SUPPLEMENTARY MATERIALS

S1. Evluating the difference in drought frequency during 2004-2014

The monthly drought intensity scores at each survey location *i* are assigned as: severe (or higher intensity) drought, $d_{i,m}^{y}$ = 3; moderate drought, $d_{i,m}^{y}$ = 2; abnormally dry, $d_{i,m}^{y}$ =1; and no drought, $d_{i,m}^{y}$ = 0 where m = {April, May, June, July, August} and $y = \{2004, 2014\}$. We define annual drought intensity score for 2004 as $d_i^{04} = \sum_m d_{i,m}^{04}$ and that for 2014 as $d_i^{14} = \sum_m d_{i,m}^{14}$, i.e., the sum of drought intensity scores during growing-season months of 2004 and 2014, respectively. Therefore, $\Delta d_i^{04-14} = d_i^{14} - d_i^{04}$ provide the difference in drought frequency during 2004-2014. Finally, $\Delta d_i^{04-14} > 0$ signifies that drought intensity at location *i* was recorded to be higher in 2014 relative to 2004; $\Delta d_i^{04-14} = 0$ signifies that drought intensity was the same in both these years; and $\Delta d_i^{04-14} > 0$ signifies that drought intensity was lower in 2014 relative to 2004.

S2. Construction of Growing Degree Days (*GD*s) for each survey location

We aggregate daily maximum and minimum temperature levels at each survey location, denoted as $t_{i,d,m,y}^{\max}$ and $t_{i,d,m,y}^{\min}$ (in ^{o}C), respectively, into threshold-based seasonal heat exposure variables called growing degree-days or *GD*s. Here, subscript *i* denotes survey locations whereas subscripts (*d*, *m*, *y*) denote day *d* of month *m* = {April, May, June, July, August} in year $y = \{2004, 2014\}$. Specifically, we evaluate *GD*s for location *i* in month *m* of year *y* as specified below

$$GD_{i,m,y} = \sum_{d \in m,y} \left\{ 0.5 \left[\min\left(\max[t_{i,d,m,y}^{\max}, t^{l}], t^{h} \right) + \min\left(\max[t_{i,d,m,y}^{\min}, t^{l}], t^{h} \right) \right] - t^{l} \right\}. \tag{S1}$$

Specifically, $GD_{i,m,y}$ is heat accumulated within temperatures t^{l} and t^{h} with $t^{h} > t^{l}$. We set t^{l} = 6^{o}C and t^{h} = 26 ^{o}C based on the results reported in Arora et al. (2020). Finally, we calculate the following variables for each survey location *i*: $GD_{i}^{2004} = \sum_{m} GD_{i,m,y=2004}$; $GD_{i}^{2014} = \sum_{m} GD_{i,m,2014}$; and $\Delta GD_{i}^{04-14} = GD_{i}^{2014} - GD_{i}^{2004}$. In addition, we account for inter-seasonal impacts through change in accumulation of *GD*s during first-half of the growing season, i.e., April-June months; defined as $\Delta GD_{i,April-June}^{04-14} = GD_{i,April-June}^{2014} - GD_{i,April-June}^{2004}$ where $GD_{i,April-June}^{2014} = \sum_{\substack{m= \\ \{April, \\ May, June\}}} GD_{i,m,y=2014}$ and $GD_{i,April-June}^{2004} = \sum_{m=\{April,May,June\}} GD_{i,m,y=2004}$.

S3. Chi-squared test statistic based on contingency table analysis

Here we describe a χ^2 test of independence with an example. Specifically, we explain how to define the χ^2 independence test between $\Delta l_i^{CRP(\text{out})}$ and farmers' beliefs about precipitation change during 2004-2014. Table 4a presents a contingency table between $\Delta l_i^{CRP(\text{out})}$ and b_i^L (i.e., where precipitation levels decreased during 2004-2014); and Table 4b presents a contingency table between $\Delta l_i^{CRP(\text{out})}$ and b_i^H (i.e., where precipitation increased during 2004-2014). This exercise will yield a step-by-step construction of the χ^2 test-statistic for a 2x2 contingency table, which will then extend itself trivially to 3x2 and 5x2 contingency tables.

