Supplementary Information for the study "Evidence of climate change impacts on crop comparative advantage and land use"

Methods

Yield-weather model

Weather variables included in the yield-weather model

Historical weather data from the Global Historical Climatological Network includes 306 weather stations in North Dakota and 397 stations in South Dakota. County-level weather variables, i.e., daily minimum/maximum temperature and precipitation, are constructed as averages of the values recorded at stations within each county. All counties have at least one weather station.

We aggregate daily temperatures into threshold-based seasonal heat exposure variables called growing degree-days or *GD*s, and stress degree-days or *SD*s. Mathematical representations of *GD*s and *SD*s for county *i* in month *m* of year *t* are (Xu et al. 2013):

$$\begin{aligned} &\text{a) } GD_{i,m,t} = \sum\nolimits_{d\in m,t}\left\{0.5\left[\min\left(\max[T_{i,d,t}^{\max},T^{l}],T^{h}\right)+\min\left(\max[T_{i,d,t}^{\min},T^{l}],T^{h}\right)\right]-T^{l}\right\};\\ &\text{b) } SD_{i,m,t} = \sum\nolimits_{d\in m,t}\left\{0.5\left[\max[T_{i,d,t}^{\max},T^{k}]+\max[T_{i,d,t}^{\min},T^{k}]\right]-T^{k}\right\}. \end{aligned} \qquad \text{(S1)}$$

Here $T_{i,d,t}^{\max}$ and $T_{i,d,t}^{\min}$ are, respectively, the maximum and minimum temperature (in ^{o}C) for county *i* on day *d* of month *m* and year *t*, $GD_{i,m,t}$ is heat accumulated within temperatures T^{l} and T^{h} with $T^{h} > T^{l}$, while $SD_{i,m,t}$ is heat accumulated above T^{k} with $T^{k} > T^{h}$. Note that the temperature thresholds, i.e., T^{l}, T^{h} and T^{k}, are identified for each crop separately, discussed hereafter.

Moisture availability for crop growth is incorporated as monthly *Z* values for the Dakotas' 18 climate divisions, each containing multiple counties, downloaded from the National Oceanic and Atmospheric Administration (see web-link). Area-weighted *Z* values for all counties are preferred to precipitation as this index accounts for all of evapotranspiration, soil's water storage capacity, and precipitation. Since evapotranspiration is calculated using monthly and annual average temperatures, *Z* may be correlated with *GD* and/or *SD*. We transform *Z* to represent extreme dryness (*DRYZ*) and extreme wetness (*WETZ*) using pre-defined thresholds as follows:

$$\begin{aligned} &\text{a) } DRYZ_{i,m,t} = -\min(Z_{i,m,t} + 1.99, 0); \\ &\text{b) } WETZ_{i,m,t} = \max(Z_{i,m,t} - 2.49, 0). \end{aligned} \tag{S2}$$

where $DRYZ_{i,m,t}$ and $WETZ_{i,m,t}$ are defined as a function of $Z_{i,m,t}$ such that higher *DRYZ* (*WETZ*) indicates an higher degree of dryness (wetness). By including weather stressors from eq. (S2) in our yield-weather model we are able to test whether extreme dryness (or drought) exerts the highest yield reduction among the weather stressors, as previously pointed out by Massetti and Mendelsohn (2016). An alternative moisture deficiency index, called the Palmer Drought Severity Index, also exists but *Z* is considered to be more stable in measuring short-term moisture deficiency (Karl 1986).

Min-max versus Sinusoidal interpolation of degree-days: Summary and correlation statistics

While Schlenker and Roberts (2009), D'Agostino and Schlenker (2016) and others have implemented sinusoidal interpolations, we implemented a min-max form of interpolation on daily minimum and maximum temperatures for calculating the growing degree days and stress degree days. The definitions of *GD* and *SD* under the min-max formulation was provided in eq. (S1) of the SI.

Although the sinusoidal interpolation is formulaically different from the min-max interpolation, both accumulate degrees from intermediate temperatures between the daily maximum and minimum temperature levels given the degree-day thresholds. This particular feature allows the interpolated daily temperatures to fare better in realistically calculating the degree-days relative to only using average temperatures. For example, consider a scenario where the maximum temperature is 30^{o}C and the minimum temperature is 10^{o}C and the *SD*s are accumulated for temperatures above 25^{o}C. Then if a researcher were to rely solely on average temperature (i.e., 20^{o}C) the *SD*s would be zero, however under the sinusoidal interpolation *SD*s equal 1.1 units (see Snyder 1985) and under the min-max interpolations *SD*s equal 2.5 units.

Based on the above understanding we compiled a comparative analysis that provides evidence that the outputs of min-max and sinusoidal interpolations are highly correlated. In fact, the variable *GD* seems very close across these formulations even in the absolute sense. We present the variable summaries and correlation statistics in Tables S1-S2 and the scatter plots for all four crops in Figure S1.

<u>Identifying the yield-temperature relationship for the Dakotas' major crops: Step-functions approach</u>

Following a previous study we regress crop yields on each 1-degree Celsius bin having controlled for quadratic trends and precipitation (Schlenker and Roberts 2009). The estimated step-functions, which provide an *initial guide* to the temperature thresholds that define each crop's *GD*s and *SD*s, are presented in Figures S2-S5. The crop-specific thresholds are given as: $GD \in [7^o C, 26^o C]$, $SD \geq 30^o C$ for maize; $GD \in [6^o C, 26^o C]$, $SD \geq 32^o C$ for soy; $GD \in [6^o C, 20^o C]$, $SD \geq 27^o C$ for spring wheat; and $GD \in [6^o C, 22^o C]$, $SD \geq 27^o C$ for alfalfa.

Land Capability Classes and Subclasses: Definitions and the Natural Resources Inventory's (NRI) nomenclature

County-level soil quality variables are constructed from the NRI-based Land Capability subclasses that categorize soil deficiencies, i.e., 'dry/shallow' soils, 'poor drainage/wet' soils, 'erosive' soils, and soils with 'climatic limitations.' These subclasses are appended to the commonly-used Land Capability Classes. The land capability classification assigns progressively less suitable soils into higher classes. Soils of higher land capability categories require more intense management practices to mitigate intrinsic limitations on agricultural production. Typically, class I soils can be readily cropped; class II, III & IV lands require some additional remedies before they can be cropped; and categories V-VIII are usually inappropriate for cropping. The types and extent of remedies required for class II, III & IV lands depend on the type of impediment(s). Land capability classes II-VIII are further sub-categorized by the soil's dominant impediments. We constrain our analysis to categories II-IV, covering 85-90% of the Dakotas' county-level crop acreage.

A hierarchical nomenclature is followed for assigning subclasses when multiple impediments are present (Kligebiel and Montgomery 1961, pp. 2). Erosion [*E*] takes precedence over every other kind. Next in this ordering are excess wetness [*W*] and dry/shallow soils [*S*]. Soils are assigned a climatic limitation category [*C*] only if temperature and/or moisture-deficiencies are the only impediments to cropping. This means that [*W*] might imply shallowness as well as poor drainage limitations but poor drainage is the dominant limitation. Similarly, [*E*] could imply shallowness and/or poor drainage along with erosion as impediments, where erosion is the dominant limitation. The data do not differentiate between soils with single and multiple impediments.

We utilize the [*S*] and [*W*] sub-categories in our yield models, where [*S*] is not grouped with any other soil category. In our yield models, we include soil-weather interactions. In particular, we use the percent of land in a county under [*S*], denoted by Q_i^{dry}, and interact it with *SD*, *GD*, *DRYZ* and *WETZ*. These interactions are expected to reveal whether specific soil limitations mitigate or aggravate heat/moisture impacts on yields. We hypothesize that the yield impacts of *SD* will be aggravated due to shallow soils while that of *WETZ* might be mitigated (*relative* to [*W*]). Further, the impacts of extreme wetness could be worse on soils classified as [*W*]. The resulting coefficient estimates for Q_i^{dry} and Q_i^{wet} will capture whether dry and wet soils mitigate/aggravate the impact of each weather stressor on yields *relative to* such impacts due to excluded soil types, i.e., erosive soils and soils with climatic limitations.

<u>SD categorization: Why normalize differentiated stress-degree-day categories?</u>

To differentiate yield impacts by the intensity of heat stress, we disaggregate stress degree-days into isolated or single-day events (SD^1), continuous events of two-three consecutive-days (SD^{23}) and four-or-more consecutive days (SD^{4+}) such that $SD = SD^1 + SD^{23} + SD^{4+}$.

SD^1 is constructed by multiplying the column of total *SD*s by an indicator variable that equals 1 on an isolated hot day and 0 otherwise. SD^{23} and SD^{4+} are constructed in similar fashion. Notice that heat may not accumulate proportionately within each *SD* category. In addition, SD^1 may be a more frequent event than SD^{23}, which in turn may be more frequent than SD^{4+}. To compare coefficients across *SD* categories, we normalize such that SD^{23} (or SD^{4+}) represents a bundle of 2-or-3 (or 4-or-more) SD^1s in a consecutive sequence rather than in isolation. Below we describe our normalization factors, and also the underlying concept that ensures comparability of coefficients across disaggregated *SD* categories.

Consider representative county i in year t. Our modelling approach asserts that the yields in county i would increase from an additional *GD* and decline from an additional *SD*. Our objective is to evaluate the impact of an additional *SD* when it occurs as a single-day event versus when it occurs for 2-or-more consecutive days. In other words, we test whether an additional unit of *SD* in one category is more or less harmful than in another category by their occurrence as single-day or multi-day events.

We consider the occurrence of *SD*s (given each crop's temperature threshold for stress degree days) as single-day or consecutive 2-day events during each growing season. Let I_1 and I_2 be the respective total frequency of single-day and 2-day heat events, and so the total number of days when $SD > 0$ equals $I_1 + 2I_2$. Further, if m_1 and m_2 represent the average per day heat accumulated under the single-day and consecutive 2-day categories respectively, then $m_1 = \left(I_1\right)^{-1} \sum_{d \in I_1} (T_d - 32)$ and $m_2 = \left(2I_2\right)^{-1} \sum_{d \in I_2} (T_d - 32)$. In other words, $SD^1 = m_1 I_1$ and $SD^2 = 2m_2 I_2$. We utilize these definitions to re-write our yields-weather model as

$$\begin{aligned} Y_{i,t} &= \beta_0 + \beta_1 SD^1_{i,t} + \beta_2 SD^2_{i,t} + \text{ other controls} \\ &= \beta_0 + \beta_1 m_1 I_1 + 2\beta_2 m_2 I_2 + \text{ other controls.} \end{aligned} \tag{S3}$$

Recall that eq. (S1) is a snapshot of representative county i in year t. The quantum of heat within SD^1 and SD^2 categories may differ across three dimensions: 1) average per day heat (m_1 vs. m_2); 2) frequency of the event (I_1 vs. I_2); and 3) because two single-day events are essentially bundled up into one consecutive 2-day event. Now, assuming $m_2 = k_m m_1$ and $I_2 = k_I I_1$ for some positive constants k_m and k_I, eq. (S3) can be re-written as:

$$\begin{aligned} Y_{i,t} &= \beta_0 + \beta_1 m_1 I_1 + 2k_m k_I \beta_2 m_1 I_1 + \text{ other controls} \\ &= \beta_0 + \beta_1 SD^1_{i,t} + 2k_m k_I \beta_2 SD^1_{i,t} + \text{ other controls.} \end{aligned} \tag{S4}$$

Eq. (S4) represents a structural breakdown of *SD*s because it compares the impact of an additional unit of SD^1 on yields in isolation and in two consecutive repetitions. Since SD^1 is the common denominator of marginal response to drought stress, the coefficients β_1 and $2k_m k_I \beta_2$ are directly comparable. Alternatively, one may divide SD^2 by a normalization factor $2k_m k_I$ prior to estimating eq. (S3) in order for regression coefficients to be directly comparable. It is important to realize that the factor $2k_m k_I$ captures disproportionate heat intensity across *SD* categories.

Although we only consider one county in a given year in the above illustration, the normalization factors ($2k_m k_I$) could vary across counties and on a year-by-year basis. For the Dakotas we find that consecutive heat events were less frequent than the isolated events during 1950-2017 but heat stress, i.e., *m*, can be higher for isolated events with high temperature-levels than moderately hot consecutive events. Therefore, a normalization factor for each category (e.g., 2 for SD^2, 3 for SD^3) may not be appropriate. So we designate the spatio-temporal mean of each category, i.e., SD^1, SD^{23} and SD^{4+}, during 1950-2017 as its respective normalization factor. Although a county-wise and year-wise normalization factor would be the most accurate, we utilize static means to simplify the interpretation of the resulting variables, and thus posit the overall means to be a plausible candidate for the proposed normalization.

Estimating seasonally differentiated yield-weather relationship

The seasonality of yield-weather responses provide some useful insights (Tables S19-S20 presented below under the 'Results' section in *SI*). Early-season *SD*s are beneficial for spring wheat and soybean yields, mainly because most of the isolated *SD*s occur during mid-April to mid-June in a typical year. In the case of spring wheat late-season *GD*s are detrimental while early-season *SD*s are beneficial. This suggests that the yield-temperature relationship for this crop might differ across different stages of the growing season, requiring time varying thresholds rather than uniform thresholds, i.e., $GD \in [6^o C, 20^o C]$, throughout the season. Further, we find that for spring wheat and alfalfa yields increase with higher values of $WETZ \times SD$ in the early growing-season (April-May), as was also found earlier using spring wheat field-trial data (Tack et al. 2015), and extended now also to alfalfa. For maize and soybeans the impact of higher $WETZ \times SD$ is insignificant early in their growing-season (May-June) but is positive and significant during July-August, implying that high moisture levels mitigate the impact of heat-stress. Droughty conditions (*DRYZ*) are found to be relatively more detrimental to yields late in the growing-season for all crops.

Land use change estimation

<u>A recent study that modelled land use change in the eastern Dakotas: Brief detail and limitations</u>

Rashford et al. (2016) recently estimated the link between land use and weather using parcel-level Natural Resources Inventory (NRI) data during 1982-1997 for eastern Dakotas. Weather variables were acquired from eight sparsely located weather stations, under-representing the region's climatic variability. While including weather's time-invariant first and second moments, weather extremes were otherwise ignored where these are known to significantly harm yields (Schlenker and Roberts 2009; Massetti and Mendelsohn 2016). Moreover, a reduced-form land use model as a function of weather is unlikely to capture change in crop profits, which should drive rational land allocation decisions.

Marginal effects of crop returns on the Dakota's historical land use changes: Multinomial logistic regression

We model the Dakotas' land allocation shares to each use *u* in county *i* and year *t*, $s_{i,t}^u$, where $s_{i,t}^u \in [0,1) \ \forall i,t$ for $u \in \bar{U} = \{m,s,w,a\}$ and $s_{i,t}^g \in (0,1) \ \forall i,t$. We specify *u*'s shares with grass as the reference category. Defining $\bar{\beta}^u \triangleq \beta^u - \beta^g$, $\bar{\varepsilon}_{i,t}^u \triangleq \varepsilon_{i,t}^u - \varepsilon_{i,t}^g$, in eq. (2) we obtain

$$
\begin{aligned}
s_{i,t}^u &= \frac{\exp[\bar{\beta}^u X_{i,t} + \bar{\varepsilon}_{i,t}^u]}{1 + \sum_{v \in \bar{U}} \exp[\bar{\beta}^v X_{i,t} + \bar{\varepsilon}_{i,t}^v]}; \ u \in \bar{U}, \text{ and} \\
s_{i,t}^g &= \frac{1}{1 + \sum_{v \in \bar{U}} \exp[\bar{\beta}^v X_{i,t} + \bar{\varepsilon}_{i,t}^v]}.
\end{aligned} \tag{S5}
$$

The marginal effect of a variable $x_{i,t} \in X_{i,t}$ is given as

$$
\begin{aligned}
M(s_{i,t}^u, x_{i,t}) = \frac{\partial s_{i,t}^u}{\partial x_{i,t}} &= \frac{\bar{\beta}^u \exp[\bar{\beta}^u X_{i,t} + \bar{\varepsilon}_{i,t}^u]\left(1 + \sum_{v \in \bar{U}} \exp[\bar{\beta}^v X_{i,t} + \bar{\varepsilon}_{i,t}^v]\right)}{\left(1 + \sum_{v \in \bar{U}} \exp[\bar{\beta}^v X_{i,t} + \bar{\varepsilon}_{i,t}^v]\right)^2} - \\
&\qquad \frac{\exp[\bar{\beta}^u X_{i,t} + \bar{\varepsilon}_{i,t}^u]\sum_{v \in \bar{U}} \exp[\bar{\beta}^v X_{i,t} + \bar{\varepsilon}_{i,t}^v]}{\left(1 + \sum_{v \in \bar{U}} \exp[\bar{\beta}^v X_{i,t} + \bar{\varepsilon}_{i,t}^v]\right)^2} \\
&= s_{i,t}^u[\bar{\beta}_x^u - \sum_{v \in \bar{U}} \bar{\beta}_x^v s_{i,t}^v].
\end{aligned} \tag{S6}
$$

So the marginal effects for crop categories and grasses with respect to $x_{i,t}$ are given as

$$
\begin{aligned}
&\text{(i)} \quad M(s_{i,t}^u, x_{i,t}) = \partial s_{i,t}^u / \partial x_{i,t} = s_{i,t}^u[\bar{\beta}_x^u - \sum_{v \in \bar{U}} \bar{\beta}_x^v s_{i,t}^v]; \ u \in \bar{U} \\
&\text{(ii)} \ M(s_{i,t}^g, x_{i,t}) = \partial s_{i,t}^g / \partial x_{i,t} = -s_{i,t}^g \sum_{v \in \bar{U}} \bar{\beta}_x^v s_{i,t}^v.
\end{aligned} \tag{S7}
$$

Upon substituting $1 - s_{i,t}^c = s_{i,t}^s + s_{i,t}^w + s_{i,t}^a + s_{i,t}^g$ into eq. (S7) we have $(s_{i,t}^u)^{-1} \partial s_{i,t}^u / \partial x_{i,t} =$ $\sum_v (\beta^u - \beta^v) s_{i,t}^v$ with $u \neq v$, i.e., % change in *u*'s share due to a unit change in $x_{i,t}$ is equal to the net increase in per-acre returns generated from allocating a unit share from each competing land use to u. The relevant data definitions are provided in Table 1 and the estimates of marginal effects in eq. (S7) and their standard errors are tabulated in tables 4-5 in the main text.

