., 2016). Also, the vast majority of the existing literatures used the cross-sectional data that was collected after the extreme weather event. (Spence et al., 2011; Haden et al., 2012; Niles et al., 2013). This paper makes the following contributions to the literature. To our knowledge, no research has been done using farmer panel data before and after an extreme weather event. In addition, 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 backgrounds (McCright and Dunlap, 2011; Egan and Mullin, 2012; Myers et al., 2013; Yazar et al., 2021). Therefore, to prevent a possible bias from the term "climate change", we inquired about the changes in weather pattern.

This study examines how a natural experiment, a drought, affected farmers' weather perceptions. First, the class is identified according to the respondents' perception before experiencing drought by applying Latent Class Analysis. This analysis allows us to assume the homogeneity of the respondents in the same class. Then using difference-in-differences analysis, the extent of the drought effect is examined. The remainder of this paper is organized as follows. We describe data and methodology in the next section. Then we present a theoretical framework for econometric model, followed by estimation results. We conclude with a brief discussion.

2 Data

In 2017 an unpredicted drought hit North Dakota, South Dakota, and Montana, and decreased agricultural production, resulting over one-billion-dollar in economic losses. The drought occurred unexpectedly during the rainy season (Otkin et al., 2018) starting mid-May and spread through the Northern Great Plains until July 25th. Unforeseen low precipitation coincided with severe land surface drying caused the most driest May-July seasons over the Northern Great Plains since 2006 (Hoell et al., 2019). The drought provided a natural experiment occurred that separated farmers into the groups according to the severity of the drought that they experienced. The first survey was conducted before the drought and the respondents were chosen without considering the forthcoming drought, allowing us to examine the effect of the drought in a natural experiment setting.

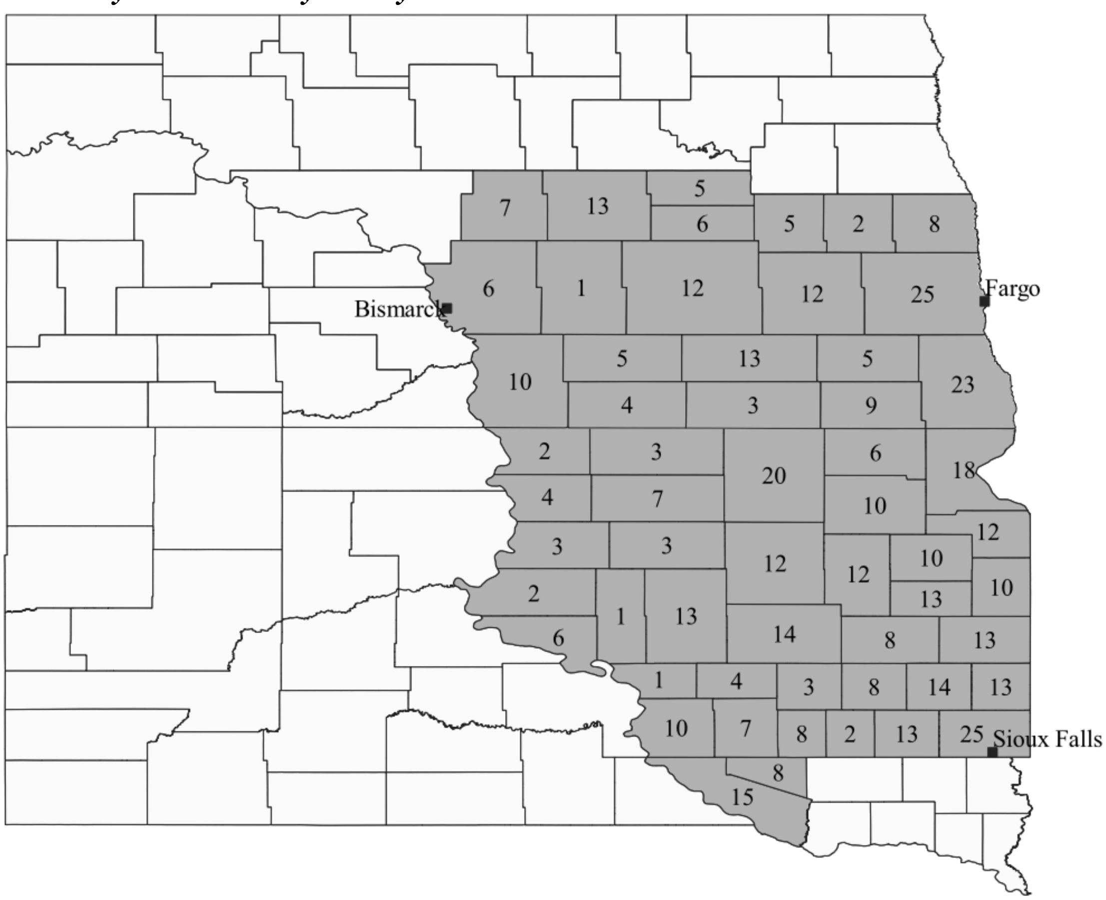
Figure 1 Timeline of Natural Experiment



The timeline for belief adaptation natural experiment depicted above is as follows; The first survey was conducted in 2015, before the drought with the farmers east of Missouri River in

