Assessing Systematic Biases in Farmers' Local Weather Change Perceptions

Gaurav Arora and Hongli Feng

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Center for Agricultural and Rural Development
Iowa State University
Ames, Iowa 50011-1070
www.card.iastate.edu

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Gaurav Arora is Associate Professor, Department of Social Sciences and Humanities, Indraprasthra Institute of Information Technology, New Delhi, India, and Faculty of Economics, Chulalongkorn University, Bangkok, Thailand. E-mail: guarav@iiitd.ac.in.

Hongli Feng is Assistant Professor, Department of Economics, Iowa State University, Ames, Iowa, 50011. E-mail: hfeng@iastate.edu.

For questions or comments about the contents of this paper, please contact Gaurav Arora, guarav@iiitdc.ac.in.

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Author Information

Gaurav Arora*
Dept. of Social Sciences and Humanities
Indraprastha Institute of Information Technology, New Delhi, India, and
Faculty of Economics, Chulalongkorn University, Bangkok, Thailand
Email: gaurav@iiitd.ac.in
Phone: +91 11 26907547

Hongli Feng
Department of Economics
Center for Agricultural and Rural Development
Iowa State University, U.S.A.
Email: hfeng@iastate.edu

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Abstract

Scientific data concerning climate change are critical for designing mitigation and adaptation strategies. Equally important is how stakeholders perceive climate change because perceptions influence decision-making. In this paper, we employ spatially-delineated primary surveys to evaluate weather perception biases among corn and soybean farmers located on western frontier of the U.S. Corn Belt where substantial loss of grassland has been documented. We characterize farmers' perception biases by measuring the gap between survey-based perception reports for three distinct weather indicators (i.e., temperature, precipitation and drought) and corresponding meteorological evidence. About 70% farmers in our sample misperceive past weather changes. Three-fourths of these misperceiving farmers over-estimate local temperatures and drought frequency and 40% of them under-estimate precipitation trends relative to past records. We further find evidence that farmers' weather change perceptions are systematically biased in a manner that would justify past land use decisions. Particularly, higher cropping incidence on previously protected grasslands effected more farmers to under-perceive drier conditions and over-perceive wetter conditions. Our investigation of perception biases across distinct weather indicators with a reference to past economic decisions enriches the understanding of climate change perceptions and related policies.

Keywords: climate change; instrumental variable; land use; primary farm surveys; spatial data; weather perception bias

JEL Codes: C21; D22; D91; Q15; R14

Introduction

Climate uncertainty is a critical risk factor in agricultural production. Large spatio-temporal datasets and sophisticated statistical models are employed to estimate the distribution of climate variables at regional, national and global scales (Bauer et al. 2015). Data-driven decision support systems are a centerpiece of policy designs that are intended to facilitate agricultural adaptation and mitigation amidst climate uncertainty. Meanwhile, forming climate change beliefs can be challenging given that farmers synthesize weather patterns based on local observations with a sparse sampling of extreme events such as floods, droughts and heat waves. Farmers' beliefs are further impacted by bounded cognitive capacity (Liverpool-Tasie et al. 2020; Maltby et al. 2021), exposure to mixed media signals (Ungar 1992; Potosky et al. 2015) and complex social, economic and cultural influences (Leiserowitz 2006; Egan and Mullin 2012; Ruiz et al. 2020). That farmer perceptions may diverge from climate change evidence has been recognized in the literature (e.g., Barnes and Toma 2012; Arbuckle et al. 2013a,b; Bayes and Druckman 2021).

Early studies in this literature documented farmer perceptions about *future* climate change (e.g., Barnes and Toma 2012; Arbuckle et al. 2013a,b) while recent papers reported perceptions about regional-level weather changes in the *past*, with a greater focus on developing country contexts in Africa and Asia (e.g., Liverpool-Tasie et al. 2020; Mahmood et al. 2021; Mairura et al. 2021). Climate/weather perceptions are modeled as a function of farmers' socio-economic and institutional environments to evaluate how such factors inform their attitudes about climate change (Haden et al. 2012; Wheeler et al. 2013). That is, whether farmers believe that climate is changing and what they perceive as climate change are understood to depend upon their social attributes such as age and education; economic situation such as income and farm size; and the willingness to mitigate climate impacts.

Despite advancements in global and local climate change estimation and the characterization of climate change perception in societies, the evidence remains rather crude for quantifying the gaps between individual perceptions and scientific data. Studies typically report an aggregate percentage measure for describing how climate perceptions compare with scientific evidence. For example, Barnes and Toma (2012) reported a survey of 540 Scottish dairy farmers where 46% believed that future global temperatures will increase. Similarly, Mahmood et al. (2021) reported that 70% of 671 farmers in northern Pakistan perceived regional temperature changes in line with the meteorological trends of past 38 years. Systematic patterns in how individual farmers' perceptions may differ from local weather observation, and the relevant drivers, remain largely unexplored.

Climate change and climate policies are known to generate unequal costs that depend upon local resource constraints and socio-cultural attributes of farmers. On the other hand, localized weather events can influence farmers' climate beliefs (Haden et al. 2012; Wheeler et al. 2013; Darabant et a. 2020) through the use of heuristics or psychological manipulations in processing weather information (Tversky and Kahneman 1974). An in-depth understanding of weather perceptions can inform climate policy designs by accounting for local climate information as well as farmers' awareness and motivation to mitigate climate impacts (Haden et al. 2012).

In this paper we analyze potential *biases* in weather change perceptions, which are defined as the gap between farmer perceptions about local weather changes and corresponding data-based evidence for three weather indicators, i.e., temperature, precipitation and droughts. Our analysis seeks to address farmers' subjective climate change attribution to a particular indicator (or a set of indicators) while many existing studies tend to examine perceptions with reference to "climate change" as a general concept (Arbuckle et al. 2013a,b; Nauges et al. 2021; Wheeler et al. 2021).

We further examine farm-level heterogeneity in weather perception biases with a focus on the role of farmers' land use decisions in comprehending such biases.

It is well-established that climate and weather perceptions influence growers' attitudes and decisions concerning climate mitigation and adaptation (Haden et al. 2012; Wheeler et al. 2013; Ojo and Baiyegunhi 2021; Jha and Gupta 2021). For example, Mase et al. (2015) reported that a decision to purchase insurance or adopt technology to mitigate climate risk was associated with farmers' climate beliefs. We emphasize that perceptions and decisions can feed into each other, i.e., perceptions affect decision making and decisions can also affect perceptions, in particular, weather perception biases. This latter channel of impacts is afforded much less attention in the literature; although some studies suggest that local experiences and economic activity can affect farmers' weather perceptions (Howe et al. 2015; Liverpool-Tasie et al. 2020).

To our best knowledge, no study has examined whether farming decisions can lead to potentially systematic biases in weather change perceptions. We argue that, in forming weather and climate perceptions, farmers may be motivated to subconsciously distort weather signals (Kunda 1990) through social mediation (Benabou 2013) and exposure to market or policy shocks (Ruiz et al. 2020; Nauges et al. 2021) for validating or justifying their past land use decisions. Understanding how past decisions can contribute to perception biases would shed light on how people process climate information in a manner that might differ from objective data.

We assess the linkage between farm decisions and weather perceptions in two steps. First, we employ two-way contingency tables to test whether farmers' weather perception biases are on-average independent of their land use decisions. In the second step, we recognize that perceptions and decisions are endogenous to each other and use economic returns as an instrument to identify the causal link between farm decisions and weather perception biases.

Economic returns directly impact land use decisions; on the other hand, we expect that economic returns will affect perceptions through land use changes, and hence provide a valid instrument to estimate the impact of decisions on weather perception biases (Wooldridge 2002, ch.5).

Our study makes three main contributions to the existing literature. First, we document farm-level biases in weather change perceptions by assessing spatially-delineated primary survey data on farmers' perceptions in relation to the local weather records. Alongside weather change perceptions these surveys provide farmers' land use information on a regional frontier between Northern Great Plains and Western Corn Belt (see Figure 1a). Our study region witnessed major concerns over rapid loss of native grassland cover to crop production during the past fifteen years (Wang et al. 2017; Wimberly et al. 2017), which provides an ideal setting to analyze potentially systematic biases in weather perceptions with a reference to past land use decisions.

Second, our inquiry moves beyond the use of a general reference to "climate change" and accounts for regional variations in distinct weather indicators (temperature, precipitation, and droughts) to test the hypothesis that perceptions are consistent with local meteorological data. Spatial heterogeneity in climate data and survey-based weather perceptions allow us to estimate farmers' weather perception *biases*, i.e., the difference between perceptions (reported in primary surveys) and meteorological data, conditional on local biophysical and socio-economic contexts. Third, we recognize that perceptions of weather and climate trends can be systematically affected by past decisions, beyond the role of perceptions in affecting farming decisions. We estimate the impact of past land use decisions on farmers' weather change (*mis*)perceptions by using instrumental variable (IV) in a two-stage least squares (2SLS) modelling approach. The theory of "motivated beliefs" provides a potential rationale for how farmers might subconsciously form weather perceptions to justify past decisions (Benabou and Tirole 2002; Steg and Vlek 2009).

Section 2 describes the data and methods, followed by section 3 where we present our results. We conclude with a discussion of our main findings in section 4.

2. Materials and Methods

2.1 *Data and Data Processing*

2.1.1 *Survey data: Farmers' weather change perceptions and land use decisions*

We utilize 1,026 responses from a survey of farmers located on the east of the Missouri River across 20 counties in North Dakota (ND) and 37 counties in South Dakota (SD), see Figure 1a. Surveys were conducted from March through May in 2015 among farmers who operated 100 or more acres of land for wheat, maize, soybeans or grass/hay cultivation. Sample observations were distributed across counties in proportion of the eligible farms and the survey response rate was 36%. These surveys were designed to primarily study farmers' cropland and pastureland use decisions during the commodities boom of 2004-2014. In other words, farmers were first inquired about their land use decisions and the potential drivers; followed by perceptions of past changes in local temperature, precipitation and droughts (discussed hereafter). We also collected data on farmland quality, income status and demographic information. The survey questionnaire pertaining to our study is provided in Supplementary Information (SM), section S1.