Weather Outcomes: Tests for stationarity and predicting farmers' weather expectations

Consider an AR(4) (Greene 2008) panel time-series process such that $E(GD_{i,t}) = \gamma_i + \gamma_t t$ to test mean and trend stationarity for county i GDs:

$$GD_{i,t} = (1-\sum_{k=1}^{4}\gamma_k)\gamma_t t + \sum_{k=1}^{4}\gamma_k GD_{i,t-k} + (1-\sum_{k=1}^{4}\gamma_k)\gamma_i + \nu_{i,t}, \qquad \text{(S8)}$$

where $\nu_{i,t}$ is assumed to be a white noise process, γ_i represents county-level means (fixed-effects). $GD_{i,t}$ must be stationary for the above process to be estimable. To test for stationarity of our weather panel data series we conduct unit-root tests for the AR process by following the Breitung and Meyer procedure (Breitung and Meyer 1994). The t-test relies on transforming eq. (S8) such that test statistic for the null hypothesis that a unit root is present, i.e., $\sum_{k=1}^{4}\gamma_k = 1$, is asymptotically normally distributed.[1] Specifically, the following transformation of eq. (S8) is made using the first value of the process $GD_{i,0}$,

$$GD_{i,t} - GD_{i,0} = \gamma_t(1-\sum_{k=1}^{4}\gamma_k)t + \sum_{k=1}^{4}\gamma_k(GD_{i,t-k} - GD_{i,0}) + \nu_{i,t} - (1-\sum_{k=1}^{4}\gamma_k)(GD_{i,0} - \gamma_i). \qquad \text{(S9)}$$

Observe that under the null hypothesis, $\sum_{k=1}^{4}\gamma_k = 1$, the impact of individual means vanishes and standard t-tests can be applied. The corresponding test statistic is termed as "unbiased test-

[1] Data transformation is necessary since under the alternative hypothesis of stationarity the t-test is subject to loss of power due to individual means. Breitung and Meyer's (1994) approach is similar to augmented Dickey-Fuller test (Greene 2008), although the latter test proposed a bias-corrected test-statistic with critical values differing from a normally distributed t-statistic.

statistic." We implement the above test procedure for individual weather series ($GD_{i,t}, SD_{i,t}$, $DRYZ_{i,t}, WETZ_{i,t}$) in SAS's "Unbiased t-test" under its *proc panel* command. $GD_{i,t}, SD_{i,t}$, $WETZ_{i,t}$ and $DRYZ_{i,t}$ are found to be time and cross-section stationary, see Tables S3-S6.

Climate change implications for regional yields and land use

<u>Acquiring climate projections: Monthly and Annual Average Mean-shifts</u>

The climate projections data were acquired from the U.S. Geological Survey's Geo-Data Portal (GDP) (Blodgett 2013)[2], which provides spatially rescaled outputs from General Circulation Models' (GCM) at a finer grid level, referred to as statistical downscaling. We utilize the "Locally Constructed Analogs (LOCA) Statistical Downscaling" algorithm to area-weighted daily climate projections for the Dakotas' 18 climate divisions from 1/16$^{\text{th}}$ degree resolution grids of the Coupled Model Intercomparison Project Phase 5 (CMIP5) archive of the GCMs.[3] The projections data were then matched to the counties contained in each climate division, and if a county overlapped with multiple climate divisions it was assigned an area-weighted average value of each weather outcome.

For a formal representation of monthly and annual mean-shift operators, each date t is composed of a year, y, month, m, and day, d. So the corresponding y' is on the same day, d, and month, m, as y but differs in year, with $y' = y + 50$. Notation-wise, we can re-write the daily-shift as $\Delta\tilde{F}_{k,y',y,m,d}$. Therefore the monthly and annual mean-shifts are specified as

[2] Available at http://cida.usgs.gov/gdp/. Last visited on 5/15/2019.
[3] One-sixteenth degree grid equals roughly 1.5 km in the latitude (Y) direction and 2.5 km in the longitude (X) direction.

$$\text{a) } \Delta\tilde{F}^{monthly}_{k,y',y,m} = \frac{\sum_{d\in m} \Delta\tilde{F}_{k,y',y,m,d}}{\sum_{d\in m} 1};$$
$$\text{b) } \Delta F^{annual}_{k,y',y} = \frac{\sum_{m,d\in y} \Delta\tilde{F}_{k,y',y,m,d} 1_{(m\in[4,8])}}{\sum_{m,d\in y} 1_{(m\in[4,8])}}. \qquad \text{(S10)}$$

Clearly, in eq. (S10a-b), $\Delta\tilde{F}^{monthly}_{k,y',y,m}$ varies monthly and is constant for all days within a month, while $\Delta\tilde{F}^{annual}_{k,y',y}$ varies annually and is constant for all days in a year. Based on these, the future weather variables for a representative county *i* are given as

$$\text{a) } F^{monthly}_{i,y',m} = F_{i,y,m} + \Delta\tilde{F}^{monthly}_{i,y',y,m};$$
$$\text{b) } F^{annual}_{i,y'} = F_{i,y} + \Delta\tilde{F}^{annual}_{i,y',y}. \qquad \text{(S11)}$$

In eq. (S11a-b), variables $F^{monthly}_{i,y',m}$ and $F^{annual}_{i,y'}$ are the county-level projections that we use to describe climate change relative to past weather during the 1981-2010 period. Recall that we evaluate eq. (S10-S11) for seven distinct sets of climate projections.

Predicting future Palmer's Z

Next we turn to future projections for our *Z* index that we need to predict crop yields. Since this index's future projections are unavailable, we specify a regression model for *Z* based on its physical relationship as specified in (Karl 1986). That is, monthly *Z*s depend upon monthly precipitation, evapotranspiration and water holding capacity for typical soil profiles in the region. The Thornthwaite's potential evapotranspiration equation specifies monthly evapotranspiration as a highly non-linear function of monthly precipitation, monthly average temperature, average day-length in a month, and an empirically generated constant (Thornthwaite 1948). We find that higher-order monthly temperature and precipitation terms lead to high multicollinearity. Models with lower-order temperature and precipitation polynomials are found to reduce multicollinearity. Based on this information, we specify the following model for predicting the Z index:

$$Z_{k,t} = \beta_0 + \sum\nolimits_{\gamma \in \{1,2,\dots,6\}} \beta_{Z,\gamma} Z_{k,t-\gamma} + \beta_1 \tilde{P}_{k,t} + \beta_2 \tilde{P}_{k,t}^2 + \beta_3 \tilde{P}_{k,t} \tilde{T}_{k,t} + \sum\nolimits_M \beta_M T_{k,t} 1_M + \sum\nolimits_k \lambda_k 1_k,$$

with notation

k : Climate Division k,

t : date (Year*100+Month),

$Z_{t-\gamma}$: Lagged Zs (6-month lags), (S12)

$\tilde{P}_{k,t}$: Standardized monthly precipitation; $\tilde{P}_{k,t} = (P_{k,t} - \bar{P}) / \sigma(P_{k,t})$,

$\tilde{T}_{k,t}$: Standardized monthly temperature; $\tilde{T}_{k,t} = (T_{k,t} - \bar{T}) / \sigma(T_{k,t})$,

1_M : Month-dummy,

1_k : Climate divisional fixed-effects (dummy variables).

Here $\bar{P}$ and $\bar{T}$ are mean precipitation and temperature respectively, while $\sigma(P_{k,t})$ and $\sigma(T_{k,t})$ represent their respective standard deviations. We maximize regression fit while estimating eq. (S12) to ensure that projected Z values are reliable. We use historical Z values during 1895-2017 for 18 climate divisions in North and South Dakota. Climate division dummy variables are intended to control for soil's water holding capacity. The interaction term $T_{k,t} 1_M$ controls for the accumulated heat in month M due to average temperature and average length of the day in that month. Quadratic precipitation terms are included along with precipitation-temperature interaction terms to, at least partially, control for the non-linear relationship. Table S11 presents the estimation results. Future Z projections are obtained by taking the product of coefficients from eq. (S12) and projected weather outcomes, see Figure S9 for results.

Study Area

Historical Yields of all major crops in the Dakotas

Annual county-level yields data for all major crops in the Dakotas' 119 counties during 1950-2017 are acquired from National Agricultural Statistical Service's (NASS) QuickStats 2.0 portal. The average yield trends across Dakotas' counties are visualized in Figure S6.

Correlation between regional-level prices from USDA's Economic Research Service (ERS) and commodity Futures prices

We utilized the annual February prices for December futures contracts for maize, November futures contracts for soybeans and September futures contracts for spring wheat to control for landowner expectations of their harvest's future market valuation. However, alfalfa futures are not traded and instead we use regional-level prices for alfalfa. Here we compare maize, soybeans and spring wheat's future contract prices with their regional counterparts to ascertain whether regional-level prices are a viable candidate for landowners' expectations of actual market valuations of these commodities. In Figure S7 we plot the annual soybean November futures prices, maize December futures prices and spring wheat September futures prices with the corresponding regional level prices made available by ERS's 'Commodity Costs and Returns 2016 dataset.' We find that the historical ERS prices for South and North Dakota correlate strongly with their contemporaneous futures prices. We conclude that it is reasonable to use region-level alfalfa prices to control for landowners' pre-planting expectation of this crop's actual harvest-time market price.

Results

Yield-weather regressions

Table S16 presents the full yields-weather regression model (corresponding to Table 2 in the main text).

Spatial correlation among weather variables

Potential spatial correlation among weather variables might bias the standard errors of parameter estimates in our yield-weather model. We utilize Conley's (1999) procedure to control for error spatial autocorrelation by defining a cutoff along the x- and y-axes such that each county has at least one neighbor. Counties whose coordinates lie within the designated cutoffs are considered to be neighbors. A sandwich variance-covariance matrix is estimated, which is the weighted sum of covariances among spatially-connected neighbors. The weighting used is the inverse of the squared Euclidean distances among neighboring counties. The model inferences were found to be largely similar upon controlling for spatial autocorrelation in errors. Specifically, the significance levels of about 6% cases (four out of sixty-four coefficients) were different between the cases when spatial autocorrelation was controlled and not controlled (Table S17).

Land Use Share Regressions: Weak instruments

Staiger and Stock (1997) provided a decision rule for weak instruments such that when the regression F-statistic is less than 10 we infer that the instrument is weak. However, the above rule was developed for a single endogenous variable. Stock and Yogo (2005) extended this decision rule for more than one endogenous regressor, where the critical F-value = 20.27 is more appropriate. We tabulate the F-statistic for the first stage of the IV regressions (see eq. (4) in the main text) in Table S22. Clearly, the weak instruments problem exists only in the case of disaster payments. Although the estimated coefficient of $G_{dis\text{-}pay}$ in tables 4 and 5 (of the main text) might be biased with relatively large standard errors (less precision), we found the overall land use shares model specification to be robust to including or excluding $G_{dis\text{-}pay}$.

Land Use Share Regressions: Tests for over-identifying assumptions

The Sargan test for over-identifying restrictions was implemented as described in Wooldridge (2002, pp. 123). Specifically, the estimated residuals of equation (6) in the main text are then regressed on all IVs and the respective exogenous variables from the equations in system (6). The R^2 value of this auxiliary regression is multiplied by the number of observations (N), which is chi-squared distributed. That is, $NR^2 \sim \chi^2_Q$, where Q is the number of over-identifying restrictions, which is equal to the total number of instruments including the county fixed-effects. The null hypothesis of the Sargan test is that the excluded instruments are correctly excluded from the land use shares models and that these are uncorrelated with the regression errors. The results for eastern counties (with soybeans) and western counties (without soybeans) are presented in Table S23. In estimating our land use share system, we fail to reject the over-identifying restrictions for maize, soybeans and alfalfa while we reject these restrictions for spring wheat indicating that the spring wheat share model is mis-specified with regards to the excluded instruments. The results are presented in Table S23.

Block-bootstrap estimation of our modelling framework

We bootstrap our sequential estimation framework with multi-crop equations (yields, government payments and land use shares) to check the robustness of our estimation results. Given that the unit of analysis for crop yields and cropland use shares is counties while the Palmer Z index was obtained for climate divisions that may contain multiple counties, explanatory variables might be spatially correlated. There are 18 climate divisions and 118 counties in the Dakotas. Therefore, we implement a block bootstrap procedure with 18 climate divisions as designated blocks and by sampling (with replacement) all 1,224 (18 climate divisions x 68 years) unique climate division-year pairs. The process is iterated 500 times.

We run the yield-weather model, i.e., model (1) in the main text, for each iteration and summarize the mean and standard error of regression coefficients. Across all 500 iterations there were a total of 3,531,000 observations for maize, 1,559,000 observations for soybeans, 3,645,500 observations for spring wheat and 3,171,000 observations for alfalfa. The differences in observations across crop-type are due to inavailability of some county-level yields data. The block bootstrapped estimates of coefficient and their standard errors for the yield-weather model are provided in Table S24. Clearly, the block bootstrapped estimates are *very* close to the ones we achieve using actual data (see Table S16 in the supplementary material). This finding corroborates well with one where we implemented Conley's (1999) procedure to control for spatial autocorrelation in regression errors, and the model inference remained largely similar (see Table S17).

The block bootstrap coefficients of the land use shares regressions were estimated in three steps: first, the yield-weather model output is combined with market prices to obtain profit expectations of farmers; second, the government payments are estimated as a function of expected weather; and finally, the land use shares are estimated using expected profits and expected government payments. While the first step models crop-specific yield during 1950-2017, the second and third steps are estimated using data during 1996-2016 using the latest available government payments data for insurance subsidy and disaster payments. In order to implement the block bootstrap in an integrated manner we retain the resampled climate divisions and years from the above step (i.e., block-bootstrap estimation of yield-weather model) and truncate the resampled data across the 500 iteration to retain years 1996-2016.

We present the block bootstrapped estimates of the coefficients of government payments data and their standard errors in Table S25. These block bootstrap estimates are largely similar to those using *actual* data for the individual government payment models (see Table S21). Some major exceptions include the coefficients of *SD* and *DRYZ* for soybean subsidy, which are now significant with the same sign as compared to those reported in Table S21. However, the sign and statistical significance of the intercept and the time-trends coefficients in the disaster payments model have reversed when compared to those using actual data.

Finally, the block bootstrap estimates of the marginal effects of each explanatory variable on Dakotas' land use shares are presented in Tables S26-S27. We separately estimate land use shares in the 55 eastern Dakota counties (including soybean shares) and the 63 western Dakota counties (excluding soy shares), corresponding to tables 4 and 5 in the main text. To obtain the block bootstrap estimates, we first evaluate the marginal effects for each of the 500 resampled datasets using equations (S7) and then report their average values and standard errors.

While the block bootstrap based marginal effects estimate for individual land use shares in the eastern and western portions of the Dakotas remain largely the same (in size and significance) as when estimated using actual county-level data, some discrepancies occur in the standard errors. The coefficients of about 8% (9 out of a total of 109) of the explanatory variables (in red color) under block bootstrap estimation are statistically insignificant while they were significant when using the actual data. On the other hand, about 4.6% (5 out of a total of 109) of the explanatory variables (in blue color) have statistically significant coefficients under block bootstrap estimation, which were found to be insignificant when using the actual data. The sign of all coefficients in these discrepant cases remain the same.