North and South Dakota. After 2 years, the drought arrived which we consider it as a nature's treatment. In 2018, repeated survey was conducted. In 2015, out of 3,000 samples, 1,050 completed surveys were received (36.2% response rate. In 2018, after the drought, the follow up survey was sent to 884 respondents who completed the survey in 2015 and were less than 70 years old at the time of the survey and we received 517 surveys back (61.9% response rate). Among 517 surveys, we use the 506 that were sufficiently complete for the analysis. Figure 2 shows the number of responses across counties of North Dakota and South Dakota.

Figure 2 Survey Distribution by County Level



Survey respondents are screened only to include farmers who operated at least 100 acres and grew at least some wheat, maize, soybeans or grass/hay (Wimberly et al., 2017). The respondents were asked to mark 'less drought', 'same', or 'more drought' compared to the past 10 years for the weather pattern perception and ‘No impact’, ‘Slight impact’, ‘Some impact’, ‘Quite a bit of impact’, or ‘Great impact’ to describe how much impact weather pattern change has on their agricultural decision. In addition, demographics such as age, education and income, farm business characteristics; ownership status and the characteristics of soil; slope and Land Capability Classes (LCC) are used to control the effect of weather. Variable description and summary statistics are presented in Table 1.

Table 1 Variable description and Summary Statistics

Variable	Description	N[1)]	Mean	S.D
drou15	Drought pattern perception in 2015. Less drought (=1); Same (=2); More drought (=3) compared to the past 10 years.	472	1.89	0.70
drou18	Drought pattern perception in 2018. Less drought (=1); Same (=2); More drought (=3) compared to the past 10 years.	473	2.16	0.74
farm15	Impact of weather change on agricultural land use decision in 2015. No impact (1) to Great impact (5)	502	2.56	1.21
farm18	Impact of weather change on agricultural land use decision in 2015. No impact (1) to Great impact (5)	497	2.62	1.18
age	Year of birth	504	1960.2	9.93
edu	Highest education level completed. Less than high school (1); high school (2); some college/technical school (3); 4-year college degree (4); Advanced degree (Masters, etc.) (5)	503	3.04	0.84
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)	496	3.91	1.31
ownership	Ownership status of the land. Own all the acre farmed (1); own most of the acres farmed and rent the remainder (2); own and rent roughly equal number of farmland acres (4); rent most of the acres farmed and own the remainder (4); rent all the acres farmed (5)	496	2.79	1.16
lcc4	Percentage of the soils with Land Capability Classification (LCC; Helms, 1992) less than or equal to IV within 1 mile radius	506	95.41	11.44
slope	Percentage of the soils with slope less than or equal to 4 within 1 mile radius.	506	48.52	36.73

drainage	=1 if adopted or increased use of tile drainage on cropland acres between 2005 and 2015; = 0 otherwise.	499	0.23	0.42
notill	=1 if adopted or increased use of no-till crop system between 2005 and 2015; = 0 otherwise.	498	0.51	0.50

1) N represents the number of observations.

To collect actual drought data by location, the Drought Index from U.S. Drought Monitor as recorded on July 25th, 2017, was used. This date was during the week that the drought was the most wide spread. The U.S. Drought Monitor is produced jointly by the National Drought Mitigation Center (NDMC) at the University of Nebraska-Lincoln, the National Oceanic and Atmospheric Administration (NOAA), and the U.S. Department of Agriculture (USDA) using satellite-based assessments and various 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 the severity of drought under four categories. Each category is described in Table 2. U.S. Drought Monitor data is used because this index uses a variety of indices, it can comprehensively determine the severity of drought. The severity of drought experienced by each respondent was assumed to be that for the farm address as given by geographic information system (GIS) data from the U.S. Drought Monitor. In our survey responding group, they experienced D0, D1, D2, and D3 drought. No farm experienced D4 drought on July 25th, 2017. Only 13 farms did not experience drought on the selected date, so we excluded these farms and set D0 drought as our base. This is because as these farms generally experience drought in this season, there is no point of examining the effect of drought, rather the severity of the drought should be taken into consideration. Description of drought variable is presented in Table 2.