We assess the representativeness of our survey data relative to the 2017 Census of Agriculture. Our sample constitutes farmers with 100 or more farmland acres, a criterion used to screen out very small farms or hobby farmers. With a conservative corn yield of $120 bushels per acre and corn price of $3 per bushel, a 100-acre farm will generate at least $36,000 in sales. In contrast, for Census purposes, any plot that generates $1,000 or more in revenues is interpreted as a farm. Our screening criterion will imply some differences between our sample and the Census data. For example, about 25% farms in our sample were 2,000 acres or larger in size, which is well-aligned with the upper quartile of Census farms in the Dakotas. The average farm size (1,650 acres) in our surveys was larger than the average Census farm (1,450 acres). More than 95% farmers in our sample reported $50,000 or more in annual farm sales, which equals the median value of annual sales among Census farms. Farmers' median age in our surveys, i.e., 50-59 years, was representative of the Census data. A representativeness assessment based on the 2012 Census of Agriculture revealed similar patterns of comparison (Wimberly et al., 2017). Data summaries are presented in Table 1 and further discussed in the next section.

With regards to weather perceptions data, farmers' assessment about local weather patterns in 2014 were compared to ten years ago (we allow alternative fuzzy delineations of "ten years ago" in the analysis to accommodate inaccuracy in memory recall). That is, respondents were asked to select one among the following options for *temperature*: 'warmer', 'about the same', 'cooler', 'don't know'; *precipitation*: 'more', 'about the same', 'less', 'don't know'; and *drought frequency*: 'more', 'about the same', 'less', 'don't know'. The largest proportion of farmers perceived 'about the same' temperature (57% farmers), precipitation (36% farmers) and drought frequency (45% farmers) during 2004-2014. In contrast, 22% and 14% farmers perceived 'cooler' and 'warmer' temperatures, respectively; 24% and 34% farmers perceived 'higher' and 'lower' precipitation, respectively; and 29% and 19% farmers perceived that 'less' and 'more' frequent droughts, respectively. About 5% responses were 'don't know' and 4% farmers chose not to respond about past weather perceptions.

We evaluate a causal link between farmers' weather change perceptions and their enrollment decision into the Conservation Reserve Program (CRP). The CRP is the largest land retirement program in the United States to protect highly erodible and environmentally sensitive lands (Khanna and Ando 2009). Farmers who enroll into a CRP contract must retire their croplands for an environment-friendly use for 10-15 years, thereby giving up cropping returns in lieu of a fixed annual transfer called the ‘CRP rental payment’. The Dakotas experienced a dramatic decline in CRP acreage during 2004-2014 (Haiar 2022). For example, South Dakota’s CRP coverage declined from 1.45 million acres in 2004 to 930,000 acres in 2014 when 47% of statewide CRP contracts were due for renewal in 2007; implying that many farmers may have actively decided upon renewal of CRP contracts during our study period.

Cultivating on CRP lands typically entails substantial costs, including one-time land preparation cost and variable production costs during each subesquent season. Such costs would only be justified if a farmer expects high crop returns, which in turn depend on favorable weather conditions. Given that weather is uncertain and constitutes complex changes in temperature, precipiation, or both (as outlined in the Introduction section) there is scope for cognitive errors in farmers’ weather change perceptions. We will evaluate whether farmers (mis)perceive local weather to systematically favor potentially high crop returns after they had also chosen to undertake cropping on lands that were originally protected under the CRP contract.

2.1.2 *Weather data*: *Temperature, precipitation and drought frequency* (*2004-2014*)

We match our geo-referenced farm survey data to weather station-based temperature and precipitation data, and spatial vector maps of a drought index (discussed hereafter). Daily records of temperature and precipitation levels were acquired from 825 weather stations made available by the Global Historical Climatology Network (GHCN) (Menne et al. 2012). Figure 1a presents the spatial distribution of our survey respondents and GHCN stations in the area. We first assign each survey location a ‘daily temperature level’ and a ‘daily precipitation level’ as the mean value of corresponding records from the *nearest* three weather stations. Distribution of weather outcomes was very similar between nearest-three and nearest-five weather stations.

The *average* value of daily temperature levels during April-August months was denoted as the 'growing-season temperature' whereas the *sum* of daily precipitation levels during April-August was denoted as the 'growing-season precipitation' for each survey location. We note here that high-resolution climate data from satellite sensors provide alternative evidence for local weather changes. We investigate robustness of our results by analyzing farmers weather perceptions in relation to the PRISM data (Oregon State University), which is organized in 4km x 4km grids, besides the weather station records. Our findings are consistent between the use of these datasets (*SM*, section S2 for details). We present results based on weather station data because people (including farmers) commonly learn about local weather from meteorological stations.

To assess farmers' drought perceptions, we utilize vector maps made available by the U.S. Drought Monitor (USDM) on a weekly basis since the year 2000. The USDM is jointly produced by the National Drought Mitigation Centre (University of Nebraska-Lincoln), U.S. Department of Agriculture and the National Oceanic and Atmospheric Administration. These maps divide continental U.S. into six drought intensity categories: 'exceptional drought'; 'extreme drought'; 'severe drought'; 'moderate drought'; 'abnormally dry'; and 'no drought'. In Figures 1(b-d) we illustrate drought situation in the Dakotas through USDM vector maps during the August months of 2004, 2006 (i.e., drought year) and 2014. We assign each survey location a comparison of category-wise count of drought incidences during the second week of growing-season month (April-August) in 2004 and 2014.

2.2 *Analysis of farmers' local weather change perceptions*

2.2.1 *A multivariate model to assess consistency between perceptions and data-based evidence*

We model the ordinal survey responses for farmers' local weather perceptions as an ordered logistic regression function (McCullagh 1980) of data-based weather records conditional on soil attributes and farmers' age, education, and income. The ordinal logistic model is appropriate because farmer responses represented a clear ordering of how weather outcomes change during 2004-2014 (e.g., from low to high temperature; or from less to more precipitation). Specifically, farmer i's weather change perceptions, denoted as $\Delta\tilde{w}_i$, were recorded in an ordered fashion corresponding to weather change data, denoted as $\boldsymbol{\Delta w_i}$, for three indicators: temperature (t), precipitation (p) and drought frequency (d). As such we define $\Delta\tilde{w}_i$ as

$$\Delta\tilde{w}_i = \begin{cases} 1 \text{ if } i \text{ believed } \Delta w_i < 0, \text{ i.e., } w_i \text{ was lower in 2014 relative to 2004 (e.g., less precipitation)} \\ 2 \text{ if } i \text{ believed } \Delta w_i \approx 0, \text{ i.e., } w_i \text{ was about the same in 2014 relative to 2004} \\ 3 \text{ if } i \text{ believed } \Delta w_i > 0, \text{ i.e., } w_i \text{ was higher in 2014 relative to 2004 (e.g., more precipitation).} \end{cases}$$

We describe data-based weather records as $\boldsymbol{\Delta w_i} \in \{\boldsymbol{\Delta t_i^{04-14}}, \boldsymbol{\Delta p_i^{04-14}}, \boldsymbol{\Delta d_i^{04-14}}\}$, where $\Delta t_i^{04-14} \equiv$ average growing-season temperature in 2014 *minus* its 2004 counterpart; $\Delta p_i^{04-14} \equiv$ total growing-season precipitation in 2014 *minus* its 2004 counterpart; and $\Delta d_i^{04-14} \equiv$ growing-season drought intensity in 2014 *minus* its 2004 counterpart. See *SM*, section S3 for details on $\boldsymbol{\Delta d_i^{04-14}}$ variable.

We recognize that farmer perceptions may represent a comparison of weather conditions in 2014 with their counterparts *circa* 2004 (rather than *precisely* for 2004). To account for limited recall capacity for past events we consider two auxiliary measures that approximate $\boldsymbol{\Delta w_i}$. First, we assign 2004 weather to be an average of weather records in 2003, 2004 and 2005. Second, our study region experienced widespread drought and heat waves during the 2006 growing-season (Davey 2006, MacPherson 2006, USDA 2007) and floods in 2011 (Murphy 2011; USGS 2019). We evaluate how farmers' recall of salient weather events in the *recent* past might affect their weather perceptions (Moore et al. 2019; Sloggy et al. 2022). To do so, we specify $\boldsymbol{\Delta w_i}$ alternatively based on the initial weather conditions in 2006 and 2011, respectively.

The ordered logit model for $\Delta\tilde{w}_i$ is specified as

$$\Delta\tilde{w}_i \le 1 : \log\left(\frac{\theta_{i,1}}{\theta_{i,2}+\theta_{i,3}}\right) = \gamma_1 + \beta_w \Delta w_i + \vec{x}_i\vec{\eta} + \varepsilon_{1i}$$

$$\Delta\tilde{w}_i \le 2 : \log\left(\frac{\theta_{i,1}+\theta_{i,2}}{\theta_{i,3}}\right) = \gamma_2 + \beta_w \Delta w_i + \vec{x}_i\vec{\eta} + \varepsilon_{2i}, \tag{1}$$

where $\theta_{i,j} = \Pr(\Delta\tilde{w}_i = j)$, $\boldsymbol{j = 1,2,3}$. Model (1) specifies the proportional odds of perception responses: $\Delta\tilde{w}_i = 1$ relative to $\Delta\tilde{w}_i > 1$; and $\Delta\tilde{w}_i \le 2$ relative to $\Delta\tilde{w}_i$ =3; as a function of $\boldsymbol{\Delta w_i}$ conditional on a control vector, $\vec{x}_i$, of size 1 x *k*. Slope parameters β_w and $\vec{\eta}_{kx1}$ are assumed to be the same regardless of the partition in perception responses, which is known as the proportional odds assumption (McCullagh 1980). Parameters $\boldsymbol{\gamma_1}$ and $\boldsymbol{\gamma_2}$ characterize the average log-odds of response levels $\Delta\tilde{w} = 1$ (e.g., lower precipitation relative to higher or about the same values) and $\Delta\tilde{w} \in \{1,2\}$ (e.g., lower or about the same precipitation relative to a higher value), respectively. Note that $\beta_w < 0$ will signify a positive correlation between weather change records and farmers' perceptions because $\boldsymbol{\Delta w}$ measures increase in *w* during 2004-2014 whereas model (1) specifies log-odds of $\Delta\tilde{w}$ from higher to lower *w* values. Finally, $\vec{\eta}_{kx1}$ will provide an estimate of the shift in log-odds of perceiving higher to lower *w* values upon marginal increase in respective control variables. We intend to infer whether farmer perceptions are *on average* consistent with the corresponding data-based evidence. Below we formalize our hypothesis.