FIGURES (Supplementary Information)

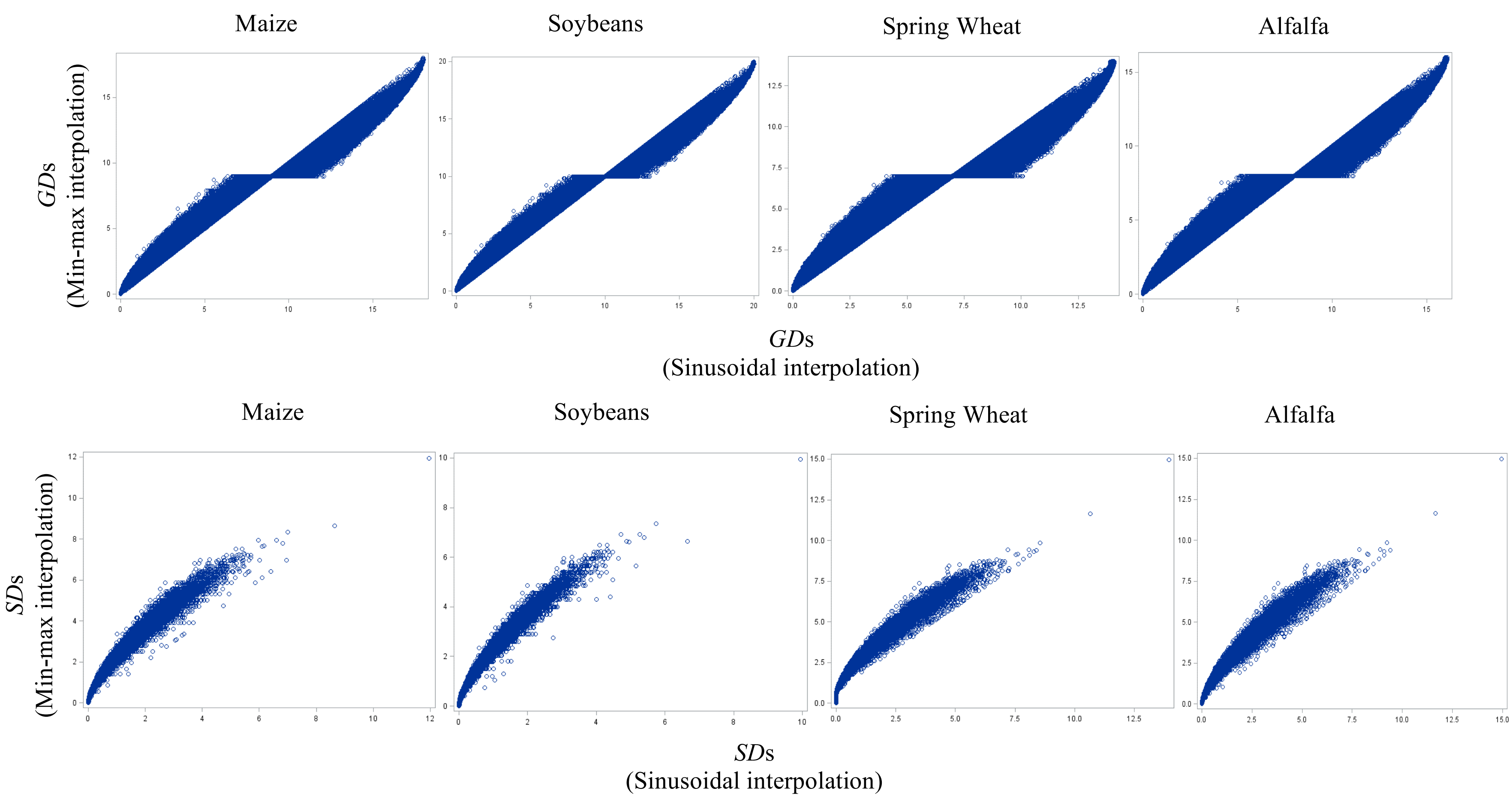


Figure S1: Scatter plots of min-max versus sinusoidal interpolations of daily growing degree-days and stress degree-days.

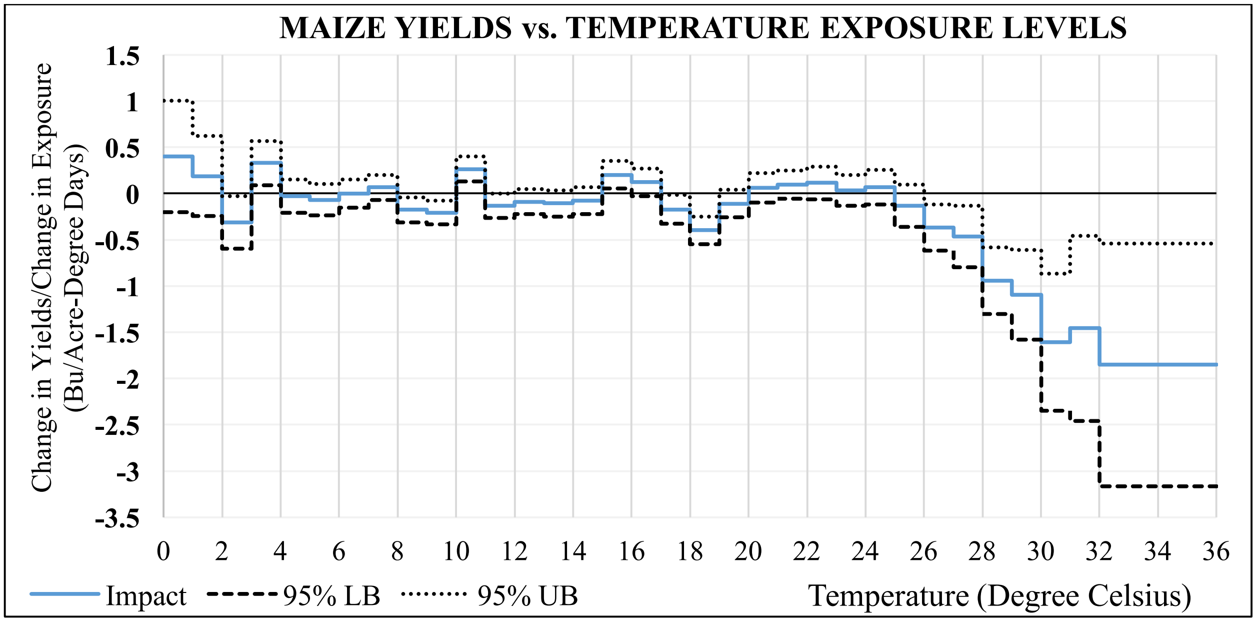


Figure S2. Maize Yields vs. Number of Days in Each Degree-Celsius Bin.
LB and UB points represent 95% confidence interval lower and upper bounds on estimated impact.

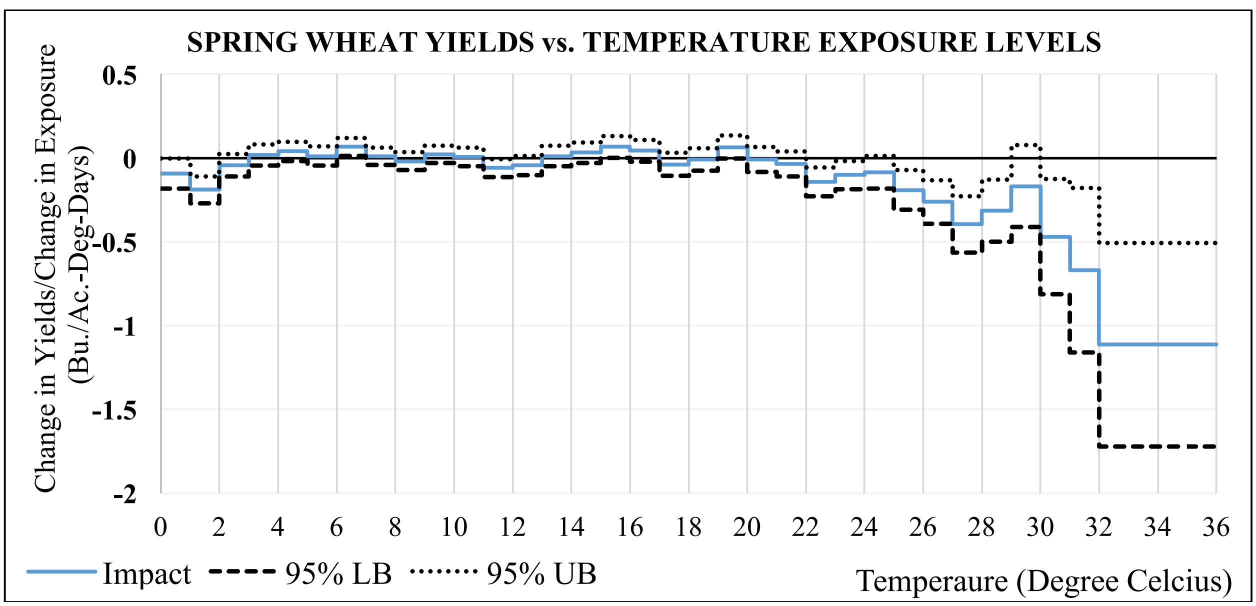


Figure S3. Spring Wheat Yields vs. Number of Days in Each Degree-Celsius Bin.
LB and UB points represent 95% confidence interval lower and upper bounds on estimated impact.

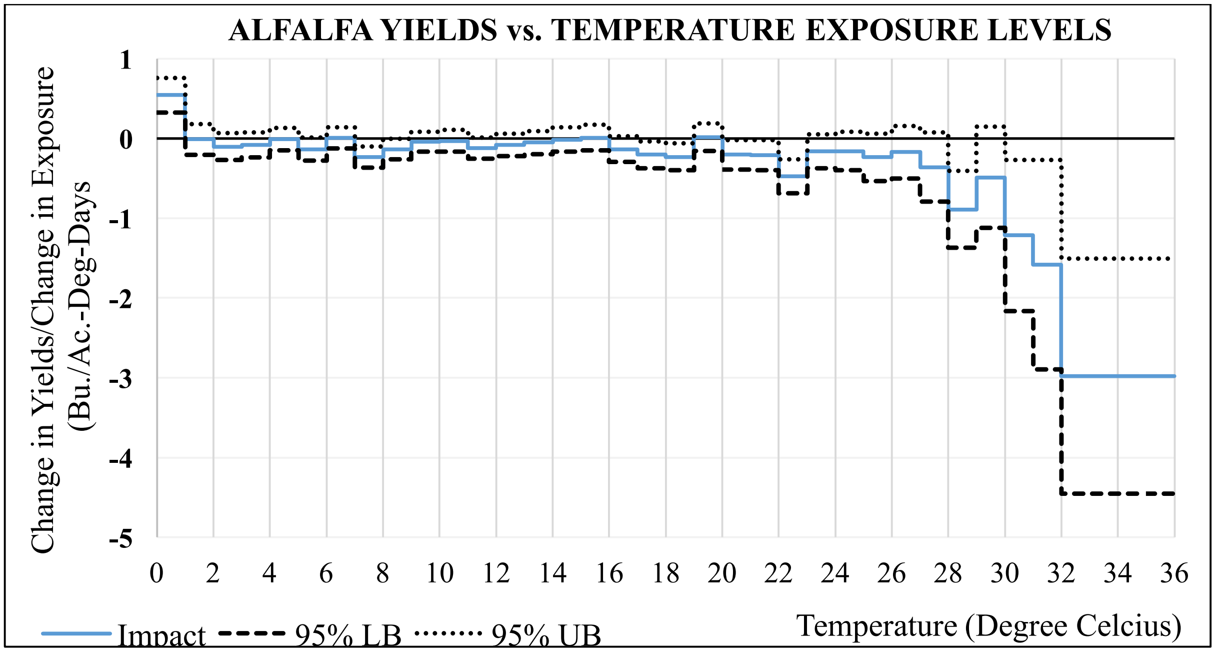


Figure S4. Alfalfa Yields vs. Number of Days in Each Degree-Celsius Bin.
LB and UB points represent 95% confidence interval lower and upper bounds on estimated impact.

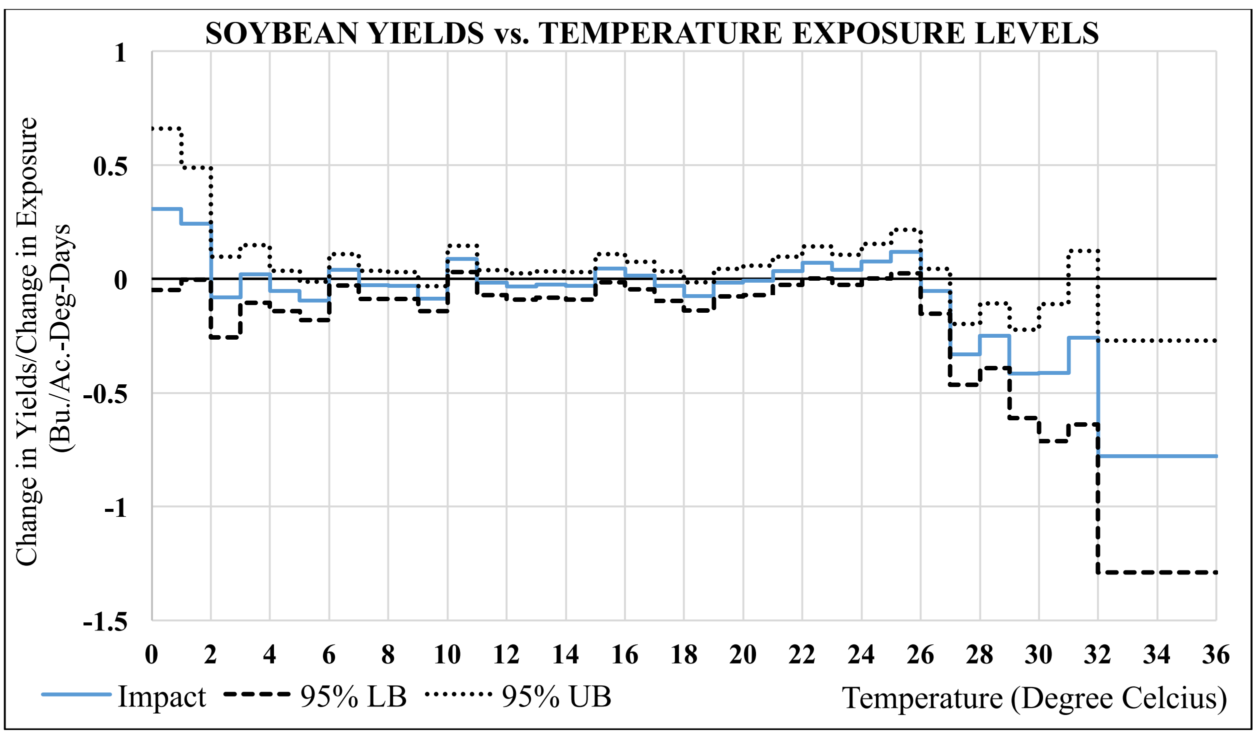


Figure S5. Soybean Yields vs. Number of Days in Each Degree-Celsius Bin.
LB and UB points represent 95% confidence interval lower and upper bounds on estimated impact.

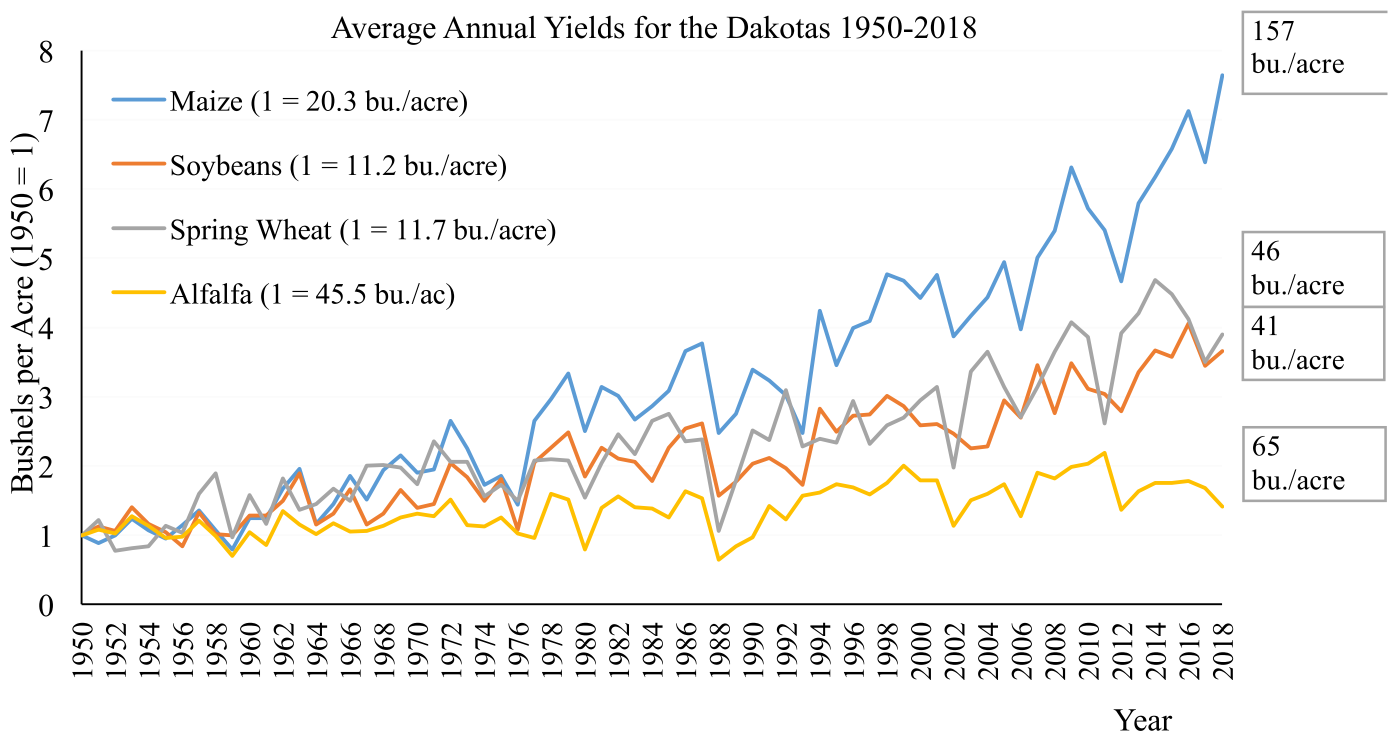


Figure S6. Historical Yields for the Dakotas' major crops, i.e., maize, alfalfa, soy and spring wheat.