Table 2 Description of Drought Variable

Drought Category	Description of the Category (U.S. Drought Monitor, 2012)	N[1)]
None	-	13

D0	Abnormally dry: going into drought, short-term dryness slows growth of crops/pastures and going out of drought, there are some lingering water deficits.	150
D1	Moderate drought : there are some damage to crop/pastures and some developing water shortages.	196
D2	Severe drought : Crop/pasture losses are likely and water shortages are common.	108
D3	Extreme drought : there are major crop/pasture losses and widespread water shortages.	39
D4	Exceptional drought : there are exceptional and widespread crop/pasture losses and shortages of water creating water emergencies.	0

1) N represents the number of observations.

2.1 Temporal Changes of Perception Responses

Summary Table with transition matrix is used to see how the responses changed between two surveys. The transition matrix allows us to see whether the previous perception about weather was hold constant or changed after experiencing drought. According to Table 3, after the extreme drought, the number of respondents who said that droughts were occurring at the same rate declined over the interval while those of the view that droughts were more common increased from 20.0% to 46.9%. Also, the proportion of people who changed their answers from “Less” to “Same” or “More” and from “Same” to “More” (39.1%) was greater than the proportion of people who changed their answers from “More” to “Same” or “Less” and from “Same” to “Less” (18.9%). This result indicates that overall, the respondents perceived that there were more droughts and changed their views after experiencing the drought.

Table 3 Drought Pattern Perception Transition Matrix

Count (%)		Views in 2018 Survey			
		Less	Same	More	Total
Views in 2015 Survey	Less	40 (9.0)	53 (11.9)	42 (9.4)	135 (30.3)
	Same	38 (8.5)	104 (23.4)	79 (17.8)	221 (50.0)
	More	10	36	43	89

	(2.3)	(8.1)	(9.7)	(20.0)
Total	88 (19.8)	193 (43.4)	164 (46.9)	445 (100.0)

In Table 4, the respondents are classified according to the severity of the drought that they experienced. In the case of the respondents who experienced the D0 drought, contrary to the overall trend, the proportion of those who answered "Less" and those who answered "Same" increased in the 2018 survey. In addition, the proportion of people who changed their answers from "Less" to "Same" or "More" and from "Same" to "More" was smaller than the proportion of those who changed their answers from "More" to "Same" or "Less" and from "Same" to "Less". However, for the other level of droughts (D1, D2, and D3), the trends coincide with the overall trends, represented in Table 3. The magnitudes of the changes in responses were different, depending on the severity of the experienced drought. The difference between D1 drought and D2 drought was marginal, but for D3 drought, more than 60% of the respondents changed their answers from "Less" to "Same" or "More" and from "Same" to "More".

Table 4 Drought Pattern Perception Transition Matrix

D0 Drought, Count (%)		Views in 2018 Survey			
		Less	Same	More	Total
Views in 2015 Survey	Less	16 (12.7)	19 (15.1)	3 (2.4)	38 (30.2)
	Same	17 (13.5)	31 (24.6)	11 (8.7)	59 (46.8)
	More	6 (4.8)	12 (9.5)	11 (8.7)	29 (23.0)
	Total	39 (31.0)	62 (49.2)	25 (19.8)	126 (100.0)
D1 Drought, Count (%)		**Views in 2018 Survey**			
		Less	Same	More	Total
Views	Less	17	16	24	57

in 2015 Survey		(9.6)	(9.0)	(13.6)	(32.2)
	Same	13 (7.3)	41 (23.2)	35 (19.8)	89 (50.3)
	More	2 (1.1)	12 (6.8)	17 (9.6)	31 (17.5)
	Total	32 (18.1)	69 (39.0)	76 (42.9)	177 (100.0)

D2 Drought, Count (%)		Views in 2018 Survey			
		Less	Same	More	Total
Views in 2015 Survey	Less	3 (3.2)	10 (10.6)	9 (9.6)	22 (23.4)
	Same	3 (3.2)	23 (24.5)	22 (23.4)	48 (51.1)
	More	1 (1.1)	9 (9.6)	14 (14.9)	24 (25.5)
	Total	7 (7.5)	42 (44.7)	45 (47.9)	94 (100.0)