Hypothesis I (Weather perceptions versus weather records): Farmer perceptions are *on average* consistent with the corresponding data-based evidence conditional on farmers' socio-economic endowments. In the setup of model (1), we formalize this hypothesis as: $\boldsymbol{H_0^{(1)} : \beta_w < 0}$

against the alternative hypothesis that $\beta_w \geq 0$.

2.2.2 *Articulating biases in past weather change perceptions*

We cross-tabulate $\boldsymbol{\Delta w_i}$ and $\Delta\tilde{w}_i$ to characterize the distribution of biased and consistent weather change perceptions of farmers. In particular, we categorize past temperature change records as: $\boldsymbol{\Delta t_i^{04-14} \leq -5\%}$; $\boldsymbol{\Delta t_i^{04-14} \in (-5\%, 5\%)}$; and $\boldsymbol{\Delta t_i^{04-14} \geq 5\%}$, to match survey response categories, $\Delta\tilde{t}_i \in \{1,2,3\}$, i.e., cooler; about the same; and warmer temperature in 2014 relative to 2004, repectively. Similarly, categories $\boldsymbol{\Delta p_i^{04-14}} \in \{\leq -5\%, (-5\%, 5\%), \geq 5\%\}$ were matched to response categories, $\Delta\tilde{p}_i \in \{1,2,3\}$, i.e., lower; about the same; and higher precipitation, repectively; and $\boldsymbol{\Delta d_i^{04-14}} \in \{<0, =0, >0\}$ matched to $\Delta\tilde{d}_i \in \boldsymbol{\{1,2,3\}}$, i.e., lower; about the same; and higher drought frequency during 2004-2014, repectively. For a check of robustness, we matched 'about the same' responses to ±10% changes in temperature and precipitation levels; and found our results to be very similar between ±5% and ±10% thresholds.

These cross-tabulations, as demonstrated in Table 3 (and discussed in section 3), provide a count of farmers in pairwise categories of survey-based weather change perceptions and the corresponding evidence from weather station data. The diagonal elements provide count of farmers in our sample having weather beliefs that are consistent with weather data while the off-diagonal elements refer to those farmers whose weather perceptions were inconsistent or biased when compared with data-based evidence. Note that perceptions may be consistent or biased even among farmers who experienced similar weather conditions in an area.

2.3 *Linking past weather change* (mis)perceptions *to land use decisions*

In Figure 2 we visualize the spatial patterns in consistent (triangle markers) and biased (star markers) perceptions about more or less frequent droughts; and higher or lower precipitation (while omitting ‘about the same’ and ‘don’t know’ responses). We observe that consistent beliefs about higher regional precipitation and less frequent droughts were clustered in proximity of the Missouri River. However, east of the River we notice a tendency to misperceive ‘drier’ weather to be ‘wetter’ in 2014 relative to 2004 (please see *SM*, section S4 for details). Regional farmlands also occurred as spatially-contiguous tracts such that grasslands located on the east of the River were subject to large-scale transitions for corn and soybean cultivation during 2004-2014 (Arora et al. 2021). These observations prompt an investigation into the relationship between farmers’ land use decisions and weather perceptions.

Here we intend to inquire whether past land use decisions could lead to a certain bias in farmers’ weather perceptions. That is, we ask whether farmers in our sample subconsciously ignored adverse weather information (e.g., drought) or were over-attentive towards favorable weather (e.g., higher precipitation) to validate a decision to undertake water-intensive cultivation on pre-existing grasslands? The motivated cognition theory of Benabou and Tirole (2002) can provide one potential economic explanation for such weather *mis*perceptions among farmers. A farmer who converts native grassland for crop production would be motivated to expect favorable crop-based returns through beliefs that prevail over the risk of droughts in her locality. On the other hand, in case the farmer decides not to convert her grassland then she would seek to validate this decision through beliefs that support frequent drought incidence, and hence low returns from cropping. Below we formalize our hypothesis.

Hypothesis II (Weather perceptions and motivated beliefs): Farmers’ weather change perceptions were motivated by their land use decisions. That is, past land use decisions of farmers were causally linked with the biases in their weather change perceptions.

To test Hypothesis II, we first conduct a Chi-squared (χ^2) test of independence between farmers *i*'s perceptions of data-based weather change records and their land use decisions (Kateri 2014, ch. 2). Second, we employ an IV approach to estimate a causal linkage between farmers' weather change perceptions and land use decisions.

We denote consistent or biased perceptions as part of *i*'s beliefs about low' *w* value in 2014 relative to 2004, i.e., $b_i^L \in \{L \to H, L \to L\}$ where $L \to H$ indicates misperception of 'low' *w* to be a 'high' value, and $L \to L$ indicates that *i* accurately perceived 'low' *w* value. Similarly, we denote $b_i^H \in \{H \to L, H \to H\}$ such that $H \to L$ indicates that 'high' *w* value was misperceived to be 'low' value, and $H \to H$ indicates a consistent belief about 'high' *w* in 2014 relative to 2004. Note that here we do not consider 'about the same' and 'don't know' responses. As noted earlier, we focus on the decision concerning CRP enrollment (denoted as Δl_i). Let Δl_i= 1 denote *i*'s decision to convert her CRP land for cropping; whereas Δl_i= 0 denotes either as re-enrollment decision of the expired CRP land or new enrollment into CRP.

We define the χ^2 statistic based on a cross-tabulation of Δl and *b* in a 2 x 2 contingency table (please see Tables 4a-b, discussed hereafter in the next section). Each cell in this table provides sample-based count of farmers, $n_{l,b}$, for decision-belief pairs $(l,b) \in \{\Delta l\} \times \{b\}$. Corresponding to each $n_{l,b}$ value we define an 'expected' count of farmers, $\hat{n}_{l,b}$, under the assumption that Δl and *b* are independent variables. The Chi-squared statistic for 2x2 contingency tables is defined as having one degree of freedom (i.e., χ_1^2). That is,

$$X \triangleq \sum_{l \in \{0,1\}} \sum_{\substack{b \in \{L \to H, L \to L\} \\ \text{or } \{H \to L, H \to H\}}} \frac{(n_{lb} - \hat{n}_{lb})^2}{\hat{n}_{lb}} \quad \chi_1^2. \tag{2}$$

If $X > \chi^2_{1*,5\%}$ (or $\leq \chi^2_{1*,5\%}$) then we will reject (or fail to reject) that land use decisions are independent of farmers' weather perceptions with 95% confidence (please see *SM,* section S5).

2.3.1 *Causal impact channel between land use decisions and weather perception biases*

The contingency tables allow us to assess the correlation between farmers' CRP land conversion decision and weather perception biases, which is not a sufficient condition to establish that these land use decisions caused systematic perception biases. This is because weather perceptions and land use decisions are endogenous (discussed in Introduction section). We identify the causal impact of CRP land conversion decisions on farmers' perception biases by specifying instruments (IV) that impact CRP land conversion directly but only influence weather perception biases through the decision channel (that is, requirements of a valid IV; see Wooldridge 2002, ch.5). The decline in CRP acreage during 2004-2014 coincided with a sharp rise in crop prices and so returns to cropping (Aakre et al. 2014; Davis and Sand 2017). Land-based net returns are known to drive land use decisions. On the other hand, we expect returns to influence perceptions through land use decisions, thereby yielding valid IVs for our study.

Whether to cultivate CRP land or keep it out of production crucially depends on the net returns that represent relative competitiveness of these land use choices. We consider two IVs based on data availability. First, we include CRP rental payments to account for annual returns from CRP lands. Higher CRP rent would generate disincentives for conversion of CRP lands. Our second instrument is the ratio of per-acre returns from croplands to those generated on grasslands. Grasslands tend to have per-acre returns that are closer to CRP rental payments. Thus, this ratio can reflect the relative competitiveness between croplands and CRP lands.