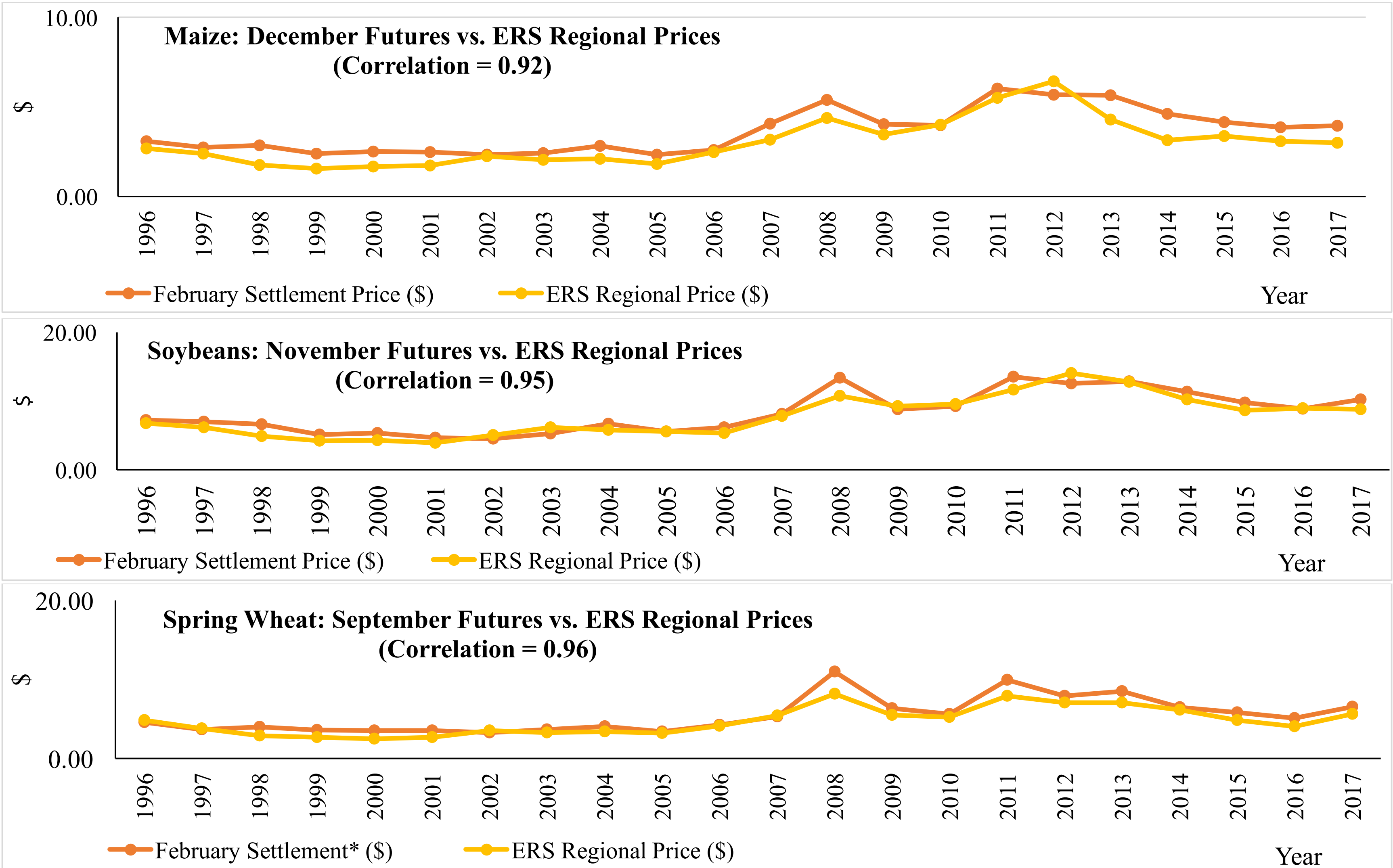
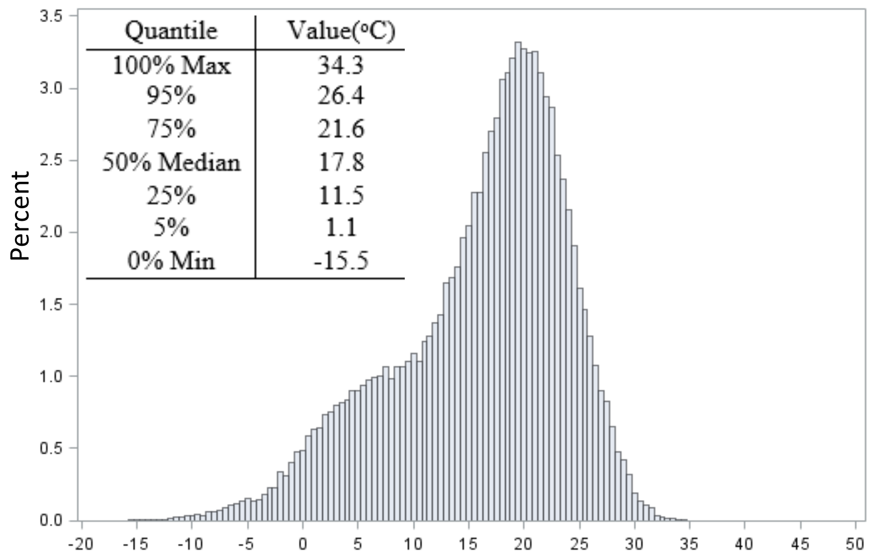
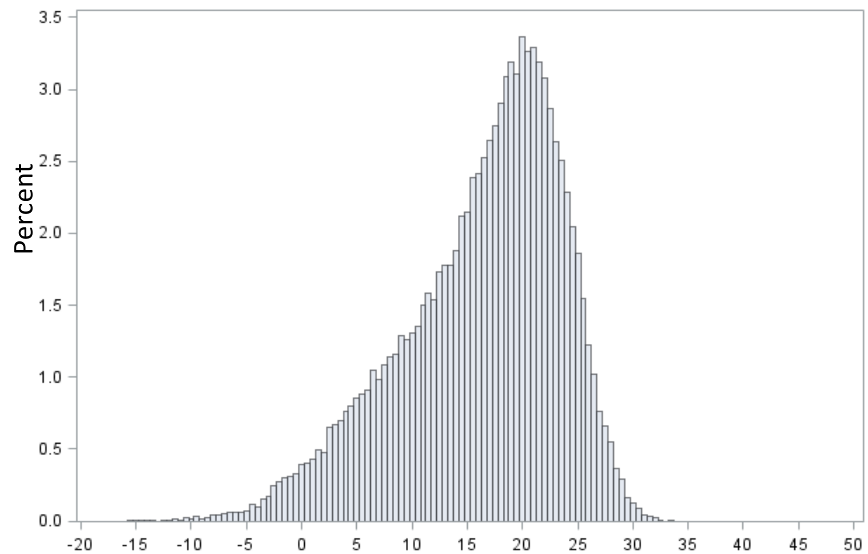


Figure S7 Comparative plots of ERS prices and futures prices for maize, soybeans and spring wheat. All prices are in dollars.
* denotes that Spring Wheat's settlement prices from the Minneapolis Grain Exchange were calculated as daily averages of 'Open' and 'Last' prices.

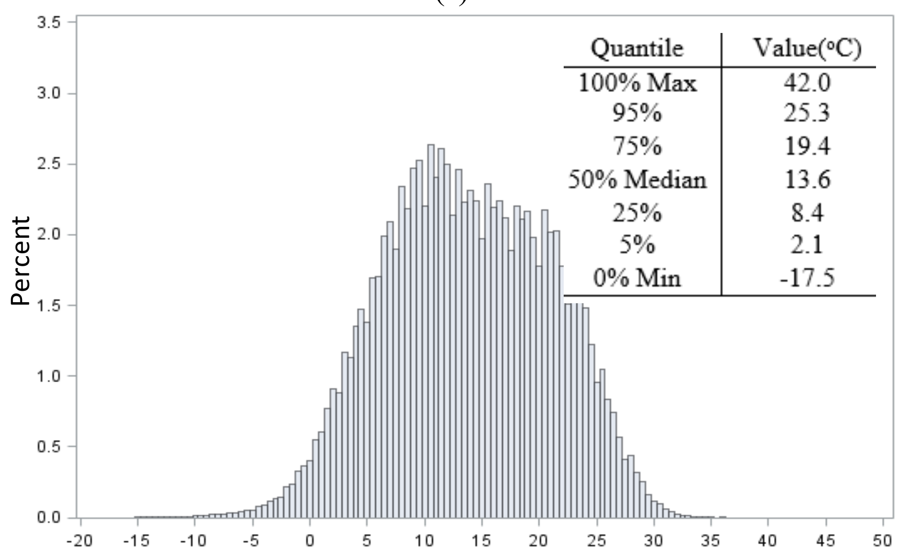
Frequency distribution of actual historical temperature versus climate model-based projections.



(a)



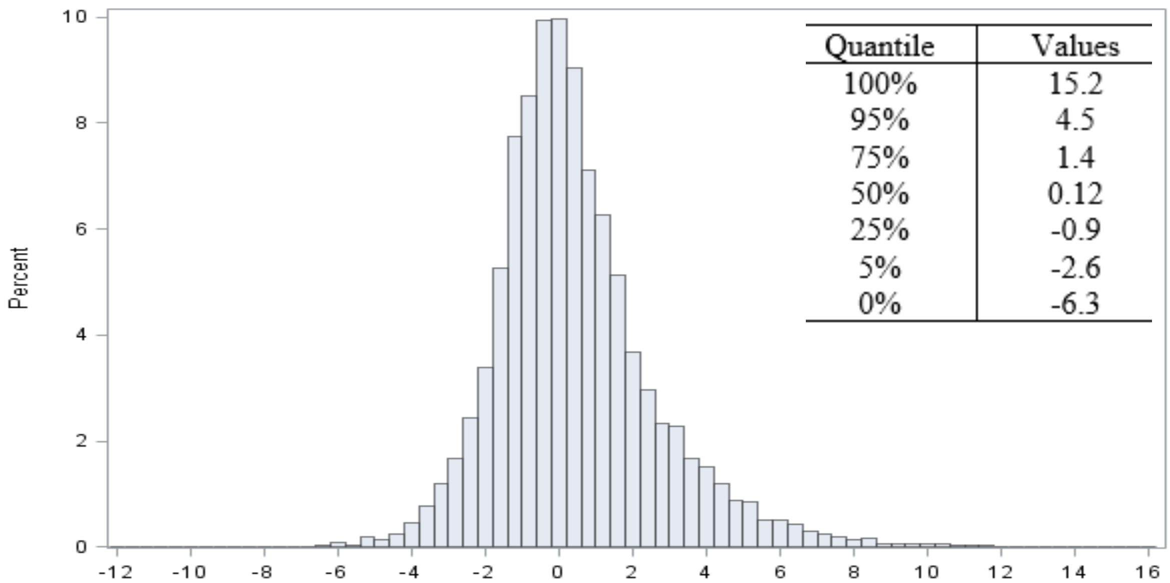
(b)



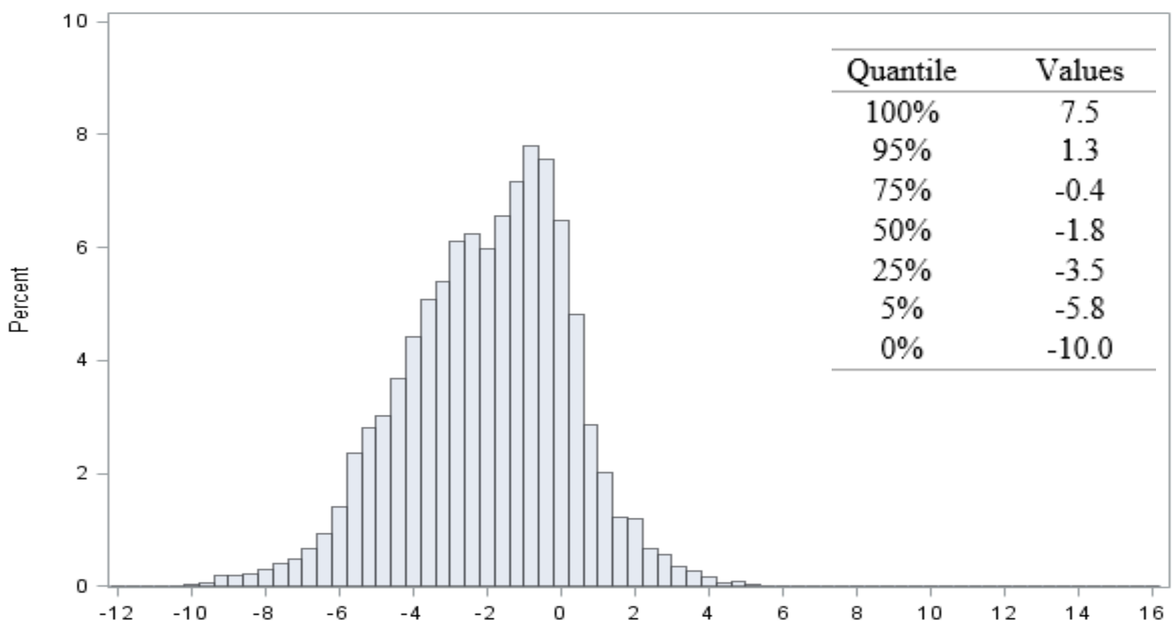
(c)

Figure S8 a-c. Comparative histograms for temperature (°C) from projections data and actual station-level realizations for the Dakotas during 1981-2005. The data in (a) and (b) are climate projections from HADGEM and CNRM climate models, respectively. Chart (c) presents actual temperature realizations as observed at the weather stations.

Future (projected) vs. past *Z* distributions

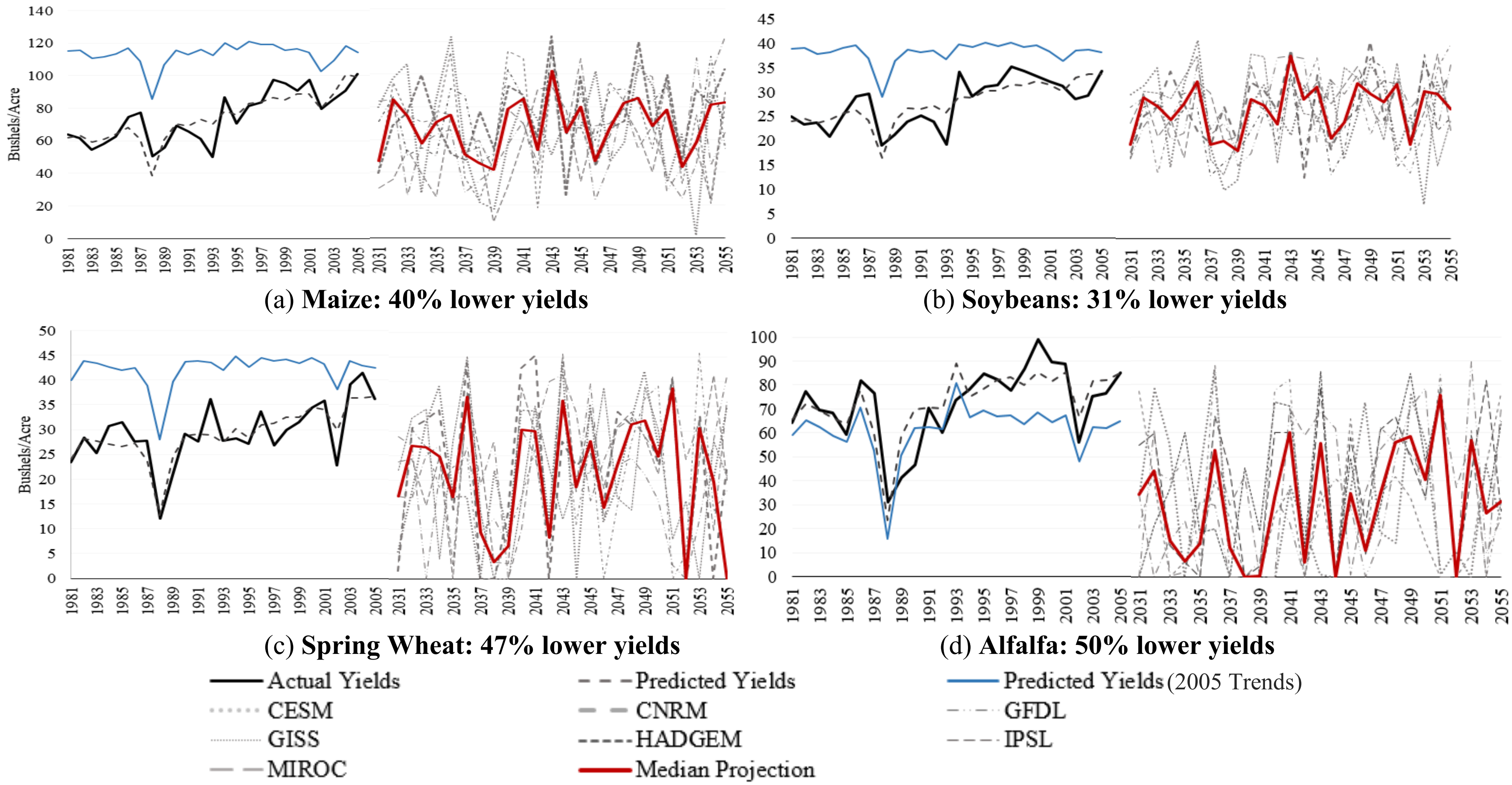


(a)



(b)

Figure S9. Distribution of growing season (April-August) *Z* values: 2030-’55 vs. 1981-2005. Panel (a) shows historical Palmer Z distribution, 1981-2005; and panel (b) shows the distribution of median Palmer Z projections based on the 31-day moving average mean-shifts from the seven climate models during 2030-’55.