D3 Drought, Count (%)		Views in 2018 Survey			
		Less	Same	More	Total
Views in 2015 Survey	Less	4 (10.8)	6 (16.2)	6 (16.2)	16 (43.2)
	Same	2 (5.4)	7 (18.9)	11 (29. 7)	20 (54.1)
	More	0 (0.0)	1 (2.7)	0 (0.0)	1 (2.7)
	Total	6 (16.2)	14 (37.8)	17 (46.0)	37 (100.0)

3 Methods

The aim of this paper is to examine the effect of drought on climate change perception and Difference-in-Differences analysis allow us to measure the treatment effect by examining the differences between the average change over time for the treatment group and the average change over time for the control group. Two identifying assumptions should be satisfied in order to apply Difference-in-Differences analysis. The first assumption is that the treatment should mean-independent to the error term. In other words, there should not be any unobserved variables that affect the perception of the farmers and determine how severe drought a farmer experiences at the same time. Because it was a natural experiment and farmers had no control over which drought they would experience, this assumption is not violated. The second assumption is that the trend over time should be the same across the treatment group and the control group (parallel trend). Commonly used methods to verify this assumption is visual inspection, comparing the plots of the treatment group and the control group. To statistically test the parallel trend assumption, Card and Krueger (2000) and Hastings (2004) included “leads” and “lags” of the treatment to the model and Besley and Burgess (2004) added time trend regressor to control the state specific trends. When these methods are not applicable the parallel trend assumption can be satisfied by selecting an appropriate control group. In this process, various matching methods such as Propensity Score Matching, are applied to avoid selection bias. As all of the available covariates are time invariant in our research, we used Latent Class Analysis and classify each data according to the class to assume parallel trend for each class. Additionally, the spatial correlation among classes is examined by estimation Moran’s I.

3. 1 Classification of Class Based on the Climate Change Perception

Latent class analysis is a method to classify each observation into classes based on the observed variables. In this paper, we classify farmers based on their pre-drought climate change perceptions; i) how drought pattern changed compared to the past 10 years and ii) how much impact weather has on their managerial decision, by applying latent class analysis.

Let $\boldsymbol{Y}_i$ be responds set of respondents i ($\boldsymbol{Y}_i \in \{y_{1i}, y_{2i}, y_{3i}, \dots, y_{Vi}\}$), and $\boldsymbol{Z}_i$ be a set of covariates which are explanatory variables for latent class variable c_i ($\boldsymbol{Z}_i \in \{z_{1i}, z_{2i}, z_{3i}, \dots, z_{Qi}\}$). There are K classes and each response can be from 1 to R, and π_k is defined as the probability of being in the kth class given $\boldsymbol{Z}_i$ ($\sum_{k=1}^{K} \pi_k = 1$). When variables $\boldsymbol{Z}_i$ and $\boldsymbol{Y}_i$are assumed to be conditionally independent given c_i, the model for latent class c_i is

$$\Pr(\boldsymbol{Y}_i|\boldsymbol{Z}_i) = \sum_{k=1}^{K}[\pi_k \cdot (\prod_{v=1}^{V} \Pr(y_{vi} = r|c_i = k)] \tag{1}$$

for k∈{1,…, K} and r∈{1,…, R}. Because the survey responses are categorical and ordered, we use an ordered logit regression to estimate the relationship between the observed variable and the latent class. The probability of being in the k class given $\boldsymbol{Z}_i$ is parameterized by a multinomial logistic regression.

$$\pi_k = \Pr(c_i = k|\boldsymbol{Z}_i) = \frac{\exp(\beta_{0k}+\sum_{q=1}^{Q}\beta_{qk}z_{qi})}{\sum_{k=1}^{K}\exp(\beta_{0k}+\sum_{q=1}^{Q}\beta_{qk}z_{iq})} \tag{2}$$

We characterized two classes of the respondents based on their responds on magnitude of weather effect on their decisions and weather perception. LCA only calculates the probability that the respondent belongs to a specific class. So we designated each respondent to a class based on the calculated probability in such a way that if the estimated probability of being in Class 1 is greater than 0.5 the respondents are classified as Class 1.

3. 2 Analysis of Spatial Correlation Between Class

We estimate Moran's I statistics in order to examine the association between the classes. Moran's I is a measure of spatial autocorrelation and it is defined as

$$I = \frac{N}{\sum_i\sum_j w_{ij}}\frac{\sum_i\sum_j w_{ij}(c_i-\bar{c})(c_j-\bar{c})}{\sum_i(c_i-\bar{c})^2} \tag{3}$$

where N is the number of observations, w is the spatial weight between i and j observations, c is the class of each observation, and $\bar{c}$ is the sample mean. The spatial weight w is calculated by inverse of a distance matrix with zero for diagonal entries. The value of I ranges between -1 and 1, indicating perfect clustering of classes when I equals 1 and perfect randomness when I equals 0.

