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A (mis)alignment of farmer experience and perceptions of climate change in the U.S. inland Pacific Northwest

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Abstract
Climate change is expected to have heterogeneous effects on agriculture across the USA, where temperature and precipitation regimes are already changing. While the overall effect of climate change on agriculture is uncertain, farmers' perceptions of current and future climate and weather conditions will be a key factor in how they adapt. This paper analyzes data from paired surveys ($N = 817$) and natural variation from baseline weather across the inland Pacific Northwest (iPNW), to determine if long-term, gradual changes in precipitation, and temperature distributions affect farmers' weather perceptions and intentions to adapt. We note that some areas in the iPNW have experienced significant changes in weather, while others have remained relatively constant. However, we find no relationship between changes in temperature and precipitation distributions and individuals' perceptions and intentions to adapt. Our findings provide evidence that gradual, long-term changes in weather are temporally incongruous with human perception, which can impede support for climate action policy and adaptation strategies.

Keywords Climate change · Perceptions · Experience · Agricultural adaptation · Wheat · Weather

1 Introduction

Climate change is expected to have heterogeneous effects on agriculture across the United States of America (USA), where temperature and precipitation regimes are already changing (Asseng et al. 2013; Reidmiller et al. 2017). Some research suggests climate change may improve agricultural production and increase yields through mechanistic crop responses to

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carbon and/or on-farm decisions (Leakey et al. 2009; Asseng et al. 2013; Stöckle et al. 2018) or by increasing the amount of land suitable for cultivating high-value crops (Parker and Abatzoglou 2018). Other studies suggest climate change will negatively impact USA and global agricultural yields and profits, primarily through drought and harmful growing degree days[1] (Lobell et al. 2008; Fisher et al. 2012; Deschênes and Greenstone 2012). However, the crop losses due to more frequent and severe temperatures and droughts may be largely mitigated through adaptive behavior, which suggests that future agricultural profitability could have little relation to climate, and depends largely on management, trade, and consumption (Nelson et al. 2014; Manning et al. 2017; Maas et al. 2016). In part, these mixed expectations for future agricultural production are related to heterogeneity across farm types, weather, irrigation, and adaptive capacity. As such, agricultural producers' (or farmers') perceptions of current and future climate and weather conditions will be a key factor in how agriculture adapts to changes in temperature and precipitation (Arbuckle et al. 2013a). To effectively target and promote adaptation to climate change, practitioners (e.g., extension agents) and researchers require a better understanding of perceptions and experiences of climate change in the agricultural industry, as well as factors leading to adaptation. Thus, this paper answers the question: DO long-term, gradual shifts in experienced weather regimes affect farmers' perceptions of climate, weather, and on-farm adaptation needs? Or are these quantifiable changes in weather occurring too gradually to influence farmer attitudes?

While some agricultural producers have begun to respond to changes in temperature and precipitation, others do not view climate change as a serious concern. For clarity, we define agricultural adaptation to climate change as any change in practice or technology that reduces the risks from climate variability and change, increases the resilience of systems to potential disruptions, or supports producers in taking advantage of future conditions. Examples of agricultural adaptation include the increased planting of drought tolerant varieties—22% of corn planted in 2016 was a drought tolerant variety (McFadden et al. 2018)—as well as changes in crop choice, irrigation decisions, and season extension strategies (Yorgey et al. 2017). While attitudes towards climate change impacts farmers' adaptation and mitigation strategies (Arbuckle et al. 2013a; Chatrchyan et al. 2017), little is known about how actual changes in local weather impact these attitudes, although it has been an area of considerable study and mixed results. A brief summary of this literature is presented below.

Much of the literature investigating the relationship between weather and farmers' opinions uses survey methods for both experienced weather and climate change beliefs (Mertz et al. 2009; Taylor et al. 2014). Insofar, as survey responses are linked to an underlying belief system, individuals with stronger climate change beliefs—anthropogenic or otherwise—are more likely to acknowledge changes in specific weather patterns (Taylor et al. 2014; Hamilton and Stampone 2013). As such, causal interpretations of studies using self-reporting for both beliefs and experienced weather are limited, where results suffer from endogeneity concerns at best, and are tautological at worst. Simply put, people who strongly believe in climate change are more likely to report a change in weather patterns (regardless of actual weather), such that a correlative relationship between reported weather and climate beliefs provides little evidence that weather causes changes in attitudes. Indeed, Weber and Sonka (1994) show that prior strong beliefs for (or against) climate change lead to biased predictions about the future and memories of past events, suggesting that self-reported weather is likely inaccurate and more

[1] Harmful growing degree days are periods where maximum temperatures exceed a crop's ability to transpire (around 30 °C), damaging the plant and reducing yields for the farmer (Schlenker and Roberts 2009).

representative of a study participant's beliefs than actual weather events. Egan and Mullin highlight this concern in their work, electing to use "scientific authorities rather than self-reports" on weather (2012, pp. 1).

Furthermore, while some studies have investigated the relationship between experience and perceptions of climate change, much of this research has investigated general populations and acute weather events (droughts, floods, etc.) (Whitmarsh 2008; Carlton et al. 2016). Few studies have investigated the effect gradual changes in weather distributions have on perceptions and intent to adopt mitigation strategies, as Weber suggests, "Climate change, as a slow and gradual modification of average climate conditions, is a difficult phenomenon to detect and track accurately based on personal experience" (Weber 2010, pp. 1). Weber's assertion suggests that adaptation strategies may be inadequate, since weather changes may go unnoticed. The Palouse region of the iPNW (described in Section 3.1) provides the variation necessary to test Weber's assertion, since some farmers have experienced significant, but gradual, changes in temperature and precipitation regimes over the past 40 years, while other farmers have experienced no significant changes in weather over the same period.