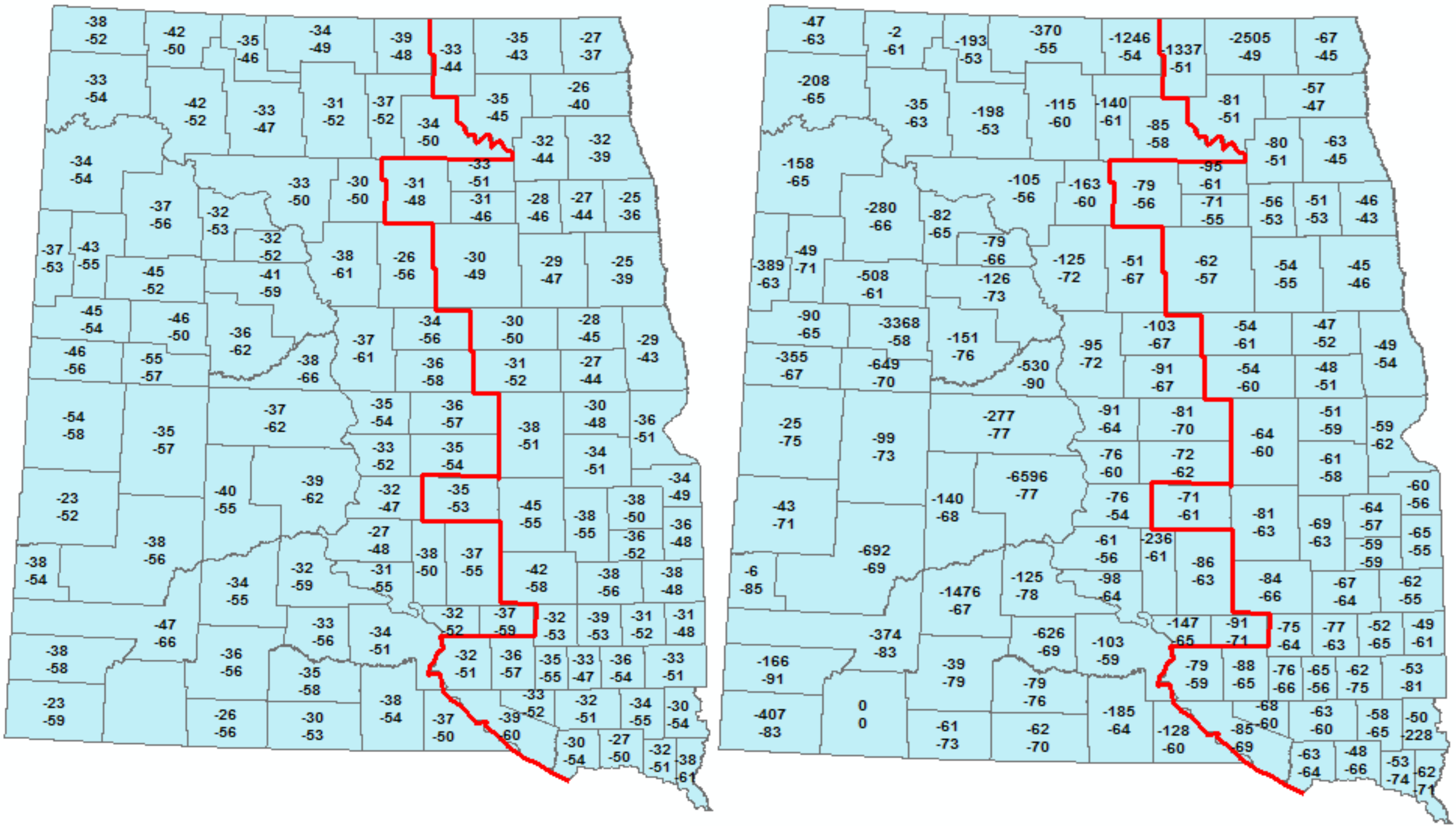
(a) **Maize: 40% lower yields**

(b) **Soybeans: 31% lower yields**

(c) **Spring Wheat: 47% lower yields**

(d) **Alfalfa: 50% lower yields**

Figure S10. Historical yields (1981-2005) vs. Projected yields (2031-’55) from the yield-weather model specification based on the **decomposed *SD*s** (eq. 1 in main text, model II estimation results in Table S16). Each year’s crop yields in the above graphs are calculated as an average of all counties in North and South Dakota. Hashed representations of projected yields are from A1B emissions scenario using seven GCMs, as mentioned earlier in Figure 3. Median projection in a given year is calculated by taking the median yield value of the seven yield projections from each of the seven climate model outputs in each county and then taking the arithmetic average across counties. We restrict spring wheat and alfalfa yield forecasts to zero for years in which these are projected to assume a negative value.



(a) **(b)**

Figure S11 a-b. Spatial distribution of percent change in yields and profits driven by projected climate change by 2030-’55 relative to 1981-2005. Panel (a) shows percent change in maize yields (bushels/acre, top number) and spring wheat yields (bushels/acre, bottom number) for each county in the Dakotas. b) Percent change in maize profits ($/acre, top number) and spring wheat profits ($/acre, bottom number) for each county in the Dakotas. Red partitioning signifies the east-west frontier such that soybean is cultivated mainly in the east.

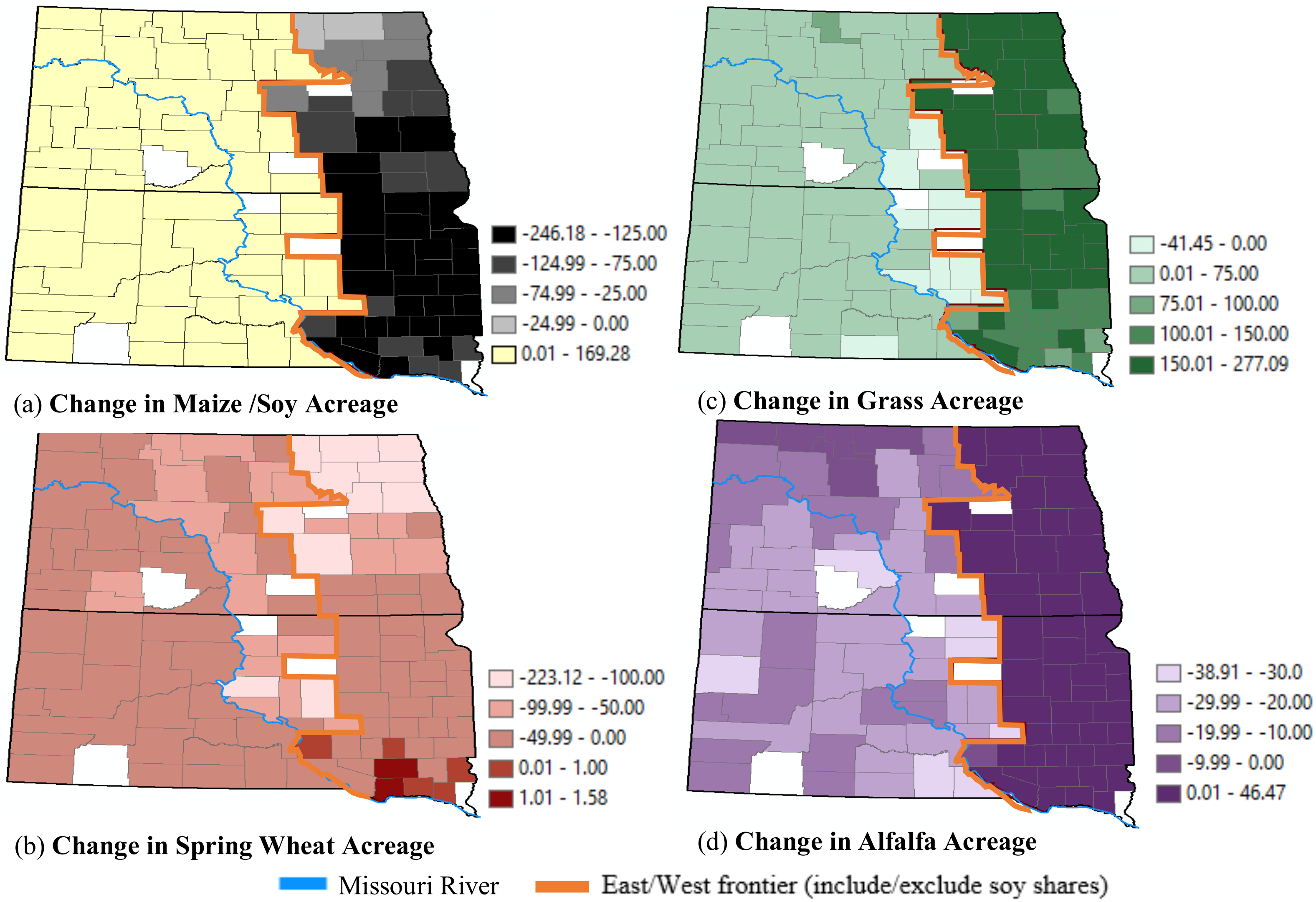


Figure S12. Climate-driven acreage changes by 2031-'55 relative to 1981-2005 from the yield-weather model specification based on the **decomposed *SDs*** (eq. 1 in main text, model II in Table S16). Land use change ranges in each panel are in acres per thousand county acres. White-colored counties signify missing yields data for one or more crops during the entire study period.

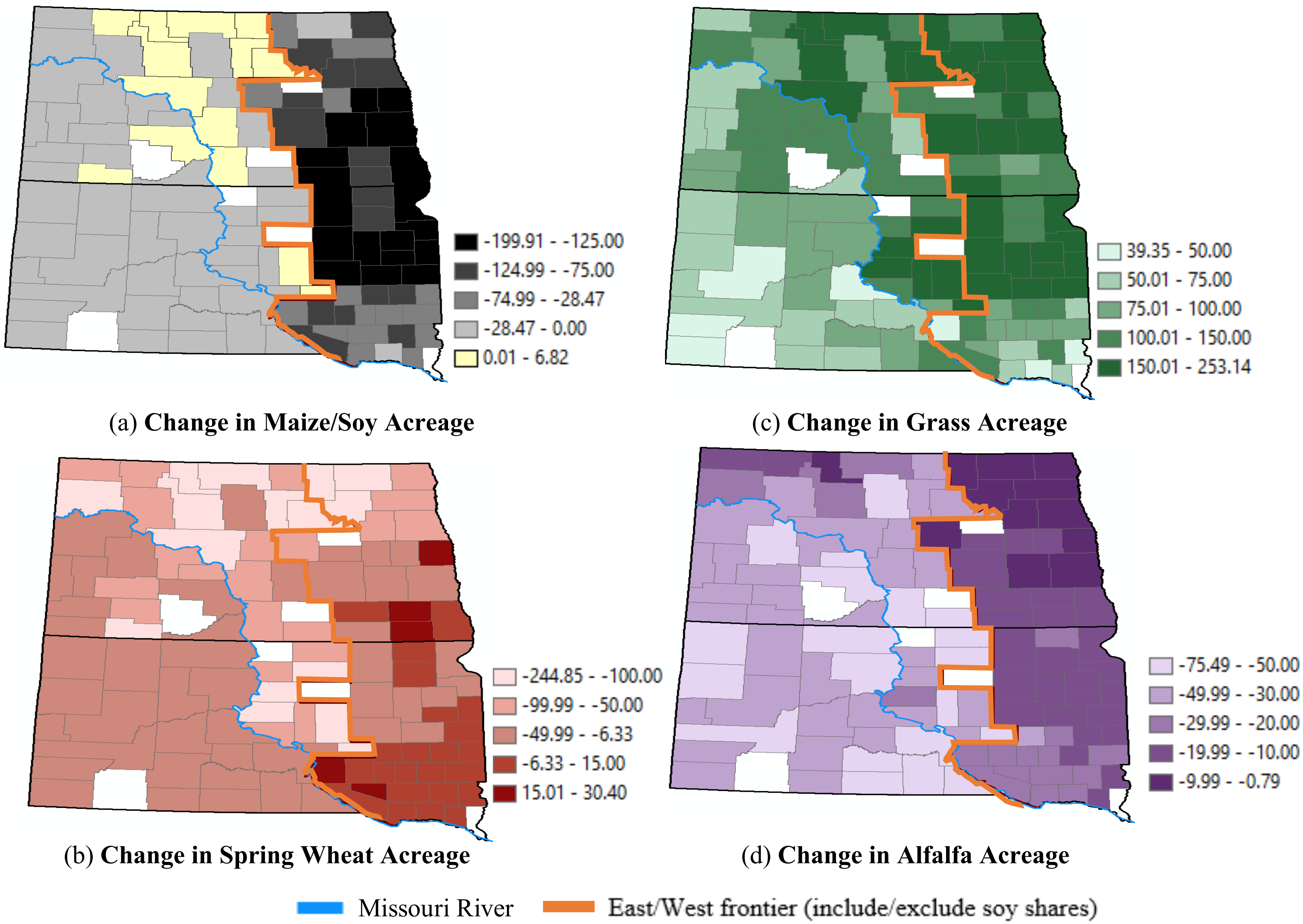
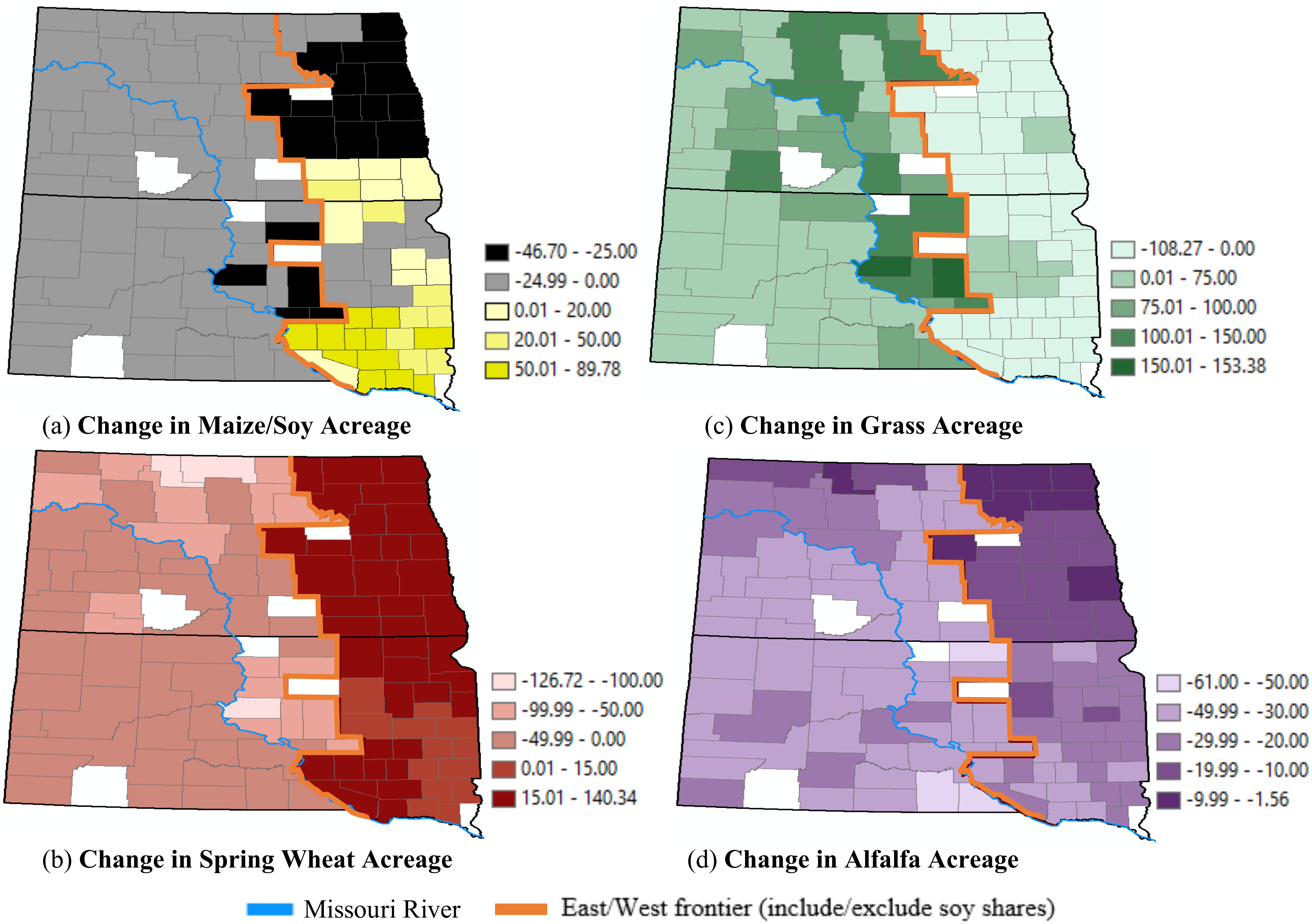


Figure S13. Projected acreage change due to climate-based temperature changes by 2031-'55 relative to the 1981-2005, holding precipitation fixed. The unit of land use change in the color legends is acres per-thousand county-acres.