In Table 4a that cross-classifies $\Delta l_i^{CRP(\text{out})}$ and b_i^L, denote $\pi_{11} = \Pr(\Delta l_i^{CRP(\text{out})} = 1, b_i^L = L \to H)$; $\pi_{12} = \Pr(\Delta l_i^{CRP(\text{out})} = 1, b_i^L = L \to L)$; $\pi_{21} = \Pr(\Delta l_i^{CRP(\text{out})} = 2, b_i^L = L \to H)$; and $\pi_{22} = \Pr(\Delta l_i^{CRP(\text{out})} = 2, b_i^L = L \to L)$. Corresponding to the probability vector $\pi = (\pi_{11}, \pi_{12}, \pi_{21}, \pi_{22})$, which is the joint distribution of $\Delta l_i^{CRP(\text{out})}$ and b_i^L, denote $n_{l,b}$ as the cell-wise frequency such that (l,b) represents the $(row, column)$ pairs and $N = \sum_{l=1}^{2}\sum_{b=1}^{2} n_{l,b}$ denotes the total sample size. Further, we define $n_{1*} = n_{11} + n_{12}$ as the frequency of CRP land conversions; $n_{2*} = n_{21} + n_{22}$ as the frequency of CRP land *non*-conversions; $n_{*1} = n_{11} + n_{21}$ as the frequency of weather change misperceptions; and $n_{*2} = n_{12} + n_{22}$ is the frequency of consistent weather beliefs in our sample.

Random variables $\Delta l_i^{CRP(\text{out})}$ and b_i^L are said to be independent if $\Pr(\Delta l_i^{CRP(\text{out})}, b_i^L) = \Pr(\Delta l_i^{CRP(\text{out})}) \times \Pr(b_i^L)$. Hence, the null hypothesis is written as $H_0 : \pi_{11} = \pi_{1*}\pi_{*1}$ and $\pi_{12} = \pi_{1*}\pi_{*2}$ and $\pi_{21} = \pi_{2*}\pi_{*1}$ and $\pi_{22} = \pi_{2*}\pi_{*2}$ where $\pi_{1*} = \Pr(\Delta l_i^{CRP(\text{out})} = 1)$, $\pi_{2*} = \Pr(\Delta l_i^{CRP(\text{out})} = 2)$, $\pi_{*1} = \Pr(b_i^L = L \to H)$ and $\pi_{*2} = \Pr(b_i^L = L \to L)$. Under the null hypothesis we write cell-wise *expected* frequencies: $\hat{n}_{11} = (n_{1*}n_{*1})/N$; $\hat{n}_{12} = (n_{1*}n_{*2})/N$; $\hat{n}_{21} = (n_{2*}n_{*1})/N$; and $\hat{n}_{22} = (n_{2*}n_{*2})/N$ (see values placed in parentheses in each cell of Table 3a). The Chi-squared test statistic for independence between $\Delta l_i^{CRP(\mathrm{out})}$ and b_i^L is a function of the sum of squared differences between these observed ($n_{l,b}$) and expected ($\hat{n}_{l,b}$) cell-frequencies. That is,

$$X \triangleq \sum_l \sum_b \frac{(n_{lb} - \hat{n}_{lb})^2}{\hat{n}_{lb}} \sim \chi_d^2 . \qquad \text{(S2)}$$

Here, X represents the χ_d^2 test-statistic with *d* degrees of freedom (Kateri 2014, ch. 2). The critical value for 2x2 contingency table: $\chi^2_{1*,0.05}$ =3.84 at 95% confidence level; for 3x2 contingency table: $\chi^2_{2*,0.05}$=5.99 at 95% confidence level; and for 5x2 contingency table: $\chi^2_{4*,0.05}$ =9.49 at 95% confidence level. If $X > \chi^2_{d*,\alpha}$ then we will reject the null hypothesis that farmland decisions (e.g., $\Delta l_i^{CRP(\mathrm{out})}$) and weather beliefs (e.g., b_i^L) are independent. If $X \le \chi^2_{d*,\alpha}$ then we will fail to reject the null hypothesis. Tables 4a-b and 5 in the main text provide more details.

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S4. Spatial characterization of bias farmers' weather change beliefs

In order to further shed lights on biases in farmers' perceptions we examine the spatial patterns of these perceptions. Table S2-S4 provides evidence of a statistically significant north-south trend in farmer perceptions about precipitation and drought frequency during 2004-2014. That is moving one unit north in latitude led to an average increase in propensity of 'higher' precipitation and 'less frequent' drought reports.