As such, this paper makes a significant contribution to previous work linking actual weather and farmer perceptions and intentions by: (1) limiting endogeneity concerns using observed, long-term weather data rather than self-reporting, and (2) by investigating how gradual changes are perceived or experienced by individuals who presumably are in-tune with such changes (i.e., dryland farmers). We investigate the relationships between wheat producers' perceptions of weather, climate, and the need for adaptation, and long-term changes in temperature and precipitation regimes in the iPNW. We use responses to paired mail surveys of farmers ($N = 817$), sent in 2012–2013 and 2015–2016. In those surveys, we asked respondents if they: (1) believed global temperatures were rising, (2) perceived changes in weather over their lifetimes, and (3) intended to implement climate change adaptations on their farm operations. We compare these responses with actual local weather trends (temperature and precipitation) for each respondent's location.

The paper is composed of four sections. Section 2 contextualizes our research in the broader literature, Section 3 describes the study area and outlines our methodology, Section 4 reports our statistical results, and Section 5 concludes with a discussion on the implications of this work.

2 Literature review

2.1 Perception of changes in climate and weather based on personal experience

Belief in, or concern, over climate change is a critical predictor of support for, and adoption of, adaptations among the general public (Semenza et al. 2008; Spence et al. 2011), and among farmers in particular (Arbuckle et al. 2013b).[2]According to Ajzen and Fishbein (1977, 2005), beliefs are a precursor to attitudes, which can ultimately lead to behavioral changes. As such, climate attitudes may be strong predictors of behaviors or acceptance of ideas, yet drawing causal links between long-term weather experiences and climate change concerns can be difficult.

[2] Studies suggest that belief in anthropogenic climate change has implications for an individual's subsequent support of mitigation and adaption actions (Arbuckle et al. 2013b; Hyland et al. 2015; Chatrchyan et al. 2017), although climate change attitudes provide weak evidence in support of actually implemented climate-related changes in agricultural production (Schattman et al. 2018a).

Climate change concerns have been attributed to numerous ideological (e.g., political affiliation) and experiential (e.g., recent flooding) factors. For instance, individuals with pro-environmental attitudes were more likely to identify climate change as a salient risk that requires adaptation (Whitmarsh 2008; Whitmarsh and O'Neill 2010). An individual's level of concern can also vary by problem scale; problems often seem more urgent when they are perceived as local (Morton et al. 2011; Spence et al. 2012). Group norms and ideology, aligned with political party affiliation, have been shown to influence an individual's belief in anthropogenic climate change, particularly in the USA (Running et al. 2017). In a comprehensive review, Weber (2010) identified factors that map to individuals' perceptions of climate change, which include group membership, risk preferences, cognitive processes, trust in the messenger, and the emotionality of the message.

While research shows that certain individual and group characteristics have a strong correlation to climate change concerns (Hamilton and Stampone 2013; McCright et al. 2016), research examining the likelihood that individuals acknowledge climate and weather shifts because of experience which has been largely inconclusive. Spence et al. (2011) found that individuals who experienced flooding expressed greater concern about climate change impacts and felt greater agency in mitigation and adaptation. On the other hand, Whitmarsh (2008) found that individuals who experienced floods or increased air pollution had similar perceptions of climate change to other participants in the survey who did not experience these events.

Results are similarly mixed in agriculture, although most research has asked agricultural actors about their views on climate change without explicitly connecting views to experiences. Notable exceptions include Arbuckle et al. (2013a, 2013b) and Niles et al. (2015, 2016). While these papers examine a similar phenomenon, concerns over reverse causality (endogeneity) limit the conclusions that can be drawn. Measuring a more discrete stressor, Carlton et al. (2016) found that the US drought of 2012 produced no significant difference in climate change attitudes or adaptation attitudes among agricultural advisors (crop advisors, NRCS agents, fertilizer dealers, etc.), although risk perceptions related to drought did increase.

2.2 Intent to adapt to climate change

While some adaptation actions may occur unintentionally, with or without acknowledgment of a problem or an explicit planning process, knowledge of climate change and trust in scientific information has been linked to the adoption of mitigation and adaptation strategies (Grothmann and Patt 2005; Anhalt-Depies et al. 2016; Roesch-McNally et al. 2017). Effective adaptation is often described as an intentional, planned process that requires an understanding of climate change impacts and vulnerabilities, and the adoption of strategies aimed at responding to those impacts while reducing vulnerability (Stein et al. 2013). In their heuristic of adaptation behavior, Moser and Ekstrom (2010) propose that adaptation planning requires understanding the need for a response. If gradual changes in weather are largely imperceptible to farmers, it is unlikely that they will be able to acknowledge this need. In farmer adaptation research, there has been some evidence that increased understanding of the causes of climate change is associated with greater intentions or action taken to adapt (Arbuckle et al. 2013a; Niles and Mueller 2016; Schattman et al. 2018b). However, there is little known about how experienced, long-term local impacts of climate change affect intention to act among farmers.