(a) **Change in Maize/Soy Acreage**

(c) **Change in Grass Acreage**

(b) **Change in Spring Wheat Acreage**

(d) **Change in Alfalfa Acreage**

Figure S14. Projected acreage change due to climate-based precipitation changes by 2031-'55 relative to the 1981-2005, holding temperature fixed. The unit of land use change in the color legends is acres per-thousand county-acres.

TABLES (Supplementary Information)

Table S1: Summary Statistics based on daily temperature data for crop-specific growing season using min-max and sinusoidal interpolations

Functional Form	Variable	Mean	Standard Deviation	Minimum	Maximum
Maize (N = 954,314)					
Min-Max	*GD*	8.05	4.53	0	18.00
Sinusoidal	*GD*	8.23	5.12	0	18.04
Min-Max	*SD*	0.25	0.75	0	11.95
Sinusoidal	*SD*	0.11	0.40	0	11.95
Soybeans (N = 954,314)					
Min-Max	*GD*	9.05	4.90	0	20.00
Sinusoidal	*GD*	9.22	5.43	0	20.05
Min-Max	*SD*	0.12	0.50	0	9.95
Sinusoidal	*SD*	0.05	0.24	0	9.95
Spring Wheat (N = 946,389)					
Min-Max	*GD*	6.26	4.04	0	14.00
Sinusoidal	*GD*	6.39	4.60	0	14.08
Min-Max	*SD*	0.38	1.01	0	14.95
Sinusoidal	*SD*	0.14	0.51	0	13.95
Alfalfa (N = 946,389)					
Min-Max	*GD*	6.66	4.45	0	16.00
Sinusoidal	*GD*	6.74	5.03	0	16.08
Min-Max	*SD*	0.38	1.01	0	14.95
Sinusoidal	*SD*	0.20	0.63	0	14.95

Table S2: Pearson correlation coefficients of daily growing and stress degree days using min-max and sinusoidal interpolations with p-value in the parentheses

Maize

Functional Form		Min-Max	Sinusoidal	Min-Max	Sinusoidal
		GD	***GD***	***SD***	***SD***
Min-Max	***GD***	1	**0.995 (<0.0001)**	0.442 (<0.0001)	0.394 (<0.0001)
Sinusoidal	***GD***		1	0.473 (<0.0001)	0.417 (<0.0001)
Min-Max	***SD***			1	**0.975 <0.0001**
Sinusoidal	***SD***				1

Soybeans

Functional Form		Min-Max	Sinusoidal	Min-Max	Sinusoidal
		GD	***GD***	***SD***	***SD***
Min-Max	***GD***	1	**0.996 (<0.0001)**	0.344 (<0.0001)	0.303 (<0.0001)
Sinusoidal	***GD***		1	0.372 <0.0001	0.325 (<0.0001)
Min-Max	***SD***			1	**0.975 (<0.0001)**
Sinusoidal	***SD***				1

Spring Wheat

Functional Form		Min-Max	Sinusoidal	Min-Max	Sinusoidal
		GD	***GD***	***SD***	***SD***
Min-Max	***GD***	1	**0.989 (<0.0001)**	0.532 (<0.0001)	0.437 (<0.0001)
Sinusoidal	***GD***		1	0.533 <0.0001	0.423 (<0.0001)
Min-Max	***SD***			1	**0.949 (<0.0001)**
Sinusoidal	***SD***				1

Alfalfa

Functional Form		Min-Max	Sinusoidal	Min-Max	Sinusoidal
		GD	***GD***	***SD***	***SD***
Min-Max	***GD***	1	**0.992 (<0.0001)**	0.542 (<0.0001)	0.487 (<0.0001)
Sinusoidal	***GD***		1	0.562 (<0.0001)	0.495 (<0.0001)
Min-Max	***SD***			1	**0.974 (<0.0001)**
Sinusoidal	***SD***				1

Notes: The correlation estimates across the weather outcomes obtained using the min-max and sinusoidal interpolation methods are presented with the red color.

Table S3. Unit Root Regressions for **Maize**'s seasonal Weather Outcomes. $H_0 : \sum_{k=1}^{4} \gamma_k = 1.$

Regressors	*GD*	*SD*	*DRYZ*	*WETZ*
Trend	0.54^{a}	-0.02	-0.001	0.02^{a}
$W_{i,t-1}$	0.64^{a}	0.40^{a}	0.04^{a}	0.01
$W_{i,t-2}$	0.10^{a}	0.03^{b}	-0.08^{a}	0.03^{a}
$W_{i,t-3}$	0.08^{a}	0.06^{a}	0.02^{c}	-0.04^{a}
$W_{i,t-4}$	0.02^{b}	0.14^{a}	0.06^{a}	-0.005
County Fixed-Effects	Yes	Yes	Yes	Yes
R^2	0.85	0.63	0.03	0.04
N	7,367	7,367	7,367	7,367
Unbiased t-test	-11.96^{a}	-11.39^{a}	-28.33^{a}	-31.55^{a}

^{a} *p<0.01*, ^{b} *p<0.05*, ^{c} *p<0.1*

Notes: Regressors $W_{i,t-k}, k \in \{1, 2, 3, 4\}$ denote lagged variables corresponding to only the dependent variable in each case.

Table S4. Unit Root Regressions for **Soybean**'s seasonal Weather Outcomes. $H_0 : \sum_{k=1}^{4} \gamma_k = 1.$

Regressors	*GD*	*SD*	*DRYZ*	*WETZ*
Trend	-0.33^{a}	-0.03^{a}	-0.001	0.02^{a}
$W_{i,t-1}$	0.70^{a}	0.36^{a}	0.04^{a}	0.003
$W_{i,t-2}$	0.07^{a}	0.003	-0.08^{a}	0.03^{a}
$W_{i,t-3}$	0.08^{a}	0.06^{a}	0.02^{c}	-0.04^{a}
$W_{i,t-4}$	0.01	0.12^{a}	0.06^{a}	-0.01
County Fixed-Effects	Yes	Yes	Yes	Yes
R^2	0.85	0.56	0.03	0.04
N	7,481	7,481	7,481	7,481
Unbiased t-test	-11.55^{a}	-12.52^{a}	-28.87^{a}	-32.20^{a}

^{a} *p<0.01*, ^{b} *p<0.05*, ^{c} *p<0.1*

Notes: Regressors $W_{i,t-k}, k \in \{1, 2, 3, 4\}$ denote lagged variables corresponding to only the dependent variable in each case.

Table S5. Unit root regressions for **Spring Wheat**'s weather outcomes. $H_0: \sum_{k=1}^{4} \gamma_k = 1.$

Regressors	*GD*	*SD*	*DRYZ*	*WETZ*
Trend	0.18^b	0.66	-0.0001	0.02^a
$W_{i,t-1}$	0.67^a	0.48^a	0.12^a	-0.05^a
$W_{i,t-2}$	0.05^a	0.10^a	-0.11^a	0.07^a
$W_{i,t-3}$	0.11^a	0.05^a	0.005	-0.08^a
$W_{i,t-4}$	0.01	0.12^a	0.06^a	-0.04^a
County Fixed-Effects	Yes	Yes	Yes	Yes
R^2	0.82	0.78	0.04	0.04
N	7,385	7,385	7,385	7,385
Unbiased t-test	-11.75^a	-10.45^a	-28.68^a	-31.61^a

^{a} *p<0.01,* ^{b} *p<0.05,* ^{c} *p<0.1*

Notes: Regressors $W_{i,t-k}, k \in \{1,2,3,4\}$ denote lagged variables corresponding to only the dependent variable in each case.

Table S6. Unit root regressions for **Alfalfa**'s weather outcomes. $H_0: \sum_{k=1}^{4} \gamma_k = 1.$

Regressors	*GD*	*SD*	*DRYZ*	*WETZ*
Trend	0.24^a	0.05^b	0.0002	0.02^a
$W_{i,t-1}$	0.67^a	0.46^a	0.12^a	-0.05^a
$W_{i,t-2}$	0.04^a	0.05^a	-0.11^a	0.07^a
$W_{i,t-3}$	0.12^a	0.06^a	0.01	-0.07^a
$W_{i,t-4}$	0.01	0.12^a	0.06^a	-0.04^a
County Fixed-Effects	Yes	Yes	Yes	Yes
R^2	0.83	0.66	0.04	0.04
N	7,465	7,465	7,465	7,465
Unbiased t-test	-11.08^a	-10.45^a	-30.25^a	-33.03^a

^{a} *p<0.01,* ^{b} *p<0.05,* ^{c} *p>0.1*

Notes: Regressors $W_{i,t-k}, k \in \{1,2,3,4\}$ denote lagged variables corresponding to only the dependent variable in each case.

Weather predictions corresponding to eq. (4) under 'Methods' in the main text

Table S7. Models for **Maize**'s Seasonal Weather Outcomes.

Regressors	*GD*	*SD*	*DRYZ*	*WETZ*
Trend	0.40[a]	-0.09[a]	0.002[c]	0.02[a]
$GD_{i,t-1}$	0.64[a]	0.02[a]	0.0004[a]	-0.001[a]
$GD_{i,t-2}$	0.12[a]	-0.002	-0.001[a]	0.001[a]
$GD_{i,t-3}$	0.07[a]	-0.002	-0.0001	-0.0003
$GD_{i,t-4}$	0.01	0.0004	0.0003[a]	0.0001
$SD_{i,t-1}$	0.09	0.37[a]	0.005[a]	-0.01[a]
$SD_{i,t-2}$	0.00	0.06[a]	0.001	0.01[a]
$SD_{i,t-3}$	0.05	0.03[c]	-0.003[a]	0.001
$SD_{i,t-4}$	0.11	0.11[a]	-0.001	0.003[b]
$DRYZ_{i,t-1}$	-5.96[a]	-2.15[a]	-0.02	-0.02
$DRYZ_{i,t-2}$	-5.28[a]	-1.98[a]	-0.11[a]	-0.06[a]
$DRYZ_{i,t-3}$	0.58	-0.27	0.02[c]	-0.08[a]
$DRYZ_{i,t-4}$	-1.25	-0.27	0.06[a]	0.04[c]
$WETZ_{i,t-1}$	6.01[a]	0.26[b]	-0.06[a]	-0.03[b]
$WETZ_{i,t-2}$	2.26[a]	0.46[a]	-0.04[a]	0.03[a]
$WETZ_{i,t-3}$	-0.88	-0.65[a]	-0.06[a]	-0.03[a]
$WETZ_{i,t-4}$	0.24	0.46[a]	0.02[c]	-0.01
County Fixed-Effects	Yes	Yes	Yes	Yes
R^2	0.85	0.66	0.06	0.06
N	7,367	7,367	7,367	7,367

[a] *p<0.01,* [b] *p<0.05,* [c] *p<0.1*

Table S8. Models for **Soybean**'s Seasonal Weather Outcomes.

Regressors	*GD*	*SD*	*DRYZ*	*WETZ*
Trend	0.18	-0.06[a]	0.002[c]	0.02[a]
$GD_{i,t-1}$	0.70[a]	0.01[a]	0.0004[a]	-0.001[a]
$GD_{i,t-2}$	0.08[a]	-0.002	-0.001[a]	0.001[a]
$GD_{i,t-3}$	0.06[a]	-0.001	-0.0001	-0.0003
$GD_{i,t-4}$	0.01	0.001	0.0003[a]	0.0001
$SD_{i,t-1}$	0.07	0.33[a]	0.006[a]	-0.02[a]
$SD_{i,t-2}$	-0.05	0.03[b]	0.001	0.01[a]
$SD_{i,t-3}$	0.25	0.03[b]	-0.005[a]	-0.0004
$SD_{i,t-4}$	0.02	0.09[a]	-0.002	0.01[a]
$DRYZ_{i,t-1}$	-6.88[a]	-1.27[a]	-0.02	-0.01
$DRYZ_{i,t-2}$	-5.19[a]	-1.26[a]	-0.10[a]	-0.07[a]
$DRYZ_{i,t-3}$	1.02	-0.15	0.02[c]	-0.07[a]
$DRYZ_{i,t-4}$	-0.83	-0.12	0.06[a]	0.04[c]
$WETZ_{i,t-1}$	6.26[a]	0.002	-0.06[a]	-0.03[b]
$WETZ_{i,t-2}$	1.89[c]	0.14[c]	-0.04[a]	0.03[a]
$WETZ_{i,t-3}$	-1.11	-0.40[a]	-0.06[a]	-0.04[a]
$WETZ_{i,t-4}$	0.86	0.26[a]	0.01[c]	-0.01
County Fixed-Effects	Yes	Yes	Yes	Yes
R^2	0.85	0.58	0.06	0.06
N	7,481	7,481	7,481	7,481

[a] $p<0.01$, [b] $p<0.05$, [c] $p<0.1$

Table S9. Models for **Spring Wheat**'s Seasonal Weather Outcomes.

Regressors	*GD*	*SD*	*DRYZ*	*WETZ*
Trend	0.14	-0.03	0.002[b]	0.02[a]
$GD_{i,t-1}$	0.67[a]	0.04[a]	0.0001	-0.0002
$GD_{i,t-2}$	0.08[a]	0.004	-0.001[a]	0.001[a]
$GD_{i,t-3}$	0.05[a]	-0.01[c]	0.001[a]	-0.0001
$GD_{i,t-4}$	0.03[b]	-0.01[a]	-0.0001	0.00003
$SD_{i,t-1}$	0.17[a]	0.38[a]	0.004[a]	-0.01[a]
$SD_{i,t-2}$	-0.10	0.07[a]	0.001	-0.0005
$SD_{i,t-3}$	0.32[a]	0.05[a]	-0.002[b]	-0.001
$SD_{i,t-4}$	-0.20[a]	0.11[a]	-0.001	0.003[a]
$DRYZ_{i,t-1}$	-5.27[a]	-1.92[a]	0.08[a]	-0.07[a]
$DRYZ_{i,t-2}$	-8.02[a]	-2.51[a]	-0.10[a]	-0.07[a]
$DRYZ_{i,t-3}$	0.20	-1.13[a]	-0.02	-0.10[a]
$DRYZ_{i,t-4}$	-0.48	-0.45[c]	0.06[a]	-0.04[b]
$WETZ_{i,t-1}$	6.74[a]	1.22[a]	-0.02[a]	-0.10[a]
$WETZ_{i,t-2}$	0.86	1.16[a]	0.02[b]	0.05[a]
$WETZ_{i,t-3}$	-3.61[a]	-1.29[a]	-0.08[a]	-0.08[a]
$WETZ_{i,t-4}$	0.69	0.54[a]	-0.03[a]	-0.06[a]
County Fixed-Effects	Yes	Yes	Yes	Yes
R^2	0.83	0.69	0.07	0.06
N	7,385	7,385	7,385	7,385

[a] *p<0.01*, [b] *p<0.05*, [c] *p<0.1*

Table S10. Models for **Alfalfa**'s Seasonal Weather Outcomes.