3.3 Economic Modelling of Effect of Drought on Climate Change Perception

The aim of this paper is to examine the effect of drought on climate change perception and Difference-in-Differences analysis allow us to measure the treatment effect by examining the differences between estimated coefficients of the treatment group and the control group. Regardless of the severity of drought experienced by farmers, their climate change perceptions before and after the drought were recorded using the same questionnaire, which allow us to apply the following method. The difference-in-differences model for the analysis is specified as

$$Perception = \alpha_0 + \alpha_1 Time + \sum_i \beta_i Treatment_i + \sum_i \gamma_i Time * Treatment_i + \sum_i \lambda_i x_i + \epsilon \quad (4)$$

where $Time$ (0=pre-treatment, 1=post-treatment) and $Treatment_i$ (1=Experienced the level i drought, 0=Did not experienced the level i drought) are dummy variables and ϵ is an error term. $Treatment_i$ is subdivided into three categories according to the severity of the drought. The variables denoted by x_i are control variables such as demographics of respondents. We used the responses from drought pattern perception and effect of weather change on decision making as dependent variables; i) how drought pattern has changed compared to the past 10 years and ii) how much impact weather has had on their managerial decisions. Both variables are ordered discrete variables; drought pattern perception includes 1 (less drought), 2 (same), and 3 (more drought) and effect of weather change on decision making variable ranges from 1 (no impact) to 5 (great impact).

4 Results

4.1 Class Identification

Applying Latent Class Analysis (LCA), the respondents are divided into two classes. Table 3 describes the estimated coefficients of each covariate. The coefficients of the land characteristic variables are positive, indicating that an one unit increase in the variable makes farmers more likely to be in Class 2. Slope variable represents percentage of the soils with slope less than or equal to 4 within 1 mile radius and LCC4 variable represents percentage of the soils with Land Capability Classification (LCC) less than or equal to IV within 1 mile radius. Therefore, a farmer with more suitable land for farming is more likely to be classified as Class 2. If the farmer chooses to apply drainage system, then the probability of one belongs to Class 2 increases. On the other hand, if they apply the no-till crop system, then they are more likely to be in Class 1.