3 Data and methods

3.1 Study area

Production of dryland field crops across the iPNW region is relatively homogeneous in types of production practices implemented, but there are significant temperature and precipitation gradients across the landscape (Schillinger et al. 2015). Oregon, Washington, and Idaho are among the top ten wheat producing states (NASS 2018). Soft wheat—the primary ingredient in pastry and cake flours—is grown almost exclusively in the iPNW, where dryland cropping systems are common (Schillinger et al. 2015; Schillinger 2017). Due to temperature and precipitation gradients, crop rotations in the region generally entail winter wheat followed by summer fallow in areas with low annual precipitation. In regions with greater precipitation, farmers generally use a continuous rotation of wheat and legumes where soil water storage is less of a concern (Maaz et al. 2017; Karimi et al. 2017). While wheat is a primary crop in the region, wheat productivity is likely to decrease in the face of heat and water stress (Rosenzweig et al. 2014; Asseng et al. 2015), although this decline may be partially mitigated by increased CO_2 fertilization (McGrath and Lobell 2013). Regardless of the aggregate effects of these changes, farmers in the region will need to adapt growing strategies to optimize production decisions (e.g., timing, crop choice) under dynamic growing season conditions (Yorgey et al. 2017).

Using this study, region allows us to observe responses to changes in climate, as the region has already experienced changes in seasonal precipitation regimes and is projected to have more frequent and severe droughts during summer months in the future (Mote and Salathe 2010). Average annual temperatures in the iPNW have increased 0.7 °C over the past century with indeterminate and non-significant changes in annual precipitation (Abatzoglou et al. 2014). However, changes in recent decades have been more substantial, with significant increases in summer temperature and weak declines in spring temperature (Abatzoglou et al. 2014). Climate projections suggest a 5–10% increase in annual precipitation by the end of the twenty-first century, with much of the increase occurring in winter and spring months. Strong warming is predicted across all seasons, but most notably summer, where temperatures may rise upwards of 6 °C by 2100 under a business-as-usual scenario (Rupp et al. 2017). Baseline and changes in weather are also geographically heterogeneous, with some areas receiving an average of approximately 200 mm of precipitation annually, and others receiving over 800 mm (Yorgey et al. 2017). Some farmers in the region may have also experienced significant changes in weather patterns over time, due to both the spatially varying changes and the impact of changes in climate against the background climatic gradient of the region. Notably, farmers in the eastern Palouse region have often been unable to plant during wet springs while farmers in the western region have suffered from insufficient water supplies and extreme heat.

To measure the effect of shifting weather distributions on climate perception and adaptation, individual farmers were surveyed across the precipitation and temperature gradients of the iPNW. Using observed weather data and responses from the survey, we link respondents to the specific weather changes they experienced, which we estimate by calculating changes in mean and variance of monthly temperature and precipitation across time.

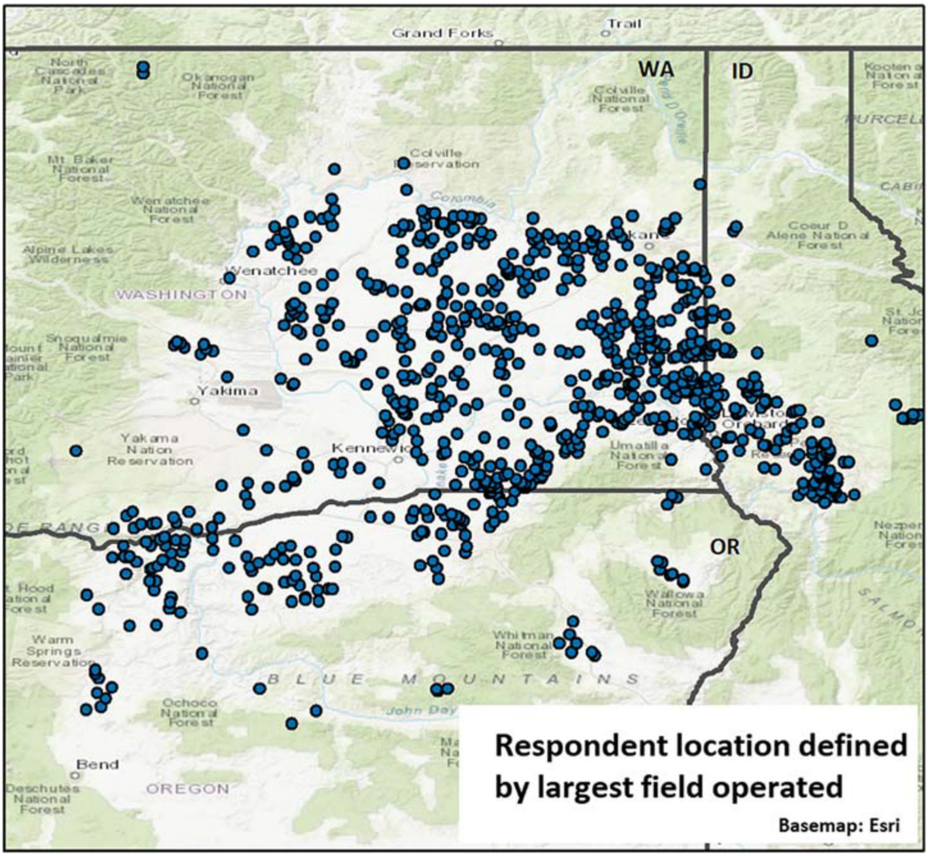

Fig. 1 Approximate location of survey respondents across the iPNW

3.2 Survey

As part of the Regional Approaches to Climate Change (REACCH) in the Pacific Northwest project, two rounds of surveys were sent to iPNW wheat producers in December–January of 2012–2013 and 2015–2016. The survey region and individuals' approximate locations are presented in Fig. 1. Both surveys were approved by the University of Idaho Institutional Review Board (Protocol #10-139) and administered by the University of Idaho Social Science Research Unit, following methods established by Dillman et al. (2014), with up to four mailings per address—two survey copies and two reminder postcards.