We employ a two-stage least squares (2SLS) regression framework to identify the impact of CRP land conversion decisions on the biases in farmers' weather perceptions. Figure 3 presents the schematic of this framework. The binary CRP land conversion decision, Δl_i, is modeled as

$$\ln\left[\frac{\Pr(\Delta l_i = 1)}{\Pr(\Delta l_i = 0)}\right] = \alpha_o + \alpha_1 rent_i + \alpha_2 ratio_i + + \vec{z}_i \vec{\delta} + \varepsilon_i \qquad (3)$$

In equation (3) we model the log-odds of each farmers *i*'s decision Δl_i=1 against Δl_i=0 as a function of two IVs: (1) change in per-acre CRP rental payments during 2004-2014, $rent_i$; and (2) ratio between cropland and grassland value changes, $ratio_i$, while controlling for land quality and farmers' socio-economic information in vector $\vec{z}_i = \{hel_i, age_i, inc_i\}$ (see Table 1). Land values are closely tied to land-based economic returns and are influenced by macroeconomic inflation and interest rates as well as idiosyncratic fads in real-estate markets. Land values directly impact land use decisions (Plantinga and Irwin 2006). Please see *SM*, section S6 for details on construction of land value variables: $rent_i$ and $ratio_i$, pertaining to each survey location. We predicted the CRP conversion probability, i.e., $\hat{p}_i^{(CRP \to crop)}$, from equation (3) to further estimate a model for weather perception biases with the following equations,

$$\ln\left[\frac{\Pr(b_i^L = \{L \to H\})}{\Pr(b_i^L = \{L \to L\})}\right] = \omega_0 + \omega_1 \hat{p}_i^{(CRP \to crop)} + \vec{c}_i \vec{\tau} + \zeta_i \qquad (4)$$

$$\ln\left[\frac{\Pr(b_j^L = \{H \to L\})}{\Pr(b_j^L = \{H \to H\})}\right] = \iota_0 + \iota_1 \hat{p}_j^{(CRP \to crop)} + \vec{c}_i \vec{\kappa} + \xi_j,\ j \neq i \qquad (5)$$

In equation (4) we model log-odds of *i*'s misperceptions against consistent perceptions of 'low' *w* value in 2014 (relative to 2004) as a function of $\hat{p}_i^{(CRP \to crop)}$ and demographic controls, $\vec{c}_i = \{age_i,$

$educ_i, inc_i\}$. Similarly, in equation (5) we model log-odds of misperceptions against consistent perceptions of 'high' w value in 2014. Given that each farmer could only over-perceive or under-perceive change we set $i \neq j$. The IV-conditioned CRP land conversion probability identifies a causal channel between land use decisions and motivated biases in weather perceptions. Overall, coefficients ω_1 and ι_1 will provide an inference on motivated weather beliefs due to farmers' past land use decisions.

Finally, we conduct specification tests for overidentifying restrictions and weak instruments with reference to the above 2SLS system. The details are outlined in the *SM*, section S6 and Table S7. In summary, we fail to reject overidentifying restricts with 95% confidence. This means that the IVs, namely $rent_i$ and $ratio_i$, are correctly excluded (with 95% confidence) from the second stage regression models (4-5). We also reject the hypothesis of weak IVs.

3. Results

Results are organized around the testing of Hypotheses I and II, and our findings will be interpreted in the context of our study region's weather conditions and survey-based socio-economic information of farmers. We present variable descriptions and data summaries in Table 1. According to the meteorological evidence as shown in Table 1, farmers in our sample experienced moderate changes in temperature (i.e., 0.2°C lower in 2014 from an average 17°C in 2004) and precipitation (i.e., 17.5 mm higher in 2014 from an average 380mm in 2004). However, there were substantial variations in weather changes across our study region (please see the standard deviation estimates for Δt^{04-14}, Δp^{04-14} and Δd^{04-14} in Table 1), which allows us to characterize farm-level heterogeneity in weather perceptions biases. Further, 30% farmers in our sample opted out of the CRP contracts for crop production during 2004-2014. We will assess whether such decisions are systematically related to farmers' weather perception biases.

3.1 *Biases in farmers' weather change perceptions*

3.1.1 *Regression based assessment of weather change beliefs relative to data-based records* [Testing of Hypothesis I]

Table 2 presents the results of our multivariate analysis of weather change perceptions in model (1), where we intend to test whether farmers' perception reports are on average consistent with data-based evidence conditional on socio-economic and geographic information. We find drought records Δd_i^{04-14} to be positively correlated with farmer perceptions $\Delta\tilde{d}_i$ in a statistically significant manner; but an additional drought only led to 4% (significant at α=0.05) increase in the odds of $\Delta\tilde{d}_i = 3$ relative to $\Delta\tilde{d}_i \leq 2$ responses. However, data-based records for Δt_i^{04-14} and Δp_i^{04-14} are not statistically significantly associated with perceptions $\Delta\tilde{t}_i$ and $\Delta\tilde{p}_i$, respectively. Therefore, we conclude that our data analysis provides very limited support for Hypothesis I.

To further understand farmer perceptions we assess robustness of our regression results to different cognitive factors such as fuzzy memory and recency saliency, as discussed earlier in section 2.2.1. We use auxiliary data to represent in local weather changes in the past ($\boldsymbol{\Delta w_i}$), i.e., (i) recent events, i.e., 2006 droughts and 2011 floods; and (ii) intra-seasonal weather changes. Specifically, we evaluate $\Delta\tilde{p}$ in relation to "high" (>15 mm) precipitation days during 2004-2014, denoted as $\Delta p_{>15mm}^{04-14}$ (where the threshold of 15mm exceeded 95th percentile of daily precipitation during 2004-2014); $\Delta\tilde{d}$ in relation to late-season (August) droughts, i.e., $\Delta d_{August}^{04-14}$; and $\Delta\tilde{t}$ in relation to the growing-degree days (*GD*s), i.e., ΔGD^{04-14}. *GD*s represent a non-linear transformation of daily temperature records to measure the beneficial heat exposure for crop production (see *SM*, section S7 and Arora et al. 2020 for details). We also evaluate $\Delta\tilde{t}$ relative to early-season (April-June) *GD*s, i.e., $\Delta GD_{April-June}^{04-14}$. Intra-seasonal dissimilarities in temperature impacts on farm outcomes have been previously reported (e.g., Tack et al. 2015; Ahmed et al. 2022). Estimation results are presented in Table 2a.

We find that high-rainfall events in more recent years, i.e., 2006 (drought year) and 2011 (flood year), are significantly corrrelated with $\Delta\tilde{p}$, unlike the high-rainfall events in 2004 that are uncorrelated with $\Delta\tilde{p}$. This likely reflects recency effects in farmers' precipitation perceptions, which may influence their farmland use and insurance uptake decisions (Doidge et al. 2019). Further, late-season droughts and early-season *GD*s exhbit a stronger association with perceptions than their respective season-wide counterparts. That is, an additional August drought ($\Delta d^{04-14}_{August}$) leads to 28% (α=0.05) higher odds of $\Delta\tilde{d}_i = 3$ relative to $\Delta\tilde{d}_i \leq 2$, and a unit increase in $\Delta GD^{04-14}_{April-June}$ leads to 18% (α=0.10) higher odds of $\Delta\tilde{t}_i = 1$ relative to $\Delta\tilde{t}_i \geq 2$. *GD*s are a better representation of heat impacts on crop physiology relative to linear temperatures (Arora et al. 2020). Moreover, farmers may be able to adapt to early-season droughts through delayed sowing (Yang et al. 2019) or resistant seeds (Wang et al. 2017) whereas late-season droughts pose a greater risk of loss.

The above results suggest that farmers tend to perceive local weather indicators with regards to their impact on crop production (rather than the simple data summaries of growing-season weather). Liverpool-Tasie et al. (2020) also suggested that climate perceptions could be related to the degree of exposure and potential for impacts on farmers' economic activities. However, we focus on how these perceptions compare with the data-based evidence for distinct weather indicators, which has received little attention in the existing studies. A recognition that farmer perceptions may differ across weather indicators, and with a reference to farm production activities, will help enrich climate change perspectives and climate policy debates.

Lastly, we find geographic and socioeconomic controls to be distinctly associated with farmer perceptions. Older farmers endowed with higher farm revenues and poor-drainage soils are less likely to perceive low precipitation and frequent droughts, which may reflect on these farmers' resilience to adverse weather as derived from demographic and biophysical attributes. However, these controls are not correlated with $\Delta\tilde{t}$, i.e., perceived weather changes (Table 2).

3.1.2 *Mismatch between farmer perceptions and weather data—evidence of potentially systematic biases* [Further evidence for Hypothesis I]

We build on the regression-based weak correlation estimates between perceptions and weather data to further tease out systematic patterns in farm-level weather perception biases in light of socioeconomic information and on-farm decisions. Specifically, we cross-tabulate weather change perceptions with corresponding data-based evidence during 2004-2014 in Tables 3a-c; where the diagonal elements represent beliefs that were consistent with weather data and the off-diagonal elements provide a count of biased beliefs in our sample. The 'don't know' and missing responses for survey-based perceptions are excluded from this part of analysis.

About 28% (283 out of 1,026) growers report beliefs that were consistent with temperature changes during 2004-2014 while such beliefs were biased for 673 farmers. Within the latter group, 531 farmers misperceived 'lower' temperature in 2014 to be either 'about the same' or 'higher' relative to the 2004 levels. Further, about 30% farmers' perceptions agreed with past precipitation data whereas 666 farmers misperceived these changes (Table 3b). Among these 666 farmers 267 of them misjudged 'higher' precipitation change to be either 'lower' or 'about the same'; 253 farmers misjudged 'lower' precipitation to be either 'lower' or 'about the same'; and 134 farmers misjudged 'about the same' precipitation to be either 'lower' or 'higher' relative to 2004 levels. Similarly, 33% growers exhibited consistent beliefs about drought frequency while

622 farmers misperceived them; and among them 462 farmers misperceived less frequent droughts to be 'more frequent' or 'about the same' (Table 3c).

In summary, the largest proportion of farmers misperceived past weather changes, which is in contrast with Hypothesis I. More importantly, Dakotas' farmers predominantly over-estimated temperature and drought levels, and under-estimated precipitation levels relative to data-based records. We want to note that observing some biases in farmers' weather perceptions is not surprising given that it is a cognitively challenging task to summarize weather trends that can evolve in multiple dimensions (e.g., temperature, precipitation, or both) and fluctuate in opposite directions. For example, a spring that is on average cooler than usual could have few very warm days. In addition, complex social, economic and political conditions drive weather perceptions (Ungar 1992; Potosky et al. 2015; Ruiz et al. 2020). However, it is the systematic one-sided biases whose in-depth understanding likely holds great potential for improved policy designs that are aimed at enhancing resilience in farm outcomes in response to climate uncertainty.

3.2 *Perception biases as motivated by land use decisions* [Testing of Hypothesis 2]

To further understand what underlies weather perception biases (as recorded in Tables 3a-c) we investigate these in relation to farmers' land use decisions in the Dakotas. Tables 4a-c provides evidence (based on the χ^2-test) for the dependence between perception biases and CRP land conversion decisions. The primary feature that underlies these results is a skew in the frequency of precipitation and drought beliefs when assessed in conjunction with farmers' decision to cultivate lands that were initially enrolled under the CRP contract. To elaborate further, consider perception biases outlined in Tables 4a-b.