We further evaluate the spatial patterns of weather perceptions in Figures 3a-c. Notice that in some localities weather perceptions occur as *spatial clusters*. For example, just north of Jamestown, ND, many farmers misperceived precipitation to have increased over the past decade whereas to its east many farmers exhibited consistent beliefs that weather conditions had become drier in their locality. Past weather beliefs also exhibit *spatial heterogeneity*. For example, closer to the Missouri River, farmer beliefs were (in general) consistent with data that droughts became less frequent. However, as one moves farther to the east of river many farmer clusters misperceived droughts to have become more frequent. Notice also that southwest of Mitchel, SD local farmers misperceived the drought conditions to have worsened, while northeast of Mitchel, where data records show that droughts had become more frequent, farmer beliefs were divided, i.e., some believed drought conditions had worsened and others believed that droughts became less frequent. These complex spatial features of weather change perceptions make it challenging to identify the relevant drivers and provide usable inputs for policy design.

S5. Summarizing weather perceptions in the context of regression controls (see Table 1)

We contextualize weather change perceptions, $\Delta\tilde{w}_i$, in terms of data-based evidence on decadal weather changes, land us changes, farmers' socio-economic information and farm-level soil quality. Please refer to Table 1 for data summary information. Dakotas' farmers on average percieved weather conditions in 2014 to be similar to weather conditions in 2004, however, we also observe considerable variation in weather beliefs across farmers. For example, while on average growers believed precipitation levels remained about the same during 2004-2014, many also believed that 2014 was either drier or wetter relative to the 2004 conditions. The data-based evidence also suggests that decadal changes in temparature (Δt^{04-14}), precipitation (Δp^{04-14}) and drought frequency (Δd^{04-14}) exhibit considerable variations even when the average changes during 2004-2014 are small.

With regards to socio-economic inforamtion in our sample, 97% of growers in our sample were male farmers and 88% declared farming as their principal occupation. An avearge grower belonged to age group of 60-69 years, had eduacation till technical school, and had annual gross farm/ranch revenue of \$500K-\$999K. Further, heavy soils (37%) and clay (23%) soils comprised dominant soil types in our sample, followed by sandy soils (17%) and highly erodible soils (*hel*, 8%). We analyze and present results on whether these socio-economic information, e.g., education status and income, and soil quality information are associated with farmers' weather beliefs.

Table S1: Summary of survey data attributes related to land use change and technology adoption variables for farmers.

Variable	Description	N	Mean	Median	SD
Δl^{crop}	=**1** if fewer cropland acres (by over 10%); =**2** if no or minor change; =**3** if more cropland acres (by over 10%) during 2004-2014.	990	2.09	2.00	0.71
Δl^{grass}	=**1** if fewer pasture/rangeland acres (by over 10%); =**2** if no or minor change; =**3** if more pasture/rangeland acres (by over 10%) during 2004-2014.	776	2.00	2.00	0.6
Δl^{tile}	=**1** if adopted or increased use of tile drainage on cropland acres; =**2** if did not increase use of tile drainage in 2014 relative to its 2004 level.	1026	1.75	2.00	0.49
$\Delta l^{CRP(\text{out})}$	=**1** if CRP land was converted to cropland; =**2** if CRP land was not converted to cropland during 2004-2014.	1026	1.70	2.00	0.52
$\Delta l^{CRP(\text{in})}$	=**1** if farmland acres were enrolled into CRP; =**2** if farmland acres were not enrolled into CRP during 2004-2014.	1026	1.75	2.00	0.51
$\Delta l^{crop,\text{5-mi}}$	=**1** if corn/soy acres 'decreased markedly' (over 10%); =**2** if 'decreased somewhat' (5-10%); =**3** if 'about the same'; **=4** if 'increased somewhat' (5-10%); **=5** if 'increased markedly' (over 10%) during 2004-2014.	1026	4.23	4.00	0.98
$\Delta l^{\text{grass,5-mi}}$	=**1** if grassland acres 'decreased markedly' (over 10%); =**2** if 'decreased somewhat' (5-10%); =**3** if 'about the same'; **=4** if 'increased somewhat' (5-10%); **=5** if 'increased markedly' (over 10%) during 2004-2014.	1026	1.95	2.00	0.94

Notes: Missing data responses were removed in data summaries presented in this table.

Table S2: Ordered logistic regressions for farmers' perceptions about local temperature changes during 2004-2014 as a function of weather station records, soil attributes, economic information and farmer demographics.