The first survey round was sent to all 1988 unique farm operations in the region that had 50 or more acres of wheat under production at any time in the 4 years prior to taking the survey (Seamon et al. 2016). These farm operations were provided by the National Agricultural Statistics Service (NASS), which identified an individual farm as any agricultural operation that consists of owned and/or leased land managed by a single farm owner/operator or operated under a single farm management plan.[3] A total of 900 completed and eligible surveys were collected, with an overall survey response rate of 45.2%.

In the second survey, we used a convenience sample that targeted 1284 farm operators. Unfortunately, we were unable to administer the second survey using the propriety sample frame from the NASS. However, both surveys sampled from agricultural producers across 33 wheat producing counties in Oregon, Washington, and Idaho. For survey number two, the first frame consisted of 209 respondents from round one who volunteered to be contacted again. The second frame consisted of producers who were classified as Oilseed and Grain Producers, which includes wheat farmers but is more inclusive of those who grow wheat in combination with other grain and oilseed crops. The total sample frame contained 1284 unique operations. A total of 462 operators completed the survey for an overall response rate of 46%. We define completed surveys here as containing no missing responses for any of the items used in the current analysis. Both survey instruments were similar in form and substance, although some questions were modified between 2012 and 2015 (Supplemental Material). However, we only used survey items that were identical across both rounds.

Farm addresses for respondents were geocoded by the latitude and longitude of their largest field. This spatial identifier does not include all fields in production for a given producer, but it located where farmers conducted significant portions of their business. Geocoding each respondent necessitated a significant loss to the number of completed surveys. While the number of completed surveys across both rounds totaled 1362, almost one-third of these could not be spatially identified, which prevented us from including them in the current analysis because weather observations could not be assigned.[4] The final survey sample thus includes 817 unique respondents from 33 counties across Washington, Oregon, and Idaho.

For this paper, we examined responses to three survey items regarding farmers' perceptions of climate changes in the region. Specifically, survey participants were asked to rate how much they agree with a series of statements on a scale of 1 (strongly agree) to 5 (strongly disagree). The statements of interest in this analysis are as follows:

1) Average global temperatures are increasing.
2) I have observed changes in weather patterns over my lifetime.
3) I will have to make serious changes to my farming operation to adjust to climate change.

3.3 Experienced weather

To determine if changes in precipitation and temperature distributions affect individuals' perceptions of climate change (or changes in weather), historic and recent observed weather must be calculated for each respondent. Using latitude and longitude of their largest field, each respondent is matched to gridded data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM; Daly et al. 2008), a widely used spatially and temporally complete high-resolution climate product that interpolates data from a variety of sources with

[3] Results from survey 1 were not weighted since the calculated base weights were very close to one (ranging between 0.957 and 1.09). This confirmed that NASS was successful in identifying a representative sample.

[4] Other analysis from the REACCH (Roesch-McNally 2018) project uses the entire sample, since it was not necessary to geolocate farms in much of this work. Moreover, we have statistically compared results from farms with and without locations and found no significant difference in their responses to the relevant survey questions ($p = .42$).

landscape factors. We extracted monthly average temperature and total precipitation for the years 1980–2015 from the PRISM LT71m time series product for the 800 m grid cell co-located with the reported location from each farm. This spatial matching allows us to link respondents to their experienced weather. However, little theory exists to identify the appropriate weather metrics to which individuals respond, or the appropriate method to determine changes in those metrics. The lack of bright-line theoretical motivation and methods complicates calculating climate perception as a function of changes in weather.

The first issue entails the choice of relevant weather variables and the corresponding moment conditions that are most likely to affect farm productivity and human perception. Simply put, do individuals respond to changes in mean, changes in variance, skewness, or some combination of each? Because there is little direction in determining the long-term moment conditions (e.g., mean vs. skewness) to which individuals respond—although there is considerable work on individuals' response to acute events—we include measures of variance and mean as explanatory variables in our survey regression [Eq. 6][5].

We focus on mean and variance values of precipitation and temperature for several reasons. First, both have well-established corresponding statistical methods and are more understandable than higher order moment conditions (e.g., skewness or kurtosis). Second, monthly mean values are easily and commonly presented numerically. Dispersion is included as a relevant metric in climate change perception because shifts in the probability of non-normal weather events are an important factor in agricultural decision making. Anthropogenic systems (agriculture, transportation, etc.) are sensitive to extreme weather events, and to efficiently adapt to these events, individuals must perceive their probability of occurrence. Thus, understanding perception responses to changes in weather variation is critical but has rarely been used in climate perception work.

Two additional complications arise when we attempt to measure changes in mean and variance for weather (temperature and precipitation). First was determining the appropriate level of aggregation. Egan and Mullin use the previous week's weather as an explanatory variable and find significant but short-lived changes in climate change perceptions correlated to the previous week's temperature (2012). Since their objective was to measure the effects of short-term weather conditions on belief in global warming, averaging temperature from the previous week seems reasonable. Hamilton and Stampone (2013) conduct a similar analysis using the 2-day prior to the interview as the signal for weather anomalies and conclude that short-term weather influences climate change attitudes. Given the large costs of agricultural adaptation, short-term weather events are unlikely to induce significant changes in agricultural management strategies; thus, we examine long-term deviations from historic values. However, we do test for short-term perception biases by including a variable for previous year's deviation from average, since the survey was conducted both in 2012 and 2015.