More farmers misperceived that weather became drier (when the data shows it became wetter) as compared to those misperceiving that weather became wetter (when the station records show change in the opposite direction). Specifically, 122 out of 223 farmers perceived that weather became drier when it became wetter from 2004 to 2014 (Table 4a). In contrast, only 92 out of 229 farmers perceived was becoming wetter when it became drier during the same period (Table 4b). Assessing beliefs conditional on CRP land conversion decisions (i.e., Δl_i=1 or 0) reveals that the misperceptions are relatively concentrated in the Δl_i=1 category. In particlar, more than twice among converting farmers misperceived 'drier' weather (Table 4a), while only one-fourth among these misperceived 'wetter' conditions in 2014 (Table 4b). Farmers in Δl_i=0 category, on the other hand, are relatively more uniformly spread out across consistent and biased perception categories (i.e., 84 versus 83 in lower precipitation case; and 81 versus 96 in higher precipitation case). A similar situation arises when we assess drought perceptions conditional on CRP land conversion decisions, see Table 4c.

The observed misperceptions in our sample reveal a disregard for lower rainfall and higher drought incidence in a manner that would signal subconscious cognitive manipulations aimed at validating the past decisions to convert CRP lands for cultivation. Lands that are enrolled under CRP contracts are typically classified as medium or low productivity lands (Claassen et al. 2010). Therefore, once a farmer opts out of the CRP contract she might believe in more favorable weather conditions relative to what the data supports; and such (mis)perceptions might be greater when the soils are less conducive for production (Wang et al. 2017).

We find some evidence in support for Hypothesis II by rejecting statistical independence between weather beliefs and land use decisions at 95% confidence. However, this does not guarantee that past decisions *caused* perception biases becasue farmer and farm characteristics such as soil quiality that influence both weather perceptions and land use decisions might underlie the above evidence for statistical dependence between them. Below we outline the results of our causal impact analysis of land use decisions on weather beliefs based on the "motivated beliefs" theory (as explained in Benabou and Tirole 2002).

3.2.1 *Motivated beliefs: Land use decisions as a causal factor of weather perception biases*

Tables 5a-b present results from our 2SLS framework (outlined in Figure 3 and discussed in section 2.3.1) to establish that Dakotas' farmers are likely to misperceive weather changes after converting their CRP lands for cultivation. In Table 5a (first-stage regression) we show that one-dollar increase in per-acre CRP rents would reduce the odds of converting CRP lands by 4% (significant at α=0.01). On the other hand, 1% higher ratio of cropland-to-grassland return increases the odds of CRP land conversion by 8%, however the latter impact is statistically insignificant. Further, CRP lands were relative more likely cultivated on highly erodile soils, which is in line with the policy mandate of CRP (discussed earlier), and among older farmers in higher income categories.

Table 5b (second-stage regression) presents our results on the causal impact of the likelihood of CRP land conversion (as estimated from first-stage regression) on the odds of biased weather beliefs relative to the odds of consistent beliefs. We find that biases in precipitation and drought perceptions were statistically significantly affected by the decision to cultivate crops on CRP lands. Specifically, a higher likelihood of CRP land conversions led to an average of 39% higher odds (significant at α=0.01) of misperceiving drier conditions; 41% (α=0.01) lower odds of misperceiving wetter conditions; and 60% (α=0.01) lower odds of misperceiving less droughts during 2004-2014 (Table 5b). Note that the impact estimate for land conversion decision, Δl_i, was lower (in absolute value) for IV-based regression relative to the non-IV case, which reveals a correction of omitted variable bias in the non-IV case due to endogeneity between farmers' decisions and weather perception biases.

4. Discussions and conclusion

There exists a well-established literature that posits perceptions of climate change and weather patterns as critical inputs for designing effective policies for climate change mitigation and adaptation. A fundamental impediment in advancing the objectives of climate policy is that individual beliefs may not be consistent with scientific evidence (Ding et al. 2011; McCright et al. 2013). Recent studies of climate change beliefs highlight the interactions between spatial climate patterns and heterogeneous individual interests/values that are tied to local resource constraints and socio-cultural factors (e.g., Howe et al. 2015; Kaufmann et a. 2017). We extend this line of research by analyzing beliefs that may be distinct across weather indicators such as temperature, precipitation and droughts. The basis of our inquiry is the complex composition of climate or weather information such that individuals may attribute climate change to spatio-temporal changes in temperature, precipitation, or both, depending on the local or regional contexts.

We study farm-level heterogeneity in perception biases for three weather indicators: temperature, precipitation, and drought frequency, in relation to local meteorological evidence and farmers' socioeconomic and geographic information. Our analysis highlights that farmers may perceive weather indicators distinctly from each other. In fact, farmers in our sample perceived local weather changes in ways that reflects on the impact of each weather indicator on their production system. We also provide evidence on the causal impact channel between farmers' land use decisions and weather beliefs. Having made the decision to pursue crop production on protected lands seemed to motivate farmers to systematically ignore adverse weather signals of the past.

In the existing literature on motivated climate change reasoning, prior beliefs and political polarization were documented as drivers of climate change beliefs. Our result that links weather perceptions to past land use decisions adds a new economic perspective to the understanding of climate change beliefs and relevant communication strategies (as originally proposed by Druckman and McGrath 2019). These authors suggested that identifying individual's goals or motivation for belief distortion can facilitate effective climate change communication. Our findings suggest an indirect economic motivation (as mediated through land use decisions) for climate change beliefs that may present a challenge for communicating scientific evidence when high commodity prices favor crop-based production.

We point to a couple of caveats in our findings. Our analysis is based on one sample of farmers in a specific region. While the sample is relatively large and representative, it is important to study weather perception biases in other regions and contexts (e.g., alternative land use types or farm management decisions). Moreover, climate and weather perceptions are based on complex cognitive processes and so more in-depth examination is necessary with methods and concepts in psychology and cognitive sciences to pinpoint key factors and mechanisms that drive perceptions. Regardless, our findings suggest that climate policy designs that solely rely on objective climate and weather data might be misguided. It will be beneficial for policymakers to devise targeted climate mitigation and adaptation strategies that take into account farmers' perceptions and beliefs.

References

Aakre, D., Haugen, R. Saxowsky, D. 2014. North Dakota Agricultural Land Valuation Model. Agribusiness and Applied Economics Miscellaneous Report# 721, Agricultural Experiment Station, North Dakota State University Fargo, ND. Online link; last accessed August 2023.

Ahmed, M.H., Tesfaye, W.M., Fassmann, F. 2022. Early growing season weather variation, expectation formation and agricultural land use decisions in Ethiopia. J Agric Econ, 74(1):1-18.

Arbuckle, J.G., Morton, L.W., Hobbs, J. 2013**a**. Farmers beliefs and concerns about climate change and attitudes toward adaptation and mitigation: Evidence from Iowa. Climatic Change, 118:551-563.

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

Arora, G., Feng, H., Anderson C.J., Hennessy, D.A. 2020. Evidence of climate change impacts on crop comparative advantage and land use. Agric Econ, 51(2):221-236.

Arora, G., Feng, H., Hennessy, D.A., Loesch, C., Kvas, S. 2021. The impact of production network economies on spatially-contiguous conservation- Theoretical model with evidence. J Environ Econ Manag, 107(C):102442.

Barnes, A., Toma, L. 2011. A typology of dairy farmer perceptions towards climate change. Climatic Change, 112:507-522.

Bauer, P., Thorpe, A., Brunet, G. 2015. The quiet revolution of numerical weather prediction. Nature, 525, 47-55.

Bayes, R., Druckman, J.N. 2021. Motivated reasoning and climate change. Curr Opin Behav Sci, 42:27-35.

Bénabou, R. (2013). Groupthink: Collective Delusions in Organizations and Markets. Rev Econ Stud, 80(2): 429-462.

Bénabou, R. (2015). The Economics of Motivated Beliefs. Revue D'économie Politique, 125(5): 665-685.

Bénabou, R., & Tirole, J. (2002). Self-confidence and Personal Motivation. Q J Econ, 117(3): 871-915.

Claassen, R., Carriazo, F., Ueda, K. 2010. Grassland conversion for crop production in the United States. OECD Agri-environmental Indicators: Lessons Learned and Future Directions. Last accessed here July 2022.

Davey, M. 2006. Drought devastates northern U.S. Plains. The New York Times. August 29, 2006. Last accessed here May 2022.

Davis, J., Sand, S. 2017. South Dakota Agricultural Land Market Trends, 1991-2017: Results from the 2017 SDSU South Dakota Farm Real Estate Survey. iGrow South Dakota State University Department of Economics, July 2017.