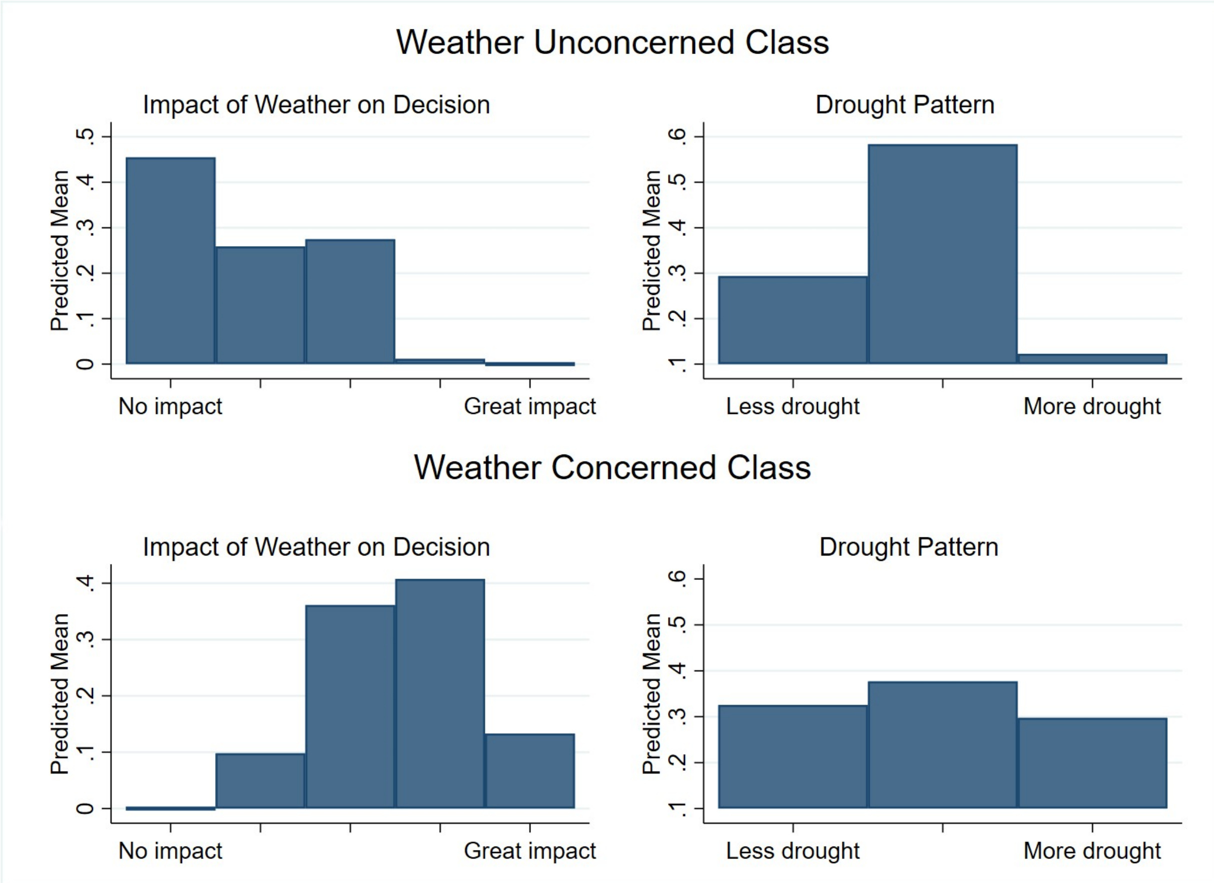
Table 3 Result of Latent Class Analysis

	Variable	Coefficient	Std. Err
Class 1	Base Outcome	-	-
Class 2	LCC4	0.194	0.017
	Slope	0.009^{**}	0.004
	Drainage	-0.807^{**}	0.365
	No-till	0.831^{**}	0.367
	Intercept	-2.909	1.934

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

From the model estimation, the expected proportion of the population is 59% for Class 1 and 41% for Class 2, which are close to the data distribution.

Figure 3 Predicted Probability of Weather Perception for Each Class



Compared to Class 1 (Weather unconcerned), Class 2 (Weather concerned) is characterized by high effect of weather on farmer's managerial decision and perception that there had been more drought compared to the past. Weather Concerned Class tend to answer that the weather has great impact on their land use decision and that there have been more drought compared to the past 10 years.

4.2 Spatial Distribution of the Classes

Figure 4 Distribution of Respondents by Class

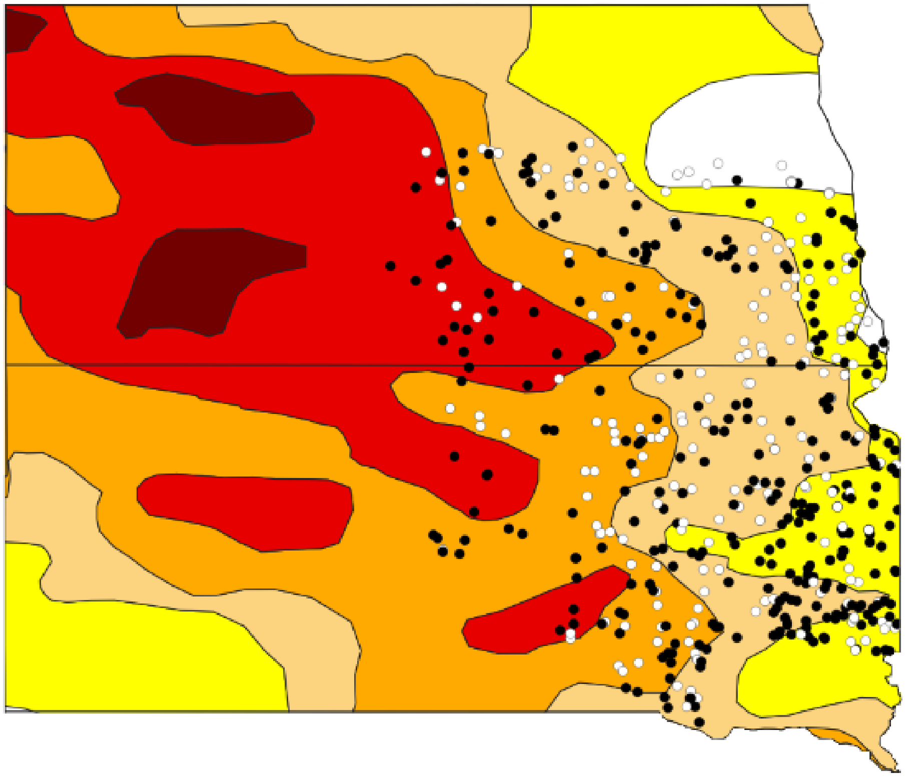
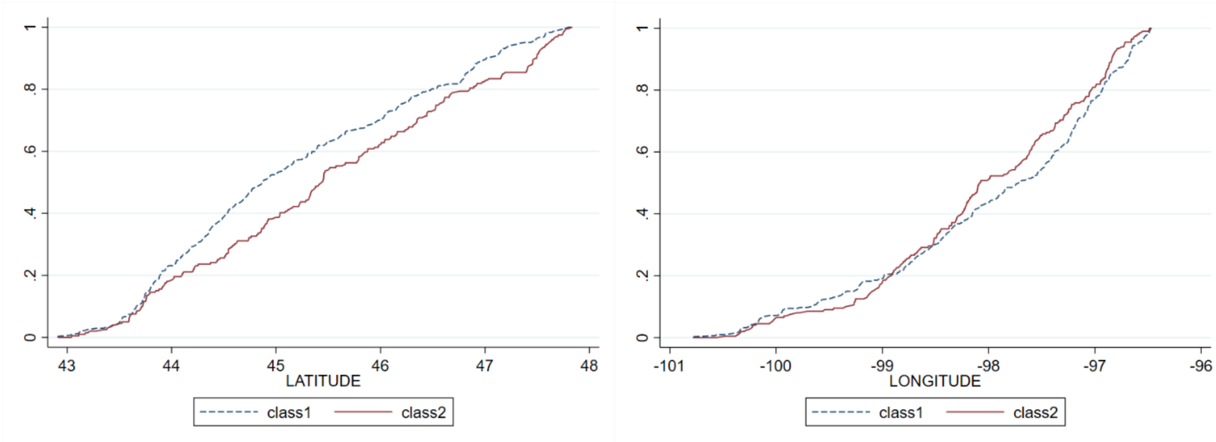