When aggregating across a long-term (35 year) time-horizon, using changes in annual mean precipitation or temperature is insufficient to capture climate impacts on agriculture and other resource-based activities (Usman and Reason 2004; Thomas et al. 2007). This is particularly true in our study, since wetter springs observed in the region (Abatzoglou et al. 2014) delay or prevent planting, while drier summers may stunt plant growth. A simple growing season average will not provide the relevant information as it relates to production decisions, particularly if opposing climate trends bisect the growing season—as they do in this case.

[5] Using kurtosis as a metric may also be relevant given the importance of tails in weather distributions, but statistical methods for these moments are less developed.

As part of this analysis, we include estimates of weather aggregated annually and illustrate how this information omits clear changes in monthly weather relevant to the farmer. Thus, the key explanatory weather variables used to predict survey responses are aggregated monthly to account for intra-seasonal variation (Lobell et al. 2006).

We use monthly average daily maximum temperature, because it is likely the most salient temperature signal for the day[6]. Daily weather is often reported with the high and low of the day; given that the low occurs while individuals are sleeping, maximum daily seems more likely to be noticed. In line with past work on precipitation, we elect to use total monthly accumulation (Mendelsohn et al. 1994; Lobell et al. 2006, 2008), and acknowledge this potential limitation since short, high-intensity events may add to total rainfall, but affect crop growth and human perceptions differently than frequent, smaller events.

Once monthly average maximum daily temperature and total precipitation are chosen as the observational unit, variance and trend coefficients are estimated for each grid cell in the PRISM dataset, such that every location has a unique set of four weather metrics (described below).

3.3.1 Changes in mean

A simple least square method is used to fit an average trend line to maximum temperature (C_{it}) and precipitation (P_{it}) data from 1980 to 2015 for each grid cell. This method provides a simple average annual change coefficient, which can be thought of as the approximate change in "means" for each cell across the iPNW written as:

$$C_{\mathrm{it}} = \alpha_{\mathrm{i}} + \delta_i Y_{\mathrm{it}} + e_{\mathrm{it}}. \tag{1}$$

$$P_{\mathrm{it}} = a_{\mathrm{i}} + \kappa_i Y_{\mathrm{it}} + v_{\mathrm{it}}. \tag{2}$$

Where i indexes individual grid cells, t indexes time, Y denotes year[7], C and P are temperature and precipitation respectively, α_i and a_i denote grid specific intercepts, and e_{it} and v_{it} encapsulate error. While annual mean trends are useful, Maaz et al. (2017) found that weather experienced from April through August has the most direct effect on cropping outcomes, and wheat yields are sensitive to soil moisture conditions in the late growing season (Feng et al. 2017). As such, we include a second model that accounts for intra-annual changes, written as:

$$C_{\mathrm{it}} = \gamma_{\mathrm{i}} + \rho_i{}'(Y_t d_{\mathrm{it}}{}') + \tau_i d'_{\mathrm{it}} + e_{\mathrm{it}}. \tag{3}$$

$$P_{\mathrm{it}} = g_i + \delta_i{}'(Y_t d_{\mathrm{it}}{}') + \tau_i d'_{\mathrm{it}} + \mu_{\mathrm{it}}. \tag{4}$$

Where d_{it} represents a vector of monthly dummy variables, g_i and γ_i are intercepts unique to each grid cell, and $Y_t d_{\mathrm{it}}{}'$ is an interaction between monthly dummies and year. This method identifies annual trends for each month ($\delta_{\mathrm{ji}} - \tau_{\mathrm{ji}}$ for each $j \in (1, 2, \ldots 12)$)[8]. To use these estimates as explanatory elements of survey responses, new variables are created from the results of estimating Eqs. 3 and 4, $\Delta P = \sum_{i=4}^{8} |\delta_{\mathrm{ji}}|$ and $\Delta T = \sum_{i=4}^{8} |\delta_{\mathrm{ji}}|$ respectively. The absolute values of coefficients are summed to capture a "total change" in weather across the growing season.

[6] Note that the results using the average daily temperature (used by Egan and Mullin 2012) are nearly identical to those using maximum temperature.

[7] Year is a countable number from 0 (1981) to 35 (2015).

[8] This is a combined model but provides equivalent point estimates as 12 individual models for each month.

Ultimately, four mean estimates for weather change are calculated: a simple linear annual trend (δ_i and κ_i), and two less interpretable, but potentially more relevant derived metrics (ΔT and ΔP), for changes in monthly temperature and precipitation during the growing season. Additionally, to adjust for the possible effects of recent weather fluctuations on survey responses, deviations from the sample mean were calculated (ϑ_i^T and ϑ_i^P) for the growing season immediately preceding the surveys in 2012 and 2015 since these years experienced different precipitation and temperatures.