Parameter	Model 1	Model 1A	Model 2	Model 2A	Model 3	Model 3A
α_1	-8.11 (7.60)	-7.94 (7.60)	-8.06 (7.60)	-8.03 (7.60)	-8.55 (7.63)	-9.64 (7.63)
α_2	-5.20 (7.60)	-5.02 (7.59)	-5.15 (7.59)	-5.11 (7.59)	-5.64 (7.62)	-6.72 (7.63)
Δt^{04-14}	0.03 (0.05)	0.05 (0.03)				
ΔGD^{04-14}			0.08 (0.12)	0.18^{*} (0.10)		
ΔGD^{06-14}					0.08 (0.12)	0.17^{**} (0.09)
age	-0.12 (0.08)	-0.12^{*} (0.07)	-0.12^{*} (0.07)	-0.12^{*} (0.07)	-0.11 (0.07)	-0.11 (0.08)
male	0.10 (0.17)	0.10 (0.17)	0.10 (0.17)	0.10 (0.17)	0.10 (0.17)	0.10 (0.17)
educ	-0.16 (0.09)	-0.15^{*} (0.09)	-0.16 (0.09)	-0.15^{*} (0.08)	-0.15^{*} (0.09)	-0.15^{*} (0.09)
occ	-0.18 (0.28)	-0.18 (0.28)	-0.18 (0.28)	-0.20 (0.28)	-0.18 (0.28)	-0.18 (0.28)
inc	0.02 (0.05)	0.02 (0.05)	0.02 (0.05)	0.02 (0.05)	0.01 (0.05)	0.01 (0.05)
hel	0.003 (0.005)	0.002 (0.005)	0.003 (0.005)	0.002 (0.005)	0.003 (0.005)	0.003 (0.005)
heavy	0.0001 (0.002)	-0.0002 (0.002)	-0.00003 (0.003)	0.0003 (0.003)	0.0004 (0.002)	0.00002 (0.003)
clay	0.003 (0.003)	0.003 (0.003)	0.003 (0.003)	0.003 (0.003)	0.002 (0.003)	0.003 (0.003)
sandy	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)
lat	-0.03 (0.07)	-0.02 (0.07)	-0.03 (0.07)	-0.03 (0.07)	-0.02 (0.07)	-0.01 (0.07)
lon	-0.09 (0.08)	-0.09 (0.08)	-0.09 (0.08)	-0.09 (0.08)	-0.09 (0.08)	-0.10 (0.08)
-2LogL	1,175.5	1,174.3	1,175.5	1,173.0	1,185.2	1,182.4
Ordered outcome						
$\Delta\tilde{t} = 1$	222					
$\Delta\tilde{t} = 2$	585					
$\Delta\tilde{t} = 3$	144					
N	951					

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

Notes:

1. ΔGD^{04-14} and ΔGD^{06-14} represent change in *GD*s during 2004-2014 and 2006-2014, respectively.
2. In model variants 1A, 2A and 3A, variables Δt^{04-14}, ΔGD^{04-14} and ΔGD^{06-14}, represent weather station-based records during the first-half (April-June) of each year's growing-season, i.e., $\Delta t^{04-14}_{April-June}$, $\Delta GD^{04-14}_{April-June}$ and $\Delta GD^{06-14}_{April-June}$, respectively.

Table S3: Ordered logistic regressions for farmers' perceptions about local precipitation changes during 2004-2014 as a function of weather station records, soil attributes, economic information and farmer demographics.