Figure 2 shows the distribution of respondents by class. Each dot represents a farm. Black dots represent 'Weather Unconcerned' class members and white dots represent 'Weather Concerned' class members. Classes are divided according to the result from latent class regression. Colored shades indicate the severity of the drought on July 25, 2017. Darker red represents greater drought severity.

Moran's I is 0.057 (S.D. 0.11) and it is statistically significant at less than 1% level. It shows that there is positive spatial correlation among classes, but the magnitude is marginal. Moran's I shows that there is little correlation, but when the latitude and longitude is considered separately, there is a pattern among the distribution of the classes.

Figure 5 Cumulative Distribution Function of Each Class by Latitude and Longitude



Above figure shows the cumulative distribution function of each class with respect to latitude and longitude. We can see that Weather Unconcerned class(class 1) is first order stochastically dominated by Weather Concerned class(class 2) with respect to the latitude, meaning that Weather Concerned class is more likely to be located in higher latitude, where the drought tends to be more severe. This result is also in line with the percentage of drainage and no-till system installation. Weather Concerned class is more likely to suffer from severe drought therefore they install no-till crop system which is a technique used to reduce the risk of drought.

4.3 Heterogenous Effect of Drought on Climate Change Perception

Difference-in-Differences (DID) Analysis is applied to see how experiencing the drought in 2017 changed the perception about drought pattern and the magnitude of weather effect on their decision making. Treatment effect are subdivided into 3 categories depending on the severity of the drought (D1, D2, D3). Dependent variables are i) weather pattern perception; the respondents were asked to choose one among 'less drought', 'same', or 'more drought', that best describes current weather pattern compared to the past 10 years, and ii) impact of weather; the respondents had to mark one of the following option for the impact of changing weather patterns on land use: 'No impact', 'Slight impact', 'Some impact', 'Quite a bit of impact', or 'Great impact'.

Table 4 and Table 5 reports the result of the DID Analysis. In interpreting the result of DID analysis, we are interested in the coefficient of the interaction term between time and treatment variables. The statistical significance of those variables indicates that the magnitude of the treatment differs between treatment group and control group within Weather Concerned Class and Weather Unconcerned Class.

Table 4 shows the result of DID analysis of drought pattern perception. The positive coefficients of the interaction terms suggest that the farmers in Weather Unconcerned class, who experienced more severe drought are more likely to respond that there had been more drought compared to the past 10 years. The magnitude of the effect between the D1 level and D3 level droughts was about 2 times different, indicating that the effect is greater when the drought is more severe. However, for the Weather Concerned class, there was no strong relation between the drought and the drought pattern perception. Only the effect of D1 level drought was significant at 10% level.