3.3.2 Changes in variance

To assign individuals with an indicator for changes in weather variation, two bins were created using data from 1981 to 1996 and 2000 to the most recent survey year (2012 for the initial survey and 2015 for the second-round survey). We transform the precipitation distribution by using the natural logarithm of precipitation such that the transformed distribution is Gaussian (e.g., Berg and Chase 1992; Yue and Hashino 2007)[9]. Variation in the first bin was compared with variation in the second bin for each grid cell, where each cell was assigned an F score to indicate the presence and size of changes in variation from the early period to the later period. F scores are calculated as the ratio of standard deviations indexed by grid (s_i) of each period for both temperature and precipitation (superscript T and P respectively):

$$f_i^{T,P} = \frac{s^2_{i,1981-1996}}{s^2_{i,2000-[\text{survey year}]}}$$

Using trend regression coefficients (δ_i, κ_i), derived monthly changes (ΔP, ΔT), F score ($f_i^{T,P}$), estimates for changes in temperature and precipitation, and means and variance for each grid cell were calculated.

3.4 Comparing experience with perception

Farmers are matched to PRISM cells based on the location of their largest field. The change estimates in temperature and precipitation are then used as explanatory variables in a second stage of regression. Responses from survey questions were included as the dependent variables and a suite of weather metrics were included as explanatory variables. Other relevant control variables were included based on past work and expert knowledge (Weber 2010; Takahashi et al. 2016). Control variables include continuous variables for respondent age and total years farming, as well as two binary (yes or no) variables for possession of a bachelor's degree and if the farm operator plans to bequeath the farm to the subsequent generation. Thus, we estimate the relationship these factors have with survey responses as:

$$y_i = \beta_0 + \delta_i \beta_1 + \alpha_i \beta_2 + \epsilon_i. \tag{6}$$

where y_i is the survey response of interest, δ_i represents a vector of weather variables including most recent growing season[10], β represents vectors of coefficients to be estimated, and ϵ_i denotes an error term. Equation 6 was estimated for each survey question, with four

[9] This transformation was necessary to fulfill the normality assumption.

[10] Four permutations of these variables are presented in the "Results" section, but results were qualitatively similar in coefficient sign and significance across most specifications.

permutations of the weather change variables described in the preceding section. Thus, twelve separate regressions are reported.

4 Results

Results from this study are presented in three parts: the results of the survey, the results from Eqs. 1, 2, 3, and 4 that measure weather change for each PRISM cell, and results from the final regressions linking experienced weather to perceptions of climate change.

4.1 Survey respondents

Results from the survey highlight key features of farmers in the area. Roughly, half of farm operators in the region have at least a bachelor's degree. On average, farmers in this region are 57-year-old and have been actively farming for 29 years Table 1.

Responses to survey questions about views and experiences of climate change were mixed. Farmer respondents, on average:

1) neither agreed nor disagreed that global temperatures were increasing,
2) agreed that they had observed weather changes in their lifetime, and
3) slightly disagreed that they would make serious changes to their operation in response to climate change.

A total of 35.4% of respondents strongly agreed that weather had changed throughout their lifetime, but only 8.4% acknowledged that global temperatures were rising, and only 2.2% strongly agreed that they would make serious changes to their farming operation to adapt to climate change

4.2 Experienced weather

Results from our weather estimates are in line with Abatzoglou et al. (2014) and suggest significant variation in both the magnitude and rates of change for temperature and precipitation in the iPNW. The distributions of temperature and precipitation trend estimates are presented in Fig. 2 (left column). On average, annual temperature increased since 1980, with

Table 1 Survey summary statistics

Demographic information					
$N = 817$		Mean	S.D.	Min	Max
Bachelor's degree		0.53	.50	1	8
Age		57	11.1	22	89
Years farming		29	12.3	1	70
Responses to survey					
	1	2	3	4	5
Average global temperatures are increasing	8.4%	32.5%	37.7%	13.2.7%	8.4%
I have observed changes in weather patterns over my lifetime	35.4%	45.3%	13.3%	5.7%	.4%
Serious changes to my farming operation to adjust to climate change	2.2%	21.4%	36.8%	20.1%	18.9%

In the Likert scale, 1 denotes strong agreement and 5 denotes strong disagreement

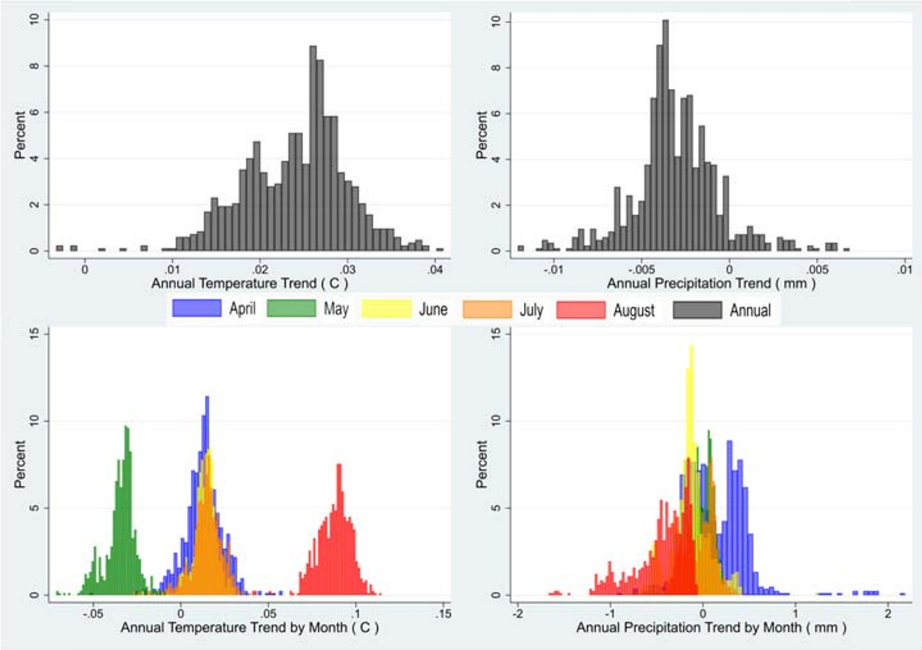

Fig. 2 Distribution of estimated trend coefficients for temperature and precipitation

annual trend estimates heavily centered between 0.1 and 0.4 °C per decade. While most cells had positive trends in temperature, there was significant variation across cells, such that weather changes varied by farm location. Average annual trends in precipitation decrease slightly (−1 mm), and most estimates were centered between − 3 and 0 mm.