Parameter	Model 1	Model 1A	Model 2	Model 2A	Model 3	Model 3A
α_1	18.41^{***} (6.56)	19.30^{***} (6.56)	19.27^{***} (6.74)	24.5^{***} (7.26)	19.80^{***} (5.95)	21.33^{***} (6.02)
α_2	20.13^{***} (6.57)	20.02^{***} (6.57)	21.00^{***} (6.75)	26.25^{***} (7.28)	21.52^{***} (5.95)	23.05^{***} (6.03)
Δp^{04-14}	-0.002^{*} (0.0009)	-0.01 (0.01)				
Δp^{06-14}			-0.00002 (0.001)	-0.03^{*} (0.02)		
Δp^{11-14}					-0.0004 (0.0007)	-0.02^{*} (0.01)
age	-0.17^{***} (0.06)	-0.18^{***} (0.06)	-0.18^{***} (0.06)	-0.18^{***} (0.06)	-0.17^{***} (0.06)	-0.17^{***} (0.06)
male	0.13 (0.17)	0.14 (0.18)	0.14 (0.18)	0.16 (0.18)	0.15 (0.17)	-0.15 (0.17)
educ	-0.001 (0.08)	0.002 (0.18)	0.002 (0.08)	-0.002 (0.08)	-0.03 (0.07)	-0.04 (0.07)
occ	-0.15 (0.23)	-0.15 (0.23)	-0.09 (0.23)	-0.12 (0.23)	-0.01 (0.20)	-0.03 (0.20)
inc	-0.11^{**} (0.04)	-0.11^{**} (0.05)	-0.12^{**} (0.05)	-0.12^{**} (0.05)	-0.11^{***} (0.04)	-0.11^{***} (0.04)
hel	-0.001 (0.004)	-0.001 (0.004)	-0.002 (0.004)	-0.002 (0.004)	-0.001 (0.004)	-0.001 (0.004)
heavy	-0.004^{**} (0.002)	-0.004^{**} (0.002)	-0.004^{**} (0.002)	-0.004^{*} (0.002)	-0.004^{*} (0.002)	-0.004^{*} (0.002)
clay	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.003)	-0.003 (0.002)	-0.002 (0.002)	-0.002 (0.002)
sandy	-0.005 (0.003)	-0.004 (0.003)	-0.004 (0.003)	-0.004 (0.003)	-0.005^{*} (0.003)	-0.005^{*} (0.003)
lat	-0.30^{***} (0.06)	-0.29^{***} (0.06)	-0.28^{***} (0.06)	-0.31^{***} (0.06)	-0.26^{***} (0.05)	-0.26^{***} (0.05)
lon	0.04 (0.07)	0.06 (0.07)	-0.07 (0.07)	0.10 (0.07)	0.08 (0.06)	0.10* (0.06)
-2LogL	1684.9	1685.6	1708.7	1706.0		
Ordered outcome						
$\Delta\tilde{p} = 1$	254					
$\Delta\tilde{p} = 2$	374					
$\Delta\tilde{p} = 3$	346					
N	964					

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

Notes:

In model variants 1A, 2A and 3A, variables Δp^{04-14}, Δp^{06-14} and Δp^{11-14} represent weather station-based records of the number of days in the growing seasons with 15mm or higher precipitation during of 2004-2014, 2006-2014 and 2011-2014 periods, i.e., $\Delta p^{04-14}_{>15mm}$, $\Delta p^{06-14}_{>15mm}$ and $\Delta p^{11-14}_{>15mm}$, respectively.

Table S4: Ordered logistic regressions for farmers' perceptions about local drought frequency during 2004-2014 as a function of weather station records, soil attributes, economic information and farmer demographics.

Parameter	Model 1	Model 1A	Model 2	Model 2A
α_1	-25.72*** (6.49)	-27.17*** (6.14)	-30.24*** (7.71)	-30.42 (7.94)
α_2	-23.39*** (6.48)	-24.84*** (6.13)	-27.92*** (7.70)	-28.09 (7.92)
Δd^{04-14}	-0.04** (0.02)	-0.28*** (0.10)		
Δd^{06-14}			-0.006 (0.02)	-0.02 (0.07)
age	0.23*** (0.06)	0.24*** (0.04)	0.23*** (0.06)	0.23*** (0.06)
male	-0.03 (0.21)	-0.03 (0.21)	-0.04 (0.21)	-0.04 (0.21)
educ	-0.01 (0.07)	-0.008 (0.07)	-0.02 (0.07)	-0.02 (0.07)
occ	0.09 (0.20)	0.09 (0.21)	0.08 (0.21)	0.08 (0.21)
inc	0.11** (0.04)	0.11** (0.04)	0.11** (0.04)	0.11** (0.04)
hel	-0.001 (0.0004)	-0.002 (0.004)	-0.001 (0.004)	-0.001 (0.78)
heavy	0.005** (0.002)	0.005** (0.002)	0.005*** (0.002)	0.005*** (0.002)
clay	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)
sandy	0.003 (0.003)	0.003 (0.003)	0.003 (0.003)	0.003 (0.003)
lat	0.32*** (0.05)	0.29*** (0.06)	0.34*** (0.06)	0.33*** (0.06)
lon	-0.09 (0.07)	-0.12* (0.06)	-0.13* (0.08)	-0.13* (0.07)
-2LogL	1895.9	1893.2	1900.7	1900.7
Ordered outcome				
$\Delta\tilde{d} = 1$	293			
$\Delta\tilde{d} = 2$	465			
$\Delta\tilde{d} = 3$	199			
N	957			

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

Notes:

In model variants 1A and 2A, variables Δd^{04-14} and Δd^{06-14}, respectively, represent drought frequency in later half, specifically during August of each year, i.e., $\Delta d_{August}^{04-14}$ and $\Delta d_{August}^{06-14}$, respectively.