Darabant, A., Habermann, B., Sisay, K., Thurnher, C., Worku, Y., Damtew, S., Lindtner, M., Burrell, L., Abiyu, A. 2020. Farmers' perceptions and matching climate records jointly explain adaptation responses in four communities around Lake Tana, Ethiopia. Climatic Change 163:

1119-11120.
Ding D, Maibach, E.W., Zhao, X., Roser-Renouf, C., Leiserowitz, A. 2011. Support for climate policy and societal action are linked to perceptions about scientific agreement. Nat Clim Change, 1:462–466.
Doidge, M., Feng, H., Hennessy, D.A. 2019. Rationality of weather predictions and insurance purchases: testing the gambler's and hot hand fallacies. Appl Econ, 51(32):3498-3515.
Druckman, J.N., McGrath, M.C. 2019. The evidence of motivated reasoning in climate change preference formation. Nat Clim Change, 9:111-119.
Egan, P.J., Mullin, M. 2012. Turning personal experience into political attitudes: The effect of local weather on America's perceptions about global warming. J Polit, 74(3):796-809.
Haden, V.R., Niles, M.T., Lubell, M., Perlman, J., 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):e52882.
Haiar, J. 2022. Government land conservation is soaring in South Dakota, but some fear a reversal. South Dakota Public Broadcasting News, April 14 2022. Online link; last accessed August 2023.
Howe, P.D., Mildenberger, M., Marlon, J.R., Leiserowitz, A. 2015. Geographic variations in opinions on climate change at state and local scales in the U.S.A. Nat Clim Change, 5:596-603.
Jha, C.K., Gupta, V. 2021. Farmer's perceptions and factors determining the adaptation decisions to cope with climate change: An evidence from rural India. Environ Sustain Indic, 10:100112.
Kaufmann, R.K., Mann, M.L., Gopal, S., Tang, X. 2017. Spatial heterogeneity of climate change as an experiential basis for skepticism. Proc Natl Acad Sci, 114 (1) 67-71.
Kateri, M. 2014. Contingency table analysis: Methods and applications using R. Springer New York.
Khanna, M., Ando, A. 2009. Science, economics and the design of agricultural conservation programmes in the US. Journal of Environmental Planning and Management, 52(5): 575-592.
Kunda. Z. 1990. The case for motivated reasoning. Psychol Bull, 108(3):480-498.
Leiserowitz, A. 2006. Climate Change Risk Perception and Policy Preferences: The role of affect, imagery, and values. Climatic Change, 77:45-72.
Liverpool-Tasie, L.S.O., Pummel, H., Tambo, J.A., Olabisi, L.S., Osutande, O. 2020. Perceptions and exposure to climate events along agricultural value chains: Evidence from Nigeria. J Environ Manag, 264:110430.
MacPherson, J. 2006. Drought dries up Dakotas' crops, livestock, and business. Associated Press. July 30, 2006. Last accessed here May 2022.
Mahmood, N., Arshad, M., Mehmood, Y., Shahzad, M.F., Kachele, H. 2021. Farmers' perceptions and role of institutional arrangements in climate change adaptation. Clim Risk Manag, 32:100288.
Mairura, F.S., Musafiri, C.M., Kiboi, M.N., Macharia, J.M., Ngetich, O.K., Shisanya, C.A., Okeyo, J.M., Mugendi, D.N., Okwuosa, E.A., Ngetich, F.K. 2021. Determinants of farmers' perceptions of climate variability, mitigation and adaptation strategies in central highlands of Kenya. Weather Clim Extremes, 34:100374.

Maltby, K.M., Simpson, S.D., Turner, R.A. 2021. Scepticism and perceived self-efficacy influence fishers' low risk perceptions of climate change. Clim Risk Manag, 31:100267.

Mase, S.M., Graming, B.M., Prokopy, L.S. 2015. Climate change beliefs, risk perceptions, and adaptive behavior among Midwestern U.S. crop farmers. Clim Risk Manag, 15:8-17.

McCright AM, Dunlap RE, Xiao C. 2013. Perceived scientific agreement and support for government action on climate change in the USA. Clim Change. 119:511–518.

McCullagh, P. 1980. Models for ordinal data. J R Stat Soc Series B (Methodol), 42(2):109-142.

Menne, M.J., Durre, I., Korzeniewski, B., McNeal, S., Thomas, K., Yin, X., Anthony, S., Ray, R., Vose, R.S., Gleason, B.E., Houston, T.G. 2012. Global Historical Climatology Network-Daily (GHCN-Daily), Version 3, NOAA National Climatic Data Center. Last accessed here April 2022.

Moore, F.C., Obradovich, N., Lehner, F., Baylis, P. 2019. Rapidly declining remarkability of termperature anomalies may obscure public perception of climate change. Proc Natl Acad Sci, 116(11): 4905-4910.

Murphy, K. 2011. Flood forces evacuations in two Midwestern states. Reuters. June 21, 2011. Last accessed here on May 27:2022.

Nauges, C., Wheeler, S.A., Fielding, K.S. 2021. The relationship between country and household wealth and climate change concern: The mediating role of control. Environ Dev Sustain, 23(1):16481-16503.

Ojo, T.O., Baiyegunhi, L.J.S. 2021. Climate change perception and its impact on net farm income of smallholder rice farmers in South-West Nigeria. J Clean Prod, 310, 127373.

Plantinga, A., Irwin, E.G. 2006. Overview of empirical models. In Economics of rural land-use change, Bell, K.P. et al. eds. page 272. Ashgate Publishing, Burlington, Vermont.

Potosky, M., Urbatsch, R., Yu, C. 2015. Temperature biases in public opinion surveys. Weather Clim Soc, 7:192-196.

Ruiz, I., Faria, S.H., Neumann, M.B. 2020. Climate change perception: Driving forces and their interactions. Environ Sci Policy, 108:112-120.

Sloggy, M.R., Suter, J.F., Rad, M.R., Manning, D.T., Goemans, C. 2022. Changing climate, changing minds? The effects of natural disasters on public perceptions of climate change. Climatic Change, 174, 17.

Steg, L., Vlek, C. 2009. Encouraging pro-environmental behaviour: An intergrated review and research agenda. J Environ Psychol, 29(3):309-317.

Tack, J., Barkley, A., Nalley, L.L., 2015. Effect of warming temperatures on U.S. wheat yields. Proc Natl Acad Sci, 12 (22):6931-6936.

Tversky, A., Kahneman, D. 1974. Judgement under uncertainty: Heuristics and biases. Sci, 185(4157):1124–1131.

Ungar, S. 1992. The rise and (relative) decline of global warming as a social problem. The Sociol Q, 33(4):483-501.

U.S. Department of Agriculture (USDA) National Agricultural Statistical Service. 2007. South Dakota Weather Summary, 2006. South Dakota Annual Statistics Bulletin, p. 11-13. Last

accessed here May 2022.
U.S. Geological Survey (USGS). 2019. April 2011 North Dakota Flood. A Report of the USGS Water Resources Division. February 25, 2019. Last accessed here May 2022.
Wang, T., Luri, M., Janssen, L., Hennessy, D.A., Feng, H., Wimberly, M., Arora, G. 2017. Determinants of motives for land use decisions at the margins of the Corn Belt. *Ecol Econ,* 134:227-237.
Wimberly, M.C., Janssen, L.L., Hennessy, D.A., Luri, M., Chowdhury, N.M., Feng, H. 2017. Cropland expansion and grassland loss in the eastern Dakotas: New insights from a farm-level survey. Land Use Policy, 63:160-173.
Wheeler, S.A., Zhuo, A., Bjornlund, H. 2013. Farmers' climate change beliefs and adaptation strategies for a water scarce future in Australia. Glob Environ Change, 23(2):537-547.
Wheeler, S.A., Nauges, C., Zhuo, A. 2021. How stable are Australian farmers' climate risk perceptions? New evidence of feedback loop between risk perceptions and behavior. Glob Environ Change, 68(1):102274.
Wooldridge, J.M. 2002. Econometric Analysis of cross section and panel data. The MIT Press, Cambridge, MA.
Yang, C., Fraga, H., van Ieperen, W., Trindade, H., Santos, J.A. 2019. Effects of climate change and adaptation options on winter wheat yield under rainfed Mediterranean conditions in southern Portugal. Climatic Change 154:159–178.

TABLES

Table 1: Summary of survey data attributes for farmers located in the eastern Dakotas.

Variable	Description	N	Mean	Median	SD
$\Delta\tilde{t}$	=**1** if 'cooler' temperature belief during 2004-2014; =**2** if 'about the same'; =**3** if 'hotter'.	956	1.92	2.00	0.62
$\Delta\tilde{p}$	=**1** if 'lower' precipitation belief during 2004-2014; =**2** if 'about the same'; =**3** if 'higher'.	974	2.09	2.00	0.78
$\Delta\tilde{d}$	=**1** if 'less droughts' belief during 2004-2014; =**2** if 'about the same'; =**3** if 'more droughts'.	961	1.90	2.00	0.71
Δt^{04-14}	Weather-station record of growing-season temperature (°C) change, 2004-2014	1,026	-0.22	-0.50	1.65
Δp^{04-14}	Weather-station record of growing-season precipitation change (mm), 2004-2014	1,026	17.45	18.00	64.43
Δd^{04-14}	USDM drought frequency record, 2004-2014	1,026	-3.43	-4.00	3.56
age	Age category (see notes)	1,026	3.30	3.00	1.08
educ	Education levels (see notes)	1,026	2.95	3.00	0.92
inc	Annual gross farm/ranch sales (see notes)	1,026	3.60	4.00	1.53
hel	Percent highly erodible soil	1,026	8.31	1.00	15.71
heavy	Percent heavy soil	1,026	37.33	30.00	32.65
lat	Coordinates along the north-south direction	1,026	45.29	45.16	1.29
lon	Coordinates along the east-west direction	1,026	-98.0	-98.0	1.07
$\Delta \boldsymbol{l}_i$	=**1** if CRP land was converted to cropland; =**0** if not converted during 2004-2014.	1026	1.70	2.00	0.52

Notes:

1. Missing data and 'Don't Know' responses were removed for summarizing $\Delta\tilde{t}$**,** $\Delta\tilde{p}$ and $\Delta\tilde{d}$.

2. Age categories were assigned as: 19-34 (**1**); 35-49 (**2**); 50-59 (**3**); 60-69 (**4**); 70+ (**5**).

3. Education levels were assigned as: Highest education level: less than high school (**1**); high school (**2**); technical school (**3**); 4-year college (**4**); advanced degree e.g. Masters, etc. (**5**).

4. Annual gross farm/ranch sales were categorized as: <$50K (**1**); $50K-$99.9K (**2**); $100K-$249.9K (**3**); $250K-$499.9K (**4**); $500K-$999.9K (**5**); $1 million+ (**6**).

Table 2: Ordered logistic regressions for farmer perceptions, $\Delta\tilde{w}$, as function of local weather change records, $\Delta \boldsymbol{w}$, conditional on farm location, and economic and demographic information.