4.3 Comparing experience with perception

Table 2 presents the results from four permutations of Eq. 6 for each survey response. Regardless of model specification and the explanatory weather variables included (ΔT, δ, ΔP, κ, f^T, f^P), long-term weather and temperature trends were mainly insignificant. The corresponding p values for many of these coefficient estimates were greater than 0.5, suggesting no significant relationship between experienced long-term weather trends and perceptions of climate or weather. Conditions of the most recent growing season are equally insignificant. A simple correlation matrix shows similar results (Supplemental Material), suggesting that stated responses have no linear relationship and very low correlation with long-term weather changes across the region (the correlation coefficient is <0.05 in most instances). There is weak evidence that changes in precipitation across the growing season may influence perceptions of weather (Table 2, column 11), since two of the four models pick up some level of significance, but significance is highly dependent on model specification.

Table 2 Survey responses as a function of experienced weather

Table 2 Survey responses as a function of experienced weather

	Make serious changes to my farming operation to adjust to climate change				Average global temperatures are increasing				Observed changes in weather patterns over my lifetime			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔT or δ	0.831	0.817	0.539	− 3.641	1.400	1.050	− 0.396	− 5.367	0.612	0.363	0.878	4.746
	(1.815)	(1.781)	(1.740)	(5.362)	(1.755)	(1.720)	(1.639)	(5.173)	(1.444)	(1.417)	(1.384)	(4.279)
ΔP or κ	− 0.038	− 0.033	− 0.046	− 18.620	− 0.038	− 0.016	− 0.055	− 18.807	− 0.090*	− 0.072	− 0.097**	− 1.360
	(0.061)	(0.058)	(0.060)	(14.847)	(0.059)	(0.056)	(0.068)	(14.209)	(0.049)	(0.046)	(0.048)	(11.796)
f^T	− 2.523	− 2.351			− 3.609	− 4.664*			− 0.529	− 1.236		
	(2.718)	(2.414)			(2.614)	(2.324)			(2.165)	(1.924)		
f^P	− 0.026	0.095			0.084	0.176			−0.412	−0.289		
	(0.515)	(0.506)			(0.494)	(0.485)			(0.411)	(0.404)		
ϑ_i^T	− 0.116		− 0.114	− 0.095	− 0.066		− 0.066	− 0.052	− 0.100		− 0.088	− 0.063
	(0.087)		(0.085)	(0.087)	(0.084)		(0.082)	(0.084)	(0.069)		(0.068)	(0.069)
ϑ_i^P	− 0.064		− 0.101	− 0.063	− 0.120		− 0.176*	− 0.130	− 0.116		− 0.111	− 0.078
	(0.104)		(0.094)	(0.088)	(0.100)		(0.091)	(0.085)	(0.082)		(0.075)	(0.070)
College (c)	− 0.026	− 0.022	− 0.018	− 0.013	− 0.235***	− 0.234***	− 0.222***	− 0.217***	0.050	0.049	0.049	0.053
	(0.076)	(0.076)	(0.076)	(0.076)	(0.074)	(0.073)	(0.073)	(0.073)	(0.061)	(0.061)	(0.060)	(0.061)
Family (q)	0.039	0.042	0.040	0.039	0.127*	0.123*	0.129*	0.127*	− 0.007	− 0.006	− 0.007	− 0.003
	(0.077)	(0.077)	(0.077)	(0.077)	(0.074)	(0.074)	(0.074)	(0.074)	(0.061)	(0.061)	(0.061)	(0.061)
Age (a)	− 0.004	− 0.004	− 0.004	− 0.004	−0.008**	− 0.007**	− 0.007**	− 0.007**	− 0.004	− 0.004	− 0.004	− 0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	6.342**	5.941**	3.597***	3.589***	7.097**	8.091***	3.313***	3.383***	3.239	3.796*	2.188***	2.109***
	(3.047)	(2.737)	(0.352)	(0.241)	(2.928)	(2.631)	(0.340)	(0.231)	(2.426)	(2.182)	(0.281)	(0.192)
$N = 817$												
adj. R^2	0.006	0.003	0.005	0.006	0.026	0.024	0.023	0.026	0.012	0.008	0.010	0.007

Standard errors in parentheses

******$p < 0.01$, $p < 0.05$, $p < 0.1$

The fit of each model is poor, which suggests either highly stochastic data-generating processes, or potentially significant–omitted explanatory variables. The first point is a common criticism of quantitative social science, namely that social phenomena are highly irregular and idiosyncratic (Hausman 2018). The second point is of concern, since it can lead to omitted variable bias[11]. For example, political leaning has a well-documented relationship to climate change perceptions, though there are endogeneity concerns with such results (Weber 2010; Kahan et al. 2012). While omitted variable bias is always possible, the nature of this analysis alleviates some concerns that it would produce inconsistent estimates. For omitted variables to affect point estimates of our weather metrics, the omitted variable must be correlated with the explanatory variables specified in Eq. 6 (Cameron and Trivedi 2005). Since weather is largely exogenous to individual characteristics, it is unlikely that unobserved factors of the individual affected coefficient estimates. Furthermore, the estimated asymptotic variance of the coefficient can still be estimated, although the measure of dispersion includes a bias term (See Cameron and Trivedi 2005 pp. 94). Thus, hypothesis testing around the coefficient is still possible. Regardless of formal hypothesis testing, our results taken as a whole suggest a very weak relationship (if any) between acknowledgment of global temperature increases and experienced weather, or between perceived changes in weather patterns and experienced weather.