Regressors	*GD*	*SD*	*DRYZ*	*WETZ*
Trend	0.18[c]	-0.03[c]	0.002[b]	0.02[a]
$GD_{i,t-1}$	0.67[a]	0.04[a]	0.0001	-0.0002
$GD_{i,t-2}$	0.08[a]	0.003	-0.001[a]	0.001[a]
$GD_{i,t-3}$	0.05[a]	-0.01	0.0005[a]	-0.0001
$GD_{i,t-4}$	0.03[b]	-0.01[a]	-0.0001	0.0001
$SD_{i,t-1}$	0.17[a]	0.38[a]	0.004[a]	-0.01[a]
$SD_{i,t-2}$	-0.11	0.07[a]	0.001	-0.001
$SD_{i,t-3}$	0.36[a]	0.05[a]	-0.002[a]	-0.001
$SD_{i,t-4}$	-0.23[a]	0.11[a]	-0.001	0.003[a]
$DRYZ_{i,t-1}$	-5.93[a]	-1.88[a]	0.08[a]	-0.07[a]
$DRYZ_{i,t-2}$	-8.87	-2.48[a]	-0.10[a]	-0.07[a]
$DRYZ_{i,t-3}$	0.11	-1.12[a]	-0.02	-0.10[a]
$DRYZ_{i,t-4}$	-0.68[a]	-0.44[c]	0.06[a]	-0.05[b]
$WETZ_{i,t-1}$	7.62[a]	1.21[a]	-0.02[a]	-0.10[a]
$WETZ_{i,t-2}$	0.81	1.13[a]	0.01[c]	0.05[a]
$WETZ_{i,t-3}$	-3.76[a]	-1.26[a]	-0.08[a]	-0.08[a]
$WETZ_{i,t-4}$	0.60	0.50[a]	-0.03[a]	-0.06[a]
County Fixed-Effects	Yes	Yes	Yes	Yes
R^2	0.84	0.69	0.06	0.06
N	7,465	7,465	7,465	7,465

[a] *p<0.01*, [b] *p<0.05*, [c] *p<0.1*

Table S11. Model for predicting Palmer Z

Variable	Estimate	Variance Inflation Factor
Intercept	2.65[a]	0
$\tilde{P}$	2.91[a]	4.5
$\tilde{P}^2$	-0.11[a]	3.0
$\tilde{P}\tilde{T}$	-0.31[a]	3.4
Z_{t-1}	0.18[a]	1.1
Z_{t-2}	0.10[a]	1.2
Z_{t-3}	0.06[a]	1.2
Z_{t-4}	0.03[a]	1.2
Z_{t-5}	0.04[a]	1.2
Z_{t-6}	0.04[a]	1.1
$T \cdot 1_{JAN}$	-0.01[a]	1.3
$T \cdot 1_{FEB}$	-0.01[a]	1.4
$T \cdot 1_{MAR}$	-0.05[a]	1.7
$T \cdot 1_{APR}$	-0.07[a]	2.3
$T \cdot 1_{MAY}$	-0.08[a]	2.5
$T \cdot 1_{JUN}$	-0.09[a]	2.3
$T \cdot 1_{JUL}$	-0.06[a]	2.1
$T \cdot 1_{AUG}$	-0.05[a]	2.1
$T \cdot 1_{SEP}$	-0.05[a]	2.3
$T \cdot 1_{OCT}$	-0.04[a]	2.1
$T \cdot 1_{NOV}$	-0.03[a]	1.6
Climate-divisions Fixed Effects	Yes	
R^2	0.912	
N	26,460	

[a] *$p<0.01$*, [b] *$p<0.05$*, [c] *$p<0.1$*

Dakota climate projections for 2031-’55 relative to 1981-2005: Monthly and annual mean-shifts

Table S12. Monthly changes in temperature (averaged over the Dakotas): Historical realizations during 1981-2005 vs. Projected (31-day M.A.) weather during 2031-’55.

Month	^{o}C (1981-2005)	^{o}C (2031-2055)	Change (^{o}C)
April	5.7	8.2	2.5
May	11.1	13.8	2.7
June	15.3	17.9	2.6
July	18.0	20.8	2.8
August	17.3	20.9	3.6
Annual (Average)	13.5	16.3	2.8

Notes: Daily temperature projections were calculated by superimposing a daily mean-shift operator on the temperatures recorded from weather stations on the same date 50 years before. The 31-day moving average mean-shift operator for a particular date was the average of daily temperature changes (obtained from climate models) for that date and for each date within the 15-days before and after that date.

Table S13. Monthly changes in precipitation (averaged over the Dakotas): Historical realizations during 1981-2005 vs. Projected (31-day M.A.) weather during 2031-’55.

Month	Hundreds of mm (1981-2005)	Hundreds of mm (2031-2055)	%Change
April	44.8	34.0	-24
May	70.9	48.0	-32
June	85.7	55.0	-36
July	74.3	48.5	-34
August	53.8	33.8	-37
Annual (Total)	329.5	219.3	-33

Notes: Daily precipitation projections were calculated by superimposing a daily mean-shift operator on the precipitation recorded from weather stations on the same date 50 years before. The 31-day moving average mean-shift operator for a particular date was the average of daily temperature changes (obtained from climate models) for that date and for each date within the 15-days before and after that date.

Table S14. Projected average change in growing-season weather (averaged over the Dakotas): Historical realizations during 1981-2005 vs. Projected (31-day moving average) weather during 2031-'55.

Crop	Variable	1981-2005 (Realized)	2031-2055 (Projected)	% Change
NORTH DAKOTA				
MAIZE	*GD*	908.3	1,106.6	21.8
	SD	15.8	43.5	175.3
	DRYZ	0.8	7.7	862.5
	WETZ	1.6	0.03	-98.0
SOY	*GD*	1,005.7	1,212.6	20.6
	SD	6.8	24.0	253.9
	DRYZ	0.6	7.7	1,275.0
	WETZ	2.0	0.03	-98.2
SPRING WHEAT	*GD*	696.4	846.3	21.5
	SD	19.1	44.5	133.0
	DRYZ	0.8	7.70	862.5
	WETZ	1.6	0.04	-97.5
ALFALFA	*GD*	726.7	912.4	25.6
	SD	3.8	13.6	257.9
	DRYZ	0.8	7.73	866.2
	WETZ	1.6	0.04	-97.5
SOUTH DAKOTA				
MAIZE	*GD*	1,084.5	1,268.3	17.0
	SD	39.4	90.5	130.0
	DRYZ	0.6	7.9	1,174.2
	WETZ	1.4	0.03	-97.7
SOY	*GD*	1,188.8	1,378.2	15.9
	SD	20.0	56.7	183.5
	DRYZ	0.5	7.9	1,310.7
	WETZ	1.3	0.03	-97.6
SPRING WHEAT	*GD*	818.8	949.4	16.0
	SD	45.0	86.0	91.1
	DRYZ	0.7	7.24	934.3
	WETZ	1.7	0.14	-91.8
ALFALFA	*GD*	894.6	1,064.6	19.0
	SD	12.7	35.0	175.6
	DRYZ	0.4	7.2	1,700.0
	WETZ	1.3	0.14	-89.2

Notes: Median climate model outputs are used to represent weather projections during 2031-'55.

Table S15. Projected average change in decomposed *SD*s: 1981-2005 vs. 2031-’55.

Crop	**Variable**	**1981-2005 (Realized)**	**2031-2055 (Projected)**	**% Change**
MAIZE	SD^{1}	1.9	1.6	-15.8
	SD^{23}	6.7	6.6	-1.5
	SD^{4+}	21.1	42.6	101.9
SOY	SD^{1}	1.1	1.5	36.4
	SD^{23}	3.2	5.6	75.0
	SD^{4+}	6.2	22.6	264.5
SPRING WHEAT	SD^{1}	1.5	1.4	-6.7
	SD^{23}	5.9	5.8	-1.7
	SD^{4+}	34.7	42.5	22.5
ALFALFA	SD^{1}	1.4	1.1	-21.4
	SD^{23}	5.3	4.0	-24.5
	SD^{4+}	29.1	12.6	-56.7

Notes: Median climate model outputs are used to represent weather projections during 2031-’55.

Table S16. The yields-weather regression model. Dependent Variable: Yields (bushels/acre)

	Maize		**Soybeans**		**Spring Wheat**		**Alfalfa**	
Variable	I	II	I	II	I	II	I	II
Intercept	23.414[a]	23.622[a]	24.091[a]	23.616[a]	25.424[a]	25.673[a]	25.051[a]	24.987[a]
t	0.746[a]	0.756[a]	0.198[a]	0.199[a]	0.655[a]	0.664[a]	-0.074	-0.079
$t65$	1.117[a]	1.101[a]	0.419[a]	0.417[a]	-0.224[a]	-0.242[a]	1.450[a]	1.452[a]
$t80$	-0.956[a]	-0.949[a]	-0.305[a]	-0.295[a]	-0.330[a]	-0.319[a]	-1.215[a]	-1.213[a]
$t95$	1.626[a]	1.614[a]	0.299[a]	0.274[a]	0.769[a]	0.761[a]	0.420[a]	0.430[a]
GD	0.006[a]	0.005[a]	0.003[a]	0.002[a]	0.003[a]	0.002[a]	0.004[a]	0.005[a]
t x GD	0.0003[a]	0.0003[a]	0.00002[b]	0.00001	0.0001[a]	0.0001[a]	0.0002[a]	0.0002[a]
SD	-0.163[a]		-0.069[a]		-0.058[a]		-0.104[a]	
t x SD	-0.006[a]		-0.001[a]		0.0005[a]		0.0001	
SD^{1}		-0.086		0.183[a]		0.038		-0.316[a]
t x SD^{1}		-0.002		0.008[a]		0.001		-0.003
SD^{23}		-0.255[c]		-0.248[a]		0.033		-0.297[b]
t x SD^{23}		-0.016[b]		-0.005		-0.002		0.014[b]
SD^{4+}		-2.072[a]		-0.452[a]		-1.538[a]		-2.677[a]
t x SD^{4+}		-0.072[a]		-0.008[a]		-0.013[a]		-0.002
$DRYZ$	-3.781[a]	-3.795[a]	-1.402[a]	-1.413[a]	-2.011[a]	-2.002[a]	-5.151[a]	-5.134[a]
t x $DRYZ$	-0.124[a]	-0.124[a]	-0.013[b]	-0.012[b]	-0.036[a]	-0.036[a]	-0.080[a]	-0.078[a]
$DRYZ$ x SD	0.026[a]	0.026[a]	0.009[a]	0.010[a]	0.005[a]	0.005[a]	0.015[a]	0.016[a]
$WETZ$	-0.272[b]	-0.277[b]	-0.026	-0.018	-0.313[a]	-0.316[a]	1.981[a]	1.975[a]
t x $WETZ$	-0.049[a]	-0.049[a]	-0.010[a]	-0.010[a]	-0.016[a]	-0.015[a]	-0.017[a]	-0.017[a]
$WETZ$ x SD	0.022[a]	0.021[a]	0.023[a]	0.023[a]	-0.001	-0.001	0.011[a]	0.010[a]
Q_i^{dry} x SD	0.00002	-0.0001	0.002	0.001	0.0003	0.0003	0.0001	-0.0001
Q_i^{dry} x $DRYZ$	-0.049[b]	-0.049[b]	0.008	0.007	-0.010	-0.009	-0.075[a]	-0.076[a]
Q_i^{wet} x $WETZ$	-0.010	-0.010	-0.008[c]	-0.008[c]	-0.033[a]	-0.033[a]	-0.022[c]	-0.021[c]
County F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.821	0.821	0.805	0.807	0.751	0.752	0.739	0.740
N	7,062		3,118		7,291		6,342	

[a] *p<0.01,* [b] *p<0.05,* [c] *p<0.1*

Note 1: Models I and II in the case of each crop represent, respectively, estimation results with composite *SD*s and decomposed *SD*s.

Note 2: For regression coefficients to be comparable across crop-types, we converted alfalfa yields from tons/acre to bushels/acres @ 1 ton = 37 bushels, available here.

Note 3: Crop prices, usually available at state-level or at higher aggregation, are not included in the commonly implemented yield-weather model. While crop acreage is generally more responsive to price, much of yield response to price arises from induced innovation with some time lag (Hayami and Ruttan 1971, pp. 59-61). Agricultural input use does respond to crop prices, potentially impacting yields, but the yield-price relationship may depend on other factors making it hard to estimate with much confidence. For example, a crop's price increase can lead to acreage expansion onto less suitable land. Furthermore, intensification of a crop within a rotation may lead to a loss in rotation benefits, such as loss of nitrogen carryover when the soy-maize rotation shifts to soy-maize-maize due to higher maize prices.

Table S17. Yield-weather model: Comparison of the heteroscedasticity-robust standard errors (1st row) and spatial autocorrelation-corrected standard errors (2nd row).

	MAIZE	SOYBEAN	SPRING WHEAT	ALFALFA
Variable	**Estimate**	**Estimate**	**Estimate**	**Estimate**
t	0.831 (0.072)[a] (0.091)[a]	0.209 (0.037)[a] (0.031)[a]	0.654 (0.026)[a] (0.036)[a]	-0.064 (0.065) (0.124)
t65	1.081 (0.116)[a] (0.159)[a]	0.385 (0.058)[a] (0.064)[a]	-0.230 (0.041)[a] (0.056)[a]	1.463 (0.113)[a] (0.166)[a]
t80	-0.858 (0.105)[a] (0.242)[a]	-0.230 (0.048)[a] (0.070)[a]	-0.292 (0.038)[a] (0.050)[a]	-1.322 (0.116)[a] (0.152)[a]
t95	1.370 (0.104)[a] (0.160)[a]	0.133 (0.043)[a] (0.066)[a]	0.654 (0.039)[a] (0.069)[a]	0.565 (0.105)[a] (0.156)[a]
GD	0.0026 (0.0009)[a] (0.0017)[c]	0.002 (0.0003)[a] (0.0003)[a]	0.002 (0.0005)[a] (0.0009)[a]	0.004 (0.001)[a] (0.002)[a]
t x *GD*	0.0002 (0.00003)[a] (0.00008)[a]	-0.000001 (0.00001) (0.00001)	0.00002 (0.00002) (0.00005)	0.0002 (0.00004)[a] (0.00014)[c]
SD	-0.148 (0.012)[a] (0.026)[a]	-0.065 (0.011)[a] (0.014)[a]	-0.055 (0.003)[a] (0.006)[a]	-0.106 (0.009)[a] (0.013)[a]
t x *SD*	-0.005 (0.0004)[a] (0.001)[a]	-0.0014 (0.0004)[a] (0.0005)[a]	-0.0002 (0.0001)[c] (0.0003)	0.00003 (0.0003) (0.001)
DRYZ	-3.637 (0.161)[a] (0.277)[a]	-1.351 (0.079)[a] (0.098)[a]	-2.015 (0.058)[a] (0.084)[a]	-5.384 (0.163)[a] (0.259)[a]
t x *DRYZ*	-0.120 (0.010)[a] (0.019)[a]	-0.006 (0.0054) (0.0051)	-0.031 (0.004)[a] (0.005)[a]	-0.091 (0.009)[a] (0.015)[a]

DRYZ x *SD*	0.026 (0.003)[a] (0.004)[a]	0.010 (0.003)[a] (0.002)[a]	0.004 (0.001)[a] (0.001)[a]	0.017 (0.002)[a] (0.004)[a]
WETZ	-0.078 (0.114) (0.160)	0.012 (0.056) (0.038)	-0.292 (0.041)[a] (0.064)[a]	2.112 (0.106)[a] (0.193)[a]
t x *WETZ*	-0.034 (0.005)[a] (0.007)[a]	-0.009 (0.002)[a] (0.002)[a]	-0.015 (0.002)[a] (0.003)[a]	-0.018 (0.005)[a] (0.008)[a]
WETZ x *SD*	0.024 (0.004)[a] (0.004)[a]	0.028 (0.004)[a] (0.004)[a]	-0.0008 (0.0010) (0.0013)	0.013 (0.003)[a] (0.003)[a]
Q_i^{dry} x *SD*	0.0002 (0.001) (0.003)	0.002 (0.0010)[c] (0.0009)[a]	-0.0003 (0.0003) (0.001)	0.0001 (0.001) (0.002)
Q_i^{dry} x *DRYZ*	-0.059 (0.021)[a] (0.023)[a]	0.003 (0.009) (0.009)	-0.010 (0.007) (0.009)	-0.094 (0.026)[a] (0.044)[a]
Q_i^{wet} x *WETZ*	-0.010 (0.012) (0.015)	-0.006 (0.004) (0.005)	-0.034 (0.005)[a] (0.007)[a]	-0.021 (0.012)[c] (0.025)
County F.E.	Yes	Yes	Yes	Yes
R^2	0.761	0.758	0. 6728	0.555
N	6935	2911	7067	6123

[a] *p<0.01,* [b] *p<0.05,* [c] *p<0.1*

Notes: As in Conley's (1999) procedure, the intercept is excluded while estimating the above models.

Decadal summaries of weather variables

Table S18. Decadal means of monthly (April-August) weather outcomes is defined in eq. (S1-S2).

Variable	1950-'60	1961-'70	1971-'80	1981-'90	1991-'00	2001-'10
MAIZE						
GD	787.35	965.65	1,014.24	1,025.29	1,019.39	973.13
SD	24.70	32.44	39.15	37.47	20.27	28.93
DRYZ	0.65	0.37	1.05	1.14	0.19	0.81
WETZ	0.83	1.63	0.82	0.76	2.43	1.49
SOYBEANS						
GD	1,094.79	1,178.12	1,194.64	1,109.21	1,092.12	987.46
SD	16.05	15.32	18.38	15.21	6.33	8.32
DRYZ	0.43	0.26	1.11	1.08	0.08	0.50
WETZ	0.68	1.63	0.76	0.73	2.28	1.74
SPRING WHEAT						
GD	595.15	727.66	767.87	778.83	748.36	715.90
SD	33.77	43.54	53.91	52.63	29.21	39.98
DRYZ	0.72	0.26	1.07	1.38	0.16	0.79
WETZ	0.58	1.68	0.92	1.05	2.45	1.26
ALFALFA						
GD	629.36	773.23	784.41	762.82	783.07	773.17
SD	33.77	43.54	44.84	35.22	29.06	42.91
DRYZ	0.72	0.26	0.95	1.64	0.13	0.78
WETZ	0.58	1.68	1.10	0.76	2.06	1.40

Seasonally-differentiated weather effects on crop yields

Table S19. Within-season weather Impacts: Maize and Soybeans.