Variable	**Model 1** Dependent Var.: $\Delta\tilde{t}$	**Model 2** Dependent Var.: $\Delta\tilde{p}$	**Model 3** Dependent Var.: $\Delta\tilde{d}$
Weather change records			
Δt^{04-14}	-0.01 (0.07)		
Δp^{04-14}		-0.001 (0.001)	
Δd^{04-14}			-0.04** (0.02)
Controls (Farm and farmer characteristics)			
age	-0.11 (0.08)	-0.21*** (0.07)	0.25*** (0.06)
inc	0.03 (0.05)	-0.12** (0.05)	0.12** (0.04)
heavy soils	0.001 (0.003)	-0.002 (0.003)	0.004** (0.002)
lat	-0.03 (0.07)	-0.29*** (0.06)	0.31*** (0.07)
-2LogL	1,102	1,577	1,804
Count of Ordered Outcomes	$\Delta\tilde{t}=1$: 222 $\Delta\tilde{t}=2$: 585 $\Delta\tilde{t}=3$: 144	$\Delta\tilde{p}=1$: 250 $\Delta\tilde{p}=2$: 363 $\Delta\tilde{p}=3$: 338	$\Delta\tilde{d}=1$: 293 $\Delta\tilde{d}=2$: 459 $\Delta\tilde{d}=3$: 199
N	951		

$^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.10$

Notes: Here we include only statistically significant results and keep the sample size same across weather indicators to facilitate a comparative analysis. Tables S2-S4, *SM* provide full results.

Table 2a: Ordered logistic regressions for $\Delta\tilde{w}$ as function of auxiliary weather change records i.e., early-season *GD*s for $\Delta\tilde{t}$; high rain events (>15mm); and late-season droughts.

Variable	**Model 1A** Dependent Var.: $\Delta\tilde{t}$	**Model 2A** Dependent Var.: $\Delta\tilde{p}$	**Model 3A** Dependent Var.: $\Delta\tilde{d}$
$\Delta GD^{04-14}_{April-June}$	0.18* (0.10)		
$\Delta GD^{06-14}_{April-June}$	0.17** (0.09)		
$\Delta p^{06-14}_{>15mm}$		-0.03* (0.02)	
$\Delta p^{11-14}_{>15mm}$		-0.02* (0.01)	
$\Delta d^{04-14}_{August}$			-0.30*** (0.10)
N	951	951	951

$^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.10$

Notes: Tables S2-S4 (*SM*) provide full results for these auxiliary models.

Table 3: Cross-tabulations between survey-based weather change perceptions and growing-season (April-August) weather change records during 2004-2014

Farmer beliefs about past temperature change: $\Delta\tilde{t}$	Weather station-based temperature change records: Δt^{04-14}			
	$\Delta t^{04-14} \le -5\%$	$\Delta t^{04-14} \in (-5\%, 5\%)$	$\Delta t^{04-14} \ge 5\%$	Total
$\Delta\tilde{t} = 1$: Cooler weather	**163**	39	21	223
$\Delta\tilde{t} = 2$: About the same	425	**108**	54	587
$\Delta\tilde{t} = 3$: Warmer weather	106	28	**12**	146
Don't Know	40	9	4	53
Missing data	13	2	2	17
Total	747	186	93	1026

(a)

Farmer beliefs about past precipitation change: $\Delta\tilde{p}$	Weather station-based precipitation change records: Δp^{04-14}			
	$\Delta p^{04-14} \le -5\%$	$\Delta p^{04-14} \in (-5\%, 5\%)$	$\Delta p^{04-14} \ge 5\%$	Total
$\Delta\tilde{p} = 1$: Less precipitation	**106**	53	95	254
$\Delta\tilde{p} = 2$: About the same	127	**75**	172	374
$\Delta\tilde{p} = 3$: More precipitation	126	81	**139**	346
Don't Know	11	5	16	32
Missing data	2	2	16	20
Total	372	216	438	1026

(b)

Farmer beliefs about drought frequency change: $\Delta\tilde{d}$	Change in recorded drought intensity scores: Δd^{04-14}			
	$\Delta d^{04-14} < 0$	$\Delta d^{04-14} = 0$	$\Delta d^{04-14} > 0$	Total
$\Delta\tilde{d} = 1$: Less drought	**240**	17	37	294
$\Delta\tilde{d} = 2$: About the same	338	**58**	71	467
$\Delta\tilde{d} = 3$: More drought	124	37	**39**	200
Don't know	34	4	7	45
Missing data	17	1	2	20
Total	753	117	156	1026

(c)

Notes: $\Delta w^{04-14} \le -5\% \equiv \frac{w_{2014} - w_{2004}}{w_{2004}} \le -0.05; |\Delta w^{04-14}| \le 5\% \equiv \left|\frac{w_{2014} - w_{2004}}{w_{2004}}\right| < 0.05;\ \Delta w^{04-14} \ge 5\% \equiv$ $\frac{w_{2014} - w_{2004}}{v_{2004}} \ge 0.05$, where w represents growing-season temperature and precipitation, respectively. Our results remain quite similar upon choosing a 10% threshold level.

Table 4: Contingency table between farmers' decision to convert CRP lands for cropping (i.e., whether a farmer converted CRP land for cropping) and their beliefs about precipitation changes during 2004-2014.

Land use decision	Beliefs about ***lower*** precipitation in 2014 relative to 2004		
	Biased beliefs ($L \rightarrow H$)	Consistent beliefs ($L \rightarrow L$)	Row Totals
Δl_i=1 (Yes)	39 (31)	17 (25)	56
Δl_i=0 (No)	83 (91)	84 (76)	167
Column Totals	122	101	223
Test statistic ($X \sim \chi_1^2$)	6.73		

(a)

Land use decision	Beliefs about ***higher*** precipitation in 2014 relative to 2004		
	Biased beliefs ($H \rightarrow L$)	Consistent beliefs ($H \rightarrow H$)	Row Totals
Δl_i=1 (Yes)	11 (21)	41 (30)	52
Δl_i=0 (No)	81 (71)	96 (106)	177
Column Totals	92	137	229
Test statistic ($X \sim \chi_1^2$)	10.13		

(b)

Land use decision	Beliefs about ***lower*** drought frequency in 2014 relative to 2004		
	Biased beliefs ($L \rightarrow H$)	Consistent beliefs ($L \rightarrow L$)	Row Totals
Δl_i=1 (Yes)	10 (20)	60 (50)	70
Δl_i=0 (No)	59 (49)	115 (125)	174
Column Totals	69	175	229
Test statistic ($X \sim \chi_1^2$)	9.48		

(c)

Notes:

- Each cell in these tables provides 'observed' frequency and 'expected frequency' (see in the parentheses) for pairwise CRP land conversion decisions (Δl_i) and weather change beliefs (b_i).
- Expected frequency values are calculated under independence assumption between Δl_i and b_i. For cell (i,j) the expected frequency equals {column-total(i) x row-total(j)}÷(total sample size). For example, for cell (1,1) in Table 4a the expected frequency equals (122x56)÷(223)= 30.6.
- The critical value for χ_1^2 at 95% confidence level is equal to 3.84.

Table 5a: Binomial logit regression for farmers' CRP land conversion decision (Δl)

Variable	**Dependent Variable:** ln[Pr(Δl=1)/ Pr(Δl=0)]
rent	-0.04*** (0.01)
ratio	0.08 (0.17)
hel	0.02*** (0.005)
age	-0.21*** (0.08)
educ	0.13 (0.09)
inc	0.43*** (0.07)
Intercept	-2.00*** (0.74)
-2LogL	934
Response counts	Δl_i=1: 226; Δl_i=0: 714
N	940

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5b: Binomial logit regression for farmers' precipitation and drought beliefs (i.e., b_i)

Variable	**Precipitation:** $\Delta p^{04-14} \le -5\%$ $b_i^L \in \{L \to H, L \to L\}$		**Precipitation:** $\Delta p^{04-14} \ge 5\%$ $b_i^H \in \{H \to L,\ H \to H\}$		**Drought:** Δd^{04-14}<0 $b_i^L \in \{L \to H, L \to L\}$	
	IV	**non-IV**	**IV**	**non-IV**	**IV**	**non-IV**
$\hat{p}_i^{(CRP \to crop)}$	0.39*** (0.15)		-0.41** (0.20)		-0.60*** (0.18)	
Δl_i		0.82** (0.36)		-0.91** (0.39)		-0.88*** (0.31)
age	0.49*** (0.16)	0.36** (0.14)	-0.36** (0.16)	-0.21 (0.14)	-0.52*** (0.14)	-0.29** (0.12)
educ	0.29* (0.18)	0.40** (0.17)	-0.05 (0.17)	-0.14 (0.15)	0.03 (0.15)	-0.15 (0.14)
inc	-0.24*** (0.15)	-0.04 (0.12)	-0.03 (0.18)	-0.25** (0.11)	-0.12 (0.16)	-0.26*** (0.10)
Intercept	-2.38** (0.94)	-2.21** (0.93)	-3.58*** (0.63)	1.80** (0.86)	-1.95*** (0.74)	1.90** (0.75)
-2LogL	288	291	295	294	411	415
Total *N*	214		223		333	
Biased#	118		90		115	
Accurate#	96		133		218	

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors in parentheses. The $\Delta d^{04-14} > 0$ case was excluded due to low count of locations (only 76) where droughts intensified during 2004-2014. Finally, temperature perceptions were not found to be associated with CRP land conversion decisions in a statistically significant manner.