While we included several control variables based on previous work in the field, college education was the only highly significant indicator of perceived climatic change. While the result was significant, it should not be interpreted as causal given endogeneity concerns (e.g., scientifically minded people may be more likely to go to college such that it is difficult to disentangle the true effect of college attendance from individual characteristics that cause people to attend college in the first place). Age was significant in respondents' perception that temperatures were warming. This finding weakly suggests that individuals with longer frames of reference may be more able to identify change because the magnitude of that change grows larger over time. Oddly, even though age was associated with an acknowledgment of warming global temperature, it did not appear to matter in an individual's intention to adapt to future climate or acknowledge changes in weather across one's lifetime.

A low statistical significance was seen in family farm planning ($p < 0.1$), suggesting that individuals passing their farm to subsequent generations were less likely to believe that global temperatures were rising. To the extent that this result is true, the phenomenon may be a result of well-documented optimism bias or other social factors (Woods et al. 2017).

5 Discussion

This analysis suggests that long-term deviations from historic weather conditions (measured as precipitation and temperature distributions) have no effect on farmers' perceptions of climate change, observation of shifting weather patterns, or intention to adapt to climate change. Our contribution is unique because we limited endogeneity concerns about past studies by using observed, long-term weather data, and we focused on a specific sub-group who must be in-tune with weather changes for their livelihoods: dryland wheat farmers.

We find little evidence that gradual changes in weather affect individuals' climate and weather perceptions or their plans to adapt. Partially, this null result may arise because past

[11] A formal (Ramsey) test was used to evaluate omitted variables and did not find evidence of omitted variables.

agricultural decisions such as crop choice and production methods are well-adapted to mean conditions in the area, and observed deviations from those conditions are insufficient to necessitate new investment. Perhaps, thresholds exist that will spur perception changes and adaptation, but given our other results, it is possible that few farmers plan to adapt, because their perceptions of shifting weather and climate regimes are not meaningfully affected by their actual experience. An inability to acknowledge these slow changes in “normal” growing season conditions suggests that farmers may not efficiently adapt to changes in growing degree days and the timing of precipitation, which may limit productivity and profitability in the region.

This study has four significant limitations. First, testing for perception differences caused by the most recent growing season conditions necessitated combining two surveys (conducted after different seasons) with disjointed sample frames. While this aggregation is a limitation, we found no significant differences across survey responses. Second, we were unable to tease out spatial weather patterns from spatially correlated perceptions that may be attributed to social norms and networks—although there is little reason to think such confounding issues exist across our study region. Third, it is difficult to quantify “weather change” such that the appropriate aggregation (spatial and temporal) choices and metrics (e.g., mean, standard deviation, frequency of extreme events) remain unclear. Current literature provides little direction as to which long-term metrics are most perceptible at human scales. Our model also lacks explicit temperature-precipitation interactions, which some have identified as necessary in predicting future agricultural productivity (Lobell and Burke 2008), but little work exists on how these interactions are perceived by producers. Lastly, our results are only applicable to long-term gradual changes. It is possible that an increase in extreme events or sufficiently large changes in climate may induce adaptation, but defining extreme events or identifying these thresholds is beyond the scope of this paper.

Despite these limitations, this paper adds to the literature on understanding climate change, weather, and perception, and supports the work by Weber (2010), as well as Haden et al. (2012) and Spence et al. (2011, 2012). Weber suggests that climate change happens on a scale that is incongruous with human ability to detect and track accurately through personal experience (2010). He suggests behavioral approaches that solidify future events and move them closer in time and space hold promise as interventions. Haden and Spence posit similar solutions and suggest that some of the incongruity between temporal and spatial scales can be ameliorated with decreased psychological distance[12]. Regardless of the tonic, our results suggest that slow changes in “normal” growing seasons may not be enough of a signal to drive behavioral change.

Understanding human psychology and the stimuli that drive changes in perception is a necessary component of building policy support for climate change or other issues. The long time horizon and gradual nature of climate change can impede experiential feedback at a scale useful in decision-making. Even extreme events may be insufficient to shift peoples’ views on climate change, since any individual event is not easily attributed to climate (Zanocco et al. 2018). However, there are some promising new methods of aligning temporal and spatial scales for improving human recognition of global changes. For example, the use of augmented

[12] Psychological distance is the cognitive separation between the self and other entities (persons, places, times, etc.) Construal level theory outlines four key dimensions of such psychological distance: geographical distance; temporal distance; distance between the perceiver and a social target; and uncertainty (Spence et al. 2011). Climate change is distant on all of these dimensions.

reality has been gaining support (see https://climatevr.yale.edu/) because it provides instant feedback on decisions that may not be naturally experienced for decades. Our research suggests the temporal scale of climate change may be too slow to alter perception or behaviors and suggests a need for new types of communication and outreach that align human-scale and global-scale experiences.

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