Growing Season: May-August	**MAIZE**	**SOYBEAN**
Variable	**Estimate**	**Estimate**
Intercept	24.732[a]	23.099[a]
t	0.757[a]	0.179[a]
t65	1.084[a]	0.459[a]
t80	-0.899[a]	-0.337[a]
t95	1.671[a]	0.340[a]
GD_MAY_JUN	0.018[a]	0.008[a]
t x *GD_MAY_JUN*	0.001[a]	0.0005[a]
GD_JUL_AUG	-0.005[b]	-0.001
t x *GD_JUL_AUG*	-0.0005[a]	-0.0004[a]
SD_MAY_JUN	0.198[a]	0.097[b]
t x *SD_MAY_JUN*	0.010[a]	0.005[a]
SD_JUL_AUG	-0.200[a]	-0.092[a]
t x *SD_JUL_AUG*	-0.009[a]	-0.003[a]
DRYZ_MAY_JUN	-2.345[a]	-0.852[a]
t x *DRYZ_MAY_JUN*	-0.125[a]	0.032[a]
DRYZ x *SD_MAY_JUN*	0.029[c]	0.010
DRYZ_JUL_AUG	-5.891[a]	-2.032[a]
t x *DRYZ_JUL_AUG*	-0.126[a]	-0.042[a]
DRYZ x *SD_JUL_AUG*	0.031[a]	0.012[a]
WETZ_MAY_JUN	-0.435[b]	-0.447[a]
t x *WETZ_MAY_JUN*	-0.045[a]	-0.009[b]
WETZ x *SD_MAY_JUN*	0.050	0.031
WETZ_JUL_AUG	0.297	0.431[a]
t x *WETZ_JUL_AUG*	-0.046[a]	-0.014[a]
WETZ x *SD_JUL_AUG*	0.060[a]	0.064[a]
Q_i^{dry} x *SD*	-0.0003	0.001
Q_i^{dry} x *DRYZ*	-0.036[c]	0.004
Q_i^{wet} x *WETZ*	-0.015	-0.008[b]
County F.E.	Yes	Yes
$\mathbf{R^2}$	0.831	0.822
N	7,062	3,118

[a] *p<0.01,* [b] *p<0.05,* [c] *p<0.1*

Table S20. Seasonal Weather Impacts: Spring Wheat and Alfalfa.

Growing Season: April-July	**SPRING WHEAT**	**ALFALFA**
Variable	**Estimate**	**Estimate**
Intercept	26.654[a]	27.047[a]
t	0.702[a]	0.003
t65	-0.338[a]	1.246[a]
t80	-0.213[a]	-0.969[a]
t95	0.757[a]	0.316[a]
GD_APR_MAY	0.021[a]	0.006
t x *GD_APR_MAY*	0.000002	-0.000002
GD_JUN_JUL	-0.008[a]	0.004[c]
t x *GD_JUN_JUL*	0.00008[c]	0.0002[b]
SD_APR_MAY	0.052[a]	-0.198[a]
t x *SD_APR_MAY*	0.011[a]	0.016[a]
SD_JUN_JUL	-0.062[a]	-0.096[a]
t x *SD_JUN_JUL*	-0.001[a]	-0.001[a]
DRYZ_APR_MAY	-1.360[a]	-3.534[a]
t x *DRYZ_APR_MAY*	-0.016[b]	-0.066[a]
DRYZ x *SD_APR_MAY*	-0.035[a]	0.044[c]
DRYZ_JUN_JUL	-2.478[a]	-5.950[a]
t x *DRYZ_JUN_JUL*	-0.030[a]	-0.064[a]
DRYZ x *SD_JUN_JUL*	0.007[a]	0.019[a]
WETZ_APR_MAY	0.022	2.555[a]
t x *WETZ_APR_MAY*	-0.013[a]	-0.043[a]
WETZ x *SD_APR_MAY*	-0.006	0.086[b]
WETZ_JUN_JUL	-0.435[a]	1.519[a]
t x *WETZ_JUN_JUL*	-0.014[a]	0.006
WETZ x *SD_JUN_JUL*	-0.002	0.010[a]
Q_i^{dry} x *SD*	-0.0003	-0.0003
Q_i^{dry} x *DRYZ*	-0.004	-0.064[b]
Q_i^{wet} x *WETZ*	-0.033[a]	-0.022[c]
County F.E.	Yes	Yes
R^2	0.769	0.743
N	7,291	6,342

[a] *$p<0.01$*, [b] *$p<0.05$*, [c] *$p<0.1$*

Table S21. Instrumental variable regressions for government payments

Regressors	Crop Insurance Subsidy			Disaster	Farm
	Maize	Soybeans	Wheat	Payments	Subsidies
Intercept	4.27[a]	-22.24[a]	10.96[a]	0.96	15.21[a]
Trends				0.16[a]	
Maize Price	0.79[a]				
Soy Price		0.39[a]			
Wheat Price			0.37[a]		
Average Price				-0.03	-0.21[a]
GD	-0.001[c]	-0.001	-0.0002	-0.006[a]	
SD	0.02[a]	0.11	0.002	0.04[a]	
DRYZ	0.14	-0.66	0.24[a]	4.89[a]	
WETZ	0.95[a]	1.56[a]	0.28[a]	3.01[a]	
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.71	0.80	0.84	0.11	0.60
N	2,346	2,344	2,375	2,320	2,346

[a] *p<0.01,* [b] *p<0.05,* [c] *p<0.1*

Notes:

1. The 'Average Price' variable above equals the unweighted mean of each year's price of maize, soybean and wheat.
2. Farm subsidies, i.e., variable $G_{farm\ subsidy}$, include Direct and Counter-Cyclical Payments, Average Crop Revenue Election Program, production flexibility contracts, market loss assistance, Loan Deficiency Payments (LDP), commodity certificates, LDP like-grazing payments, marketing loan gains, dairy program, livestock indemnity, agricultural trade adjustment assistance, hard winter wheat incentive program, and miscellaneous subsidies.

Table S22: Weak instrument tests corresponding to IV regression for land use shares estimation (see eq. (4) in the main text).

Endogenous Variable	F-statistic (1st stage IV regression)
$G^{c}_{ins.subsidy}$	34.78
$G^{s}_{ins.subsidy}$	63.66
$G^{w}_{ins.subsidy}$	81.14
$G_{dis\text{-}pay}$	0.92
$G_{farm\ subsidy}$	23.16

Table S23. Tests for over-identifying assumptions for land use share regressions.

Share Equation	$\boldsymbol{R^2}$	$\boldsymbol{N}$	$\boldsymbol{N.R^2}$	$\boldsymbol{Q}$	***p*-value**	**Inference**
Eastern Dakota Counties						
Maize	0.12	616	73.9	73	0.448	Fail to reject the null
Soybeans	0.13	616	80.1	73	0.269	Fail to reject the null
Spring Wheat	0.30	616	20.9	73	<0.0001	Reject the null
Alfalfa	0.12	616	73.9	73	0.445	Fail to reject the null
Western Dakota Counties						
Maize	0.10	780	78	79	0.323	Fail to reject the null
Spring Wheat	0.18	780	140.4	79	0.0003	Reject the null
Alfalfa	0.03	780	23.4	79	1.000	Fail to reject the null

Table S24. Block-bootstrapped yield-weather estimation with standard errors in parentheses

	Maize	Soybeans	Spring Wheat	Alfalfa
Variable				
Intercept	23.044[a] (2.902)	23.955[a] (1.496)	25.699[a] (0.989)	24.826[a] (2.717)
t	0.731[a] (0.083)	0.194[a] (0.045)	0.659[a] (0.029)	-0.104 (0.072)
t65	1.166[a] (0.133)	0.423[a] (0.071)	-0.237[a] (0.047)	1.468[a] (0.126)
t80	-1.051[a] (0.118)	-0.300[a] (0.056)	-0.332[a] (0.042)	-1.247[a] (0.127)
t95	1.653[a] (0.106)	0.293[a] (0.046)	0.768[a] (0.039)	0.459[a] (0.106)
GD	0.005[a] (0.001)	0.003[a] (0.0004)	0.003[a] (0.0005)	0.004[a] (0.001)
t x *GD*	0.0003[a] (0.00004)	0.00002[b] (0.00001)	0.00008[a] (0.00002)	0.0002[a] (0.00005)
SD	-0.152[a] (0.013)	-0.065[a] (0.014)	-0.058[a] (0.004)	-0.101[a] (0.010)
t x *SD*	-0.006[a] (0.0005)	-0.0009[a] (0.0004)	0.0006[a] (0.0001)	-0.0001 (0.003)
DRYZ	-3.683[a] (0.178)	-1.384[a] (0.092)	-2.005[a] (0.062)	-5.174[a] (0.172)
t x *DRYZ*	-0.120[a] (0.010)	-0.010[b] (0.006)	-0.034[a] (0.004)	-0.078[a] (0.010)
DRYZ x *SD*	0.025[a] (0.003)	0.009[a] (0.003)	0.005[a] (0.0008)	0.016[a] (0.002)
WETZ	-0.225[b] (0.128)	-0.032 (0.067)	-0.283[a] (0.044)	1.974[a] (0.113)
t x *WETZ*	-0.048[a] (0.006)	-0.010[a] (0.003)	-0.016[a] (0.002)	-0.016[a] (0.005)
WETZ x *SD*	0.022[a] (0.044)	0.022[a] (0.006)	-0.0002 (0.001)	0.011[a] (0.003)
Q_i^{dry} x *SD*	0.0002 (0.002)	0.001 (0.001)	0.0003 (0.0004)	-0.0003 (0.001)
Q_i^{dry} x *DRYZ*	-0.048[b] (0.023)	0.010 (0.010)	-0.011 (0.008)	-0.075[a] (0.027)
Q_i^{wet} x *WETZ*	-0.014 (0.013)	-0.010[a] (0.005)	-0.033[a] (0.005)	-0.026[a] (0.013)
County F.E.	Yes	Yes	Yes	Yes

[a] *p<0.01,* [b] *p<0.05,* [c] *p<0.1*

Table S25. Block bootstrapped IV regressions for government payments with standard errors in parentheses.

	Crop Insurance Subsidy			Disaster	Farm
	Maize	Soybeans	Wheat	Payments	Subsidies
Intercept	5.72[a]	-18.33[a]	11.426[a]	7.954[a]	15.229[a]
	(0.490)	(1.819)	(0.279)	(3.497)	(0.205)
Trends				-0.049	
				(0.075)	
Maize Price	0.76[a]				
	(0.025)				
Soy Price		0.343[a]			
		(0.042)			
Wheat Price			0.358[a]		
			(0.011)		
Average Price				-0.039	-0.215[a]
				(0.190)	(0.010)
GD	-0.0005[c]	-0.001	0.0001	-0.006[a]	
	(0.0003)	(0.0009)	(0.0003)	(0.002)	
SD	0.015[a]	0.096[a]	-0.001	0.079[b]	
	(0.006)	(0.039)	(0.003)	(0.041)	
DRYZ	-0.173	-1.926[a]	0.138[b]	2.967[a]	
	(0.133)	(0.534)	(0.080)	(0.911)	
WETZ	0.597[a]	0.618[b]	0.108[a]	1.160[b]	
	(0.072)	(0.354)	(0.054)	(0.698)	
County F.E.	Yes	Yes	Yes	Yes	Yes

[a] $p<0.01$, [b] $p<0.05$, [c] $p<0.10$

Notes:

1. The coefficients of *SD* and *DRYZ* for soybean subsidy (blue color) have the same sign as compared to when using the actual data (Table S21) but are statistically significant now.
2. The sign and statistical significance of the intercept and the time-trends coefficients in the disaster payments model (red color), have reversed when compared to those using actual data (Table S21).

Table S26. Block bootstrap estimates of the marginal effects of the change in exogenous variables on land use shares for the eastern portion of the Dakotas *including* soybean shares. Standard errors are reported in parentheses.

	Maize	**Soybeans**	**Spring Wheat**	**Alfalfa**	**Grass**
	Estimate	Estimate	Estimate	Estimate	Estimate
π^{c}	0.00009	0.00013	-0.00008	-0.00004	-0.0001
	(0.0006)	(0.00009)	(0.00005)	(0.00002)	(0.0001)
π^{s}	0.0002	-0.002[a]	-0.002[a]	0.0003[a]	0.003[a]
	(0.0002)	(0.0002)	(0.0001)	(0.00007)	(0.0003)
π^{w}	-0.0004[a]	0.0012[a]	0.0014[a]	-0.0004[a]	-0.0015[a]
	(0.0001)	(0.0002)	(0.0001)	(0.00006)	(0.0003)
π^{a}	0.0007[a]	0.0009[a]	0.0003[b]	-0.0001	-0.0015[a]
	(0.0001)	(0.0002)	(0.0001)	(0.00006)	(0.0003)
π^{cow}	0.0004[b]	0.0014[a]	0.001[a]	-0.001[a]	-0.001[b]
	(0.0003)	(0.0004)	(0.0003)	(0.0001)	(0.0006)
π^{fallow}	0.0013[b]	-0.0006	0.0005	0.001[a]	-0.002[b]
	(0.0005)	(0.0008)	(0.0005)	(0.0002)	(0.001)
π^{CRP}	-0.0013[b]	0.0010	-0.0003	0.0006[b]	-0.0001
	(0.0007)	(0.0011)	(0.0007)	(0.0003)	(0.001)
$G^{c}_{ins.subsidy}$	0.085[a]	0.018[b]	-0.026[a]	-0.003	-0.063[a]
	(0.005)	(0.008)	(0.0004)	(0.002)	(0.010)
$G^{s}_{ins.subsidy}$	-0.007	0.068[a]	0.014[b]	0.007[a]	-0.072[a]
	(0.007)	(0.010)	(0.007)	(0.003)	(0.015)
$G^{w}_{ins.subsidy}$	-0.051[a]	-0.046[a]	0.041[a]	-0.008[a]	0.056[a]
	(0.004)	(0.006)	(0.004)	(0.002)	(0.008)
$G_{dis\text{-}pay}$	-0.004[b]	-0.007[b]	-0.005[a]	0.003[a]	0.012[a]
	(0.002)	(0.003)	(0.002)	(0.0008)	(0.004)
$G_{farm\ subsidy}$	-0.034[a]	-0.038[a]	-0.015[a]	-0.005[b]	0.081[a]
	(0.005)	(0.007)	(0.004)	(0.001)	(0.009)
$Q_{\%LCC\leq 2}$	0.194 [a]	0.304[a]	0.007	-0.026[a]	-0.416[a]
	(0.034)	(0.048)	(0.029)	(0.013)	(0.066)

[a] *p<0.01,* [b] *p<0.05,* [c] *p<0.10*

Notes: The coefficient estimates in red color are statistically insignificant under block bootstrap estimation while they were significant when using the actual data. On the other hand, the coefficient estimates in blue color are statistically significant coefficients under block bootstrap estimation while they were insignificant when using the actual data (see Table 4 in the main text).

Table S27. Block bootstrap estimates of the marginal effects of the change in exogenous variables on land use shares for the western portion of the Dakotas *excluding* soybean shares. Standard errors are reported in parentheses.

	Maize	Spring Wheat	Alfalfa	Grass
Variable	Estimate	Estimate	Estimate	Estimate
π^{c}	0.00006[a]	-0.0002[a]	-0.00005	0.0002[a]
	(0.00001)	(0.00007)	(0.00004)	(0.00007)
π^{w}	-0.00005[a]	-0.0003[b]	0.00001	0.0003[a]
	(0.00002)	(0.0001)	(0.00005)	(0.0001)
π^{a}	0.00007	0.0005[a]	-0.000002	-0.0005[a]
	(0.00003)	(0.0002)	(0.00008)	(0.0002)
π^{cow}	0.0002[a]	0.002[a]	-0.0005[b]	-0.0012[a]
	(0.00004)	(0.0002)	(0.0001)	(0.0002)
π^{fallow}	0.0003[a]	0.003[a]	0.0014[a]	-0.004[a]
	(0.00007)	(0.0004)	(0.0002)	(0.0004)
π^{CRP}	-0.0005[a]	-0.003[a]	-0.0004	0.004[a]
	(0.0001)	(0.0006)	(0.0003)	(0.0006)
$G^{c}_{ins.subsidy}$	0.014[a]	-0.0009	0.007[a]	-0.018[a]
	(0.0004)	(0.002)	(0.001)	(0.002)
$G^{w}_{ins.subsidy}$	-0.001	0.065[a]	-0.002	-0.06[a]
	(0.0009)	(0.005)	(0.002)	(0.005)
$G_{dis\text{-}pay}$	-0.0007[a]	-0.001	0.002[a]	0.0002
	(0.0002)	(0.001)	(0.0005)	(0.001)
$G_{farm\ subsidy}$	-0.015[a]	-0.053[a]	-0.009[a]	0.065[a]
	(0.0007)	(0.004)	(0.002)	(0.004)
$Q_{\%LCC\leq 2}$	0.037[b]	0.321[a]	0.001	-0.320[a]
	(0.003)	(0.023)	(0.011)	(0.023)

[a] *p<0.01,* [b] *p<0.05,* [c] *p<0.10*

Notes: The coefficient estimates in red color are statistically insignificant under block bootstrap estimation while they were significant when using the actual data. On the other hand, the coefficient estimates in blue color are statistically significant coefficients under block bootstrap estimation while they were insignificant when using the actual data (see Table 5 in the main text).

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