FIGURES

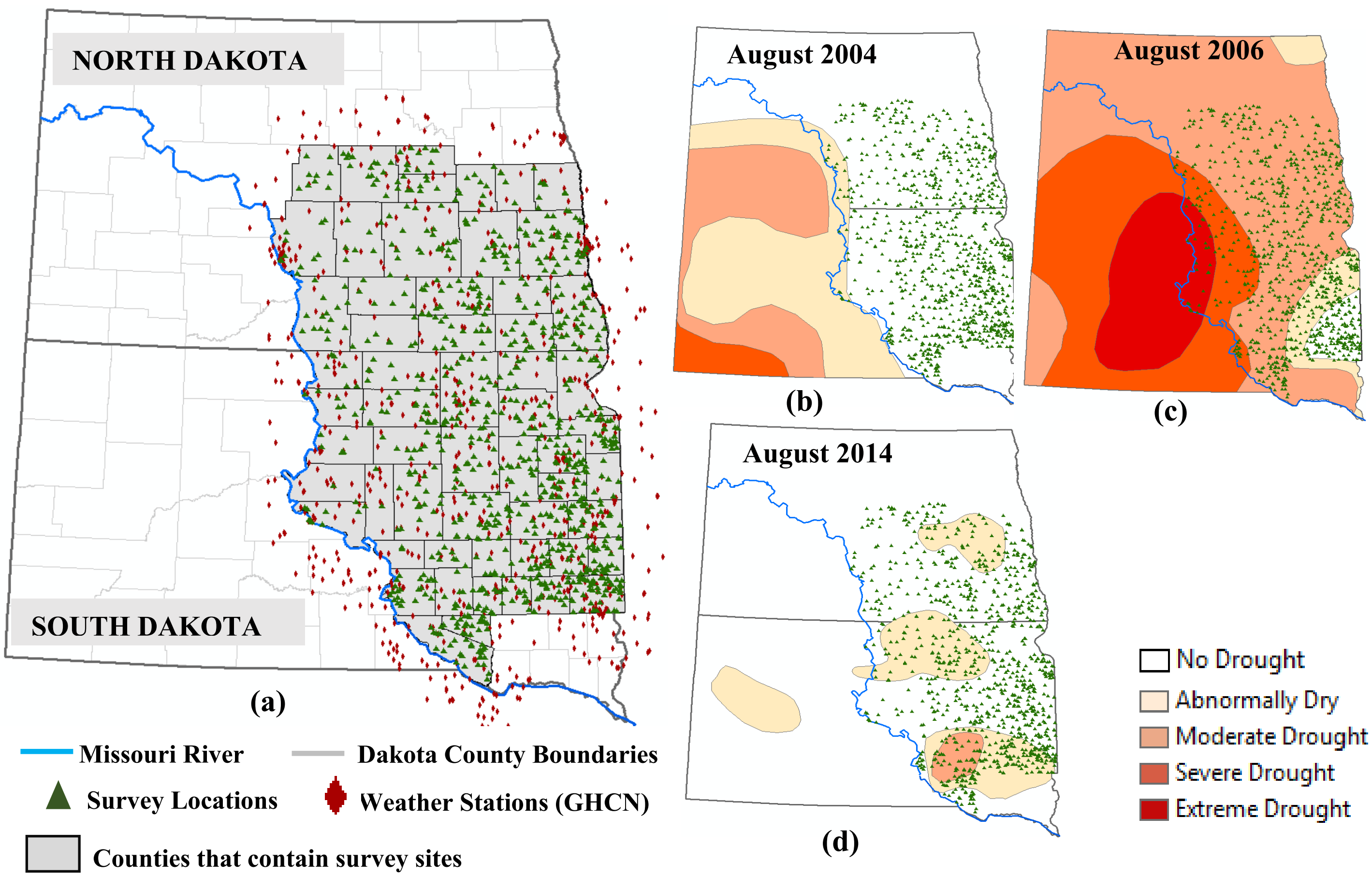

Figure 1(a): Spatial distribution of survey responses located to east of the Missouri River. GHCN weather stations (green triangles) provide temperature and precipitation summaries in each respondent's locality. **Figures 1(b)-1(d):** Drought intensity vector maps for August months in 2004, 2006 and 2014, respectively, overlain with our survey locations. *Source: The National Drought Mitigation Center (NDMC) in the United States,* https://droughtmonitor.unl.edu/About/Permission.aspx. *Maps courtesy of NDMC.*

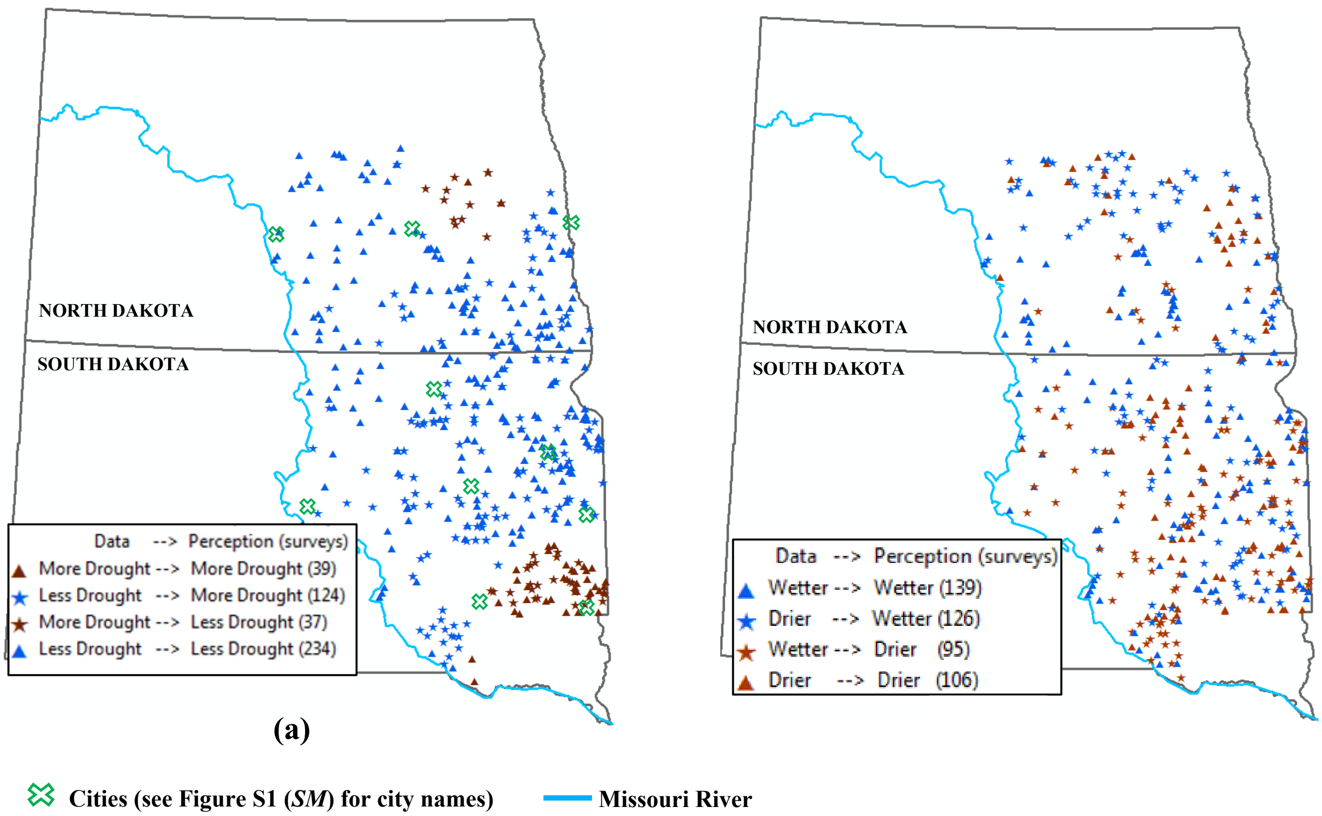

Figure 2: A spatial map of perceptions of past weather for Dakotas' farmers showing consistent beliefs (triangle markers) and biased beliefs (star markers) of change in (a) drought frequency and (b) precipitation during 2004-2014. Please see *SM* (section S4 and Figure S2) for more details and discussions related to spatial patterns in farmers' weather change perceptions.

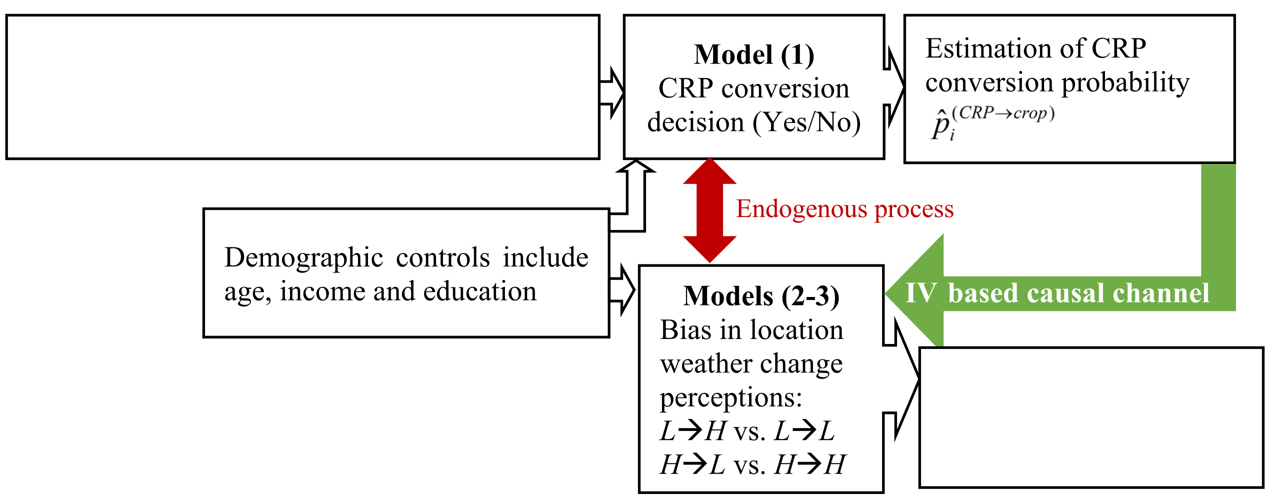

Figure 3. Schema for IV-based 2SLS regression framework to identify the causal impact of CRP land conversion decisions on biases in famers' weather change perceptions.