Table 4 Drought Pattern Perception

Variable	Weather Unconcerned		Weather Concerned	
	Coefficient	Std. Err	Coefficient	Std. Err
Time	-0.049	(0.097)	0.164	(0.060
Treatment1 (D1)	0.002	(0.093)	-0.128	(0.150)
Treatment2 (D2)	0.181	(0.110)	0.062	(0.173)
Treatment3 (D3)	-0.194	(0.141)	-0.391	(0.286)

Time*Treatment1 (D1)	0.566***	(0.128)	0.360*	(0.213)
Time*Treatment2 (D2)	0.410***	(0.153)	0.372	(0.237)
Time*Treatment3 (D3)	0.939***	(0.196)	0.278	(0.393)
Age	0.010***	(0.003)	0.006	(0.005)
Education	0.030	(0.032)	0.043	(0.053)
Earning	-0.034*	(0.021)	-0.084**	(0.035)
Ownership	0.007	(0.022)	0.119***	(0.037)
Crop ratio	-0.069	(0.106)	-0.074	(0.190)
Intercept	-17.076***	(5.602)	-8.870	(9.572)

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

Table 5 presents the results of DID analysis on the effect of drought on the decision making. Unlike the drought perception, the results yielded no statistically significant relationships between drought and its effect on decision making. The respondents of all class did not change their views on how much impact the weather change has on their agricultural decision.

Table 5 Effect of Weather on Decision Making

Variable	Weather Unconcerned		Weather Concerned	
	Coefficient	Std. Err	Coefficient	Std. Err
Time	-0.445***	(0.146)	0.847***	(0.199)

Treatment1 (D1)	0.156	(0.142)	0.358*	(0.185)
Treatment2 (D2)	0.323*	(0.169)	0.134	(0.210)
Treatment3 (D3)	-0.163	(0.221)	-0.853**	(0.359)
Time*Treatment1 (D1)	-0.075	(0.195)	-0.211	(0.259)
Time*Treatment2 (D2)	-0.247	(0.235)	-0.331	(0.287)
Time*Treatment3 (D3)	-0.162	(0.306)	0.666	(0.492)
Age	0.008*	(0.004)	-0.008	(0.006)
Education	-0.104**	(0.049)	-0.004	(0.065)
Earning	-0.003	(0.032)	0.032	(0.044)
Ownership	0.020	(0.035)	-0.041	(0.045)
Crop ratio	0.115	(0.161)	-0.156	(0.234)
Intercept	-14.036	(8.555)	18.398	(11.586)

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

5 Conclusion

Many studies have examined the relationship between climate change and people's perception (Goebbert et al., 2012; Myers et al., 2013; Carlton et al., 2016), yet little research has been done on how the perception change after experiencing climate change due to the fact that research cannot be planned because it is impossible to predict when such a weather even will occur. This study is one of the few that examines how farmer's weather perception changes after experiencing drought.

We first classify the farmers into two classes based on their pre-drought perception. According to latent class analysis, the farmers are divided into Weather Unconcerned Class and Weather Concerned Class. Weather Unconcerned Class (class 1) thinks that drought pattern in 2015 was the same compared to the past 10 years and that weather pattern change has small impact on their land use decision. On the other hand, Weather Concerned Class (class 2) thinks that there was more drought in 2015 compared to the past 10 years and that weather pattern change has big impact on their decision. This result is in line with Barnes et al. (2013) who identified classes of dairy farmers based on the statements related to climate change risk.

After determining the class of farmers, we examine the heterogenous effect of drought on perceptions. The Weather Unconcerned Class responded that the drought pattern had been the same or there had been less drought compared to the past 10 years. However, after experiencing the drought, they changed their magnitude of responds to the viewpoint that that there had been more drought. The magnitude of this change increased as the drought experienced became was more severe. On the other hand, the Weather Concerned Class showed no significant difference before and after the drought. The extent of the impact of climate change on their managerial decisions making did not change before and after the drought in both classes. Carlton et al. (2016) also found evidence that experiencing extreme drought had no impact on belief in climate change. In the case of the Weather Concerned Class, there was no significant change after the drought, because they thought that the drought had increased even before the drought. The Weather Unconcerned Class was aware of increased droughts, but the magnitude of the climate's impact on their decisions remained unchanged.

In summary, respondents recognized that there was more drought, but they thought that climate change did not have a significant impact on their behavioral changes. Nevertheless, farmers are actually making decisions based on the weather change by applying various adaptations such as drainage systems or no-till crop systems to cope with climate change. The adaptation behavior does not correspond to adaptation perception. Thus, it shows that climate change adaptation is based on factors other than direct climate experience. Secondary impacts such as crop loss or price change, from climate change may have a greater impact on farmers' adaptation to climate change. Then from an applied perspective, it would be more effective to use other factors rather than changing the perception of climate change to induce change in farmers' behavior.

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