Evidence of climate change impacts on crop comparative advantage and land use

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Abstract

Relative agricultural productivity shocks emerging from climate change will alter regional cropland use. Land allocations are sensitive to crop profits that in turn depend on yield effects induced by changes in climate and technology. We develop and apply an integrated framework to assess the impact of climate change on agricultural productivity and land use for the U.S. Northern Great Plains. Crop-specific yield-weather models reveal crop comparative advantage due to differential yield impacts of weather across the region's major crops, i.e., alfalfa, wheat, soybeans and maize. We define crop profits as a function of the weather-driven yields, which are then used to model land use allocation decisions. This ultimately allows us to simulate the impact of climate change under the RCP4.5 emissions scenario on land allocated to the region's major crops as well as to grass/pasture. Upon removing the trends effects in yields, climate change is projected to lower yields by 33%-64% over 2031-'55 relative to 1981-2005, with soybean being the least and alfalfa the most affected crops. Yield projections applied to the land use model at present-day input costs and output prices reveals that Dakotas' grass acreage will increase by up to 23%, displacing croplands. Wheat acreage is expected to increase by up to 54% in select south-eastern counties of North Dakota and South Dakota, where maize/soy acreage had increased by up to 58% during 1995-2016.

1 Introduction

Private cropland use allocations are impacted by multiple factors, including weather, soils, farming technology, local infrastructure, market price of outputs and inputs, and agri-environmental policy. Among these factors, soils and weather are location-specific natural endowments that determine the land's overall productivity. Unlike soils, weather varies year-to-year and is ex-ante unknown to farmers deciding upon their land use allocations.

Each crop's optimal heat and moisture demand during the growing-season is driven by its distinct phenology. As such the productivity impacts of climate change might be disproportionately stronger for some crops. Such differential productivity impacts might encourage landowners to reallocate acres to crops that are likely to fare better under a changed climate, potentially leading to regional land use change. Cropland reallocations in a region will likely be driven by changes in net returns or profits from individual crops. Per-acre crop profitability depends on the climate-dependent crop yields as well as crop prices and production costs (crop profit = *price* x *yield* – *cost*). To shed light on how climate change may impact land use change through differential impact on crop productivity, we specify an econometric model of past land use decisions that combines weather, crop yields, profits and land use data. In the process, we evaluate impacts of the past and future annual growing-season weather on crop-specific yields to infer about intra-region cropland allocation decisions.

Past economic analyses have utilized spatio-temporal weather variations to study national and global climate change impacts on farmland values, agricultural profits and crop yields. United States farmland values have been modelled as a function of growing-season temperature and precipitation (Mendelsohn et al. 1994; Schlenker et al. 2005, 2006). While the land value predictions were found to be sensitive to model specification, more robust predictions were reported when farm profits were used as the dependent variable (Deschênes and Greenstone 2007). Land values are closely related to farm productivity and crop prices. However, they may also be impacted by macroeconomic factors such as inflation or interest rates, or by idiosyncrasies such as fads and overreactions (Falk and Lee 1998).

Crop yield models have garnered much attention in assessing the agricultural impacts of climate change. Maize, an input-intensive crop, the world's largest by weight, and produced in regions with deep statistical records, is also the most extensively researched commodity for evaluating the impacts of climate change. A 2009 countrywide study of U.S. county-level yields of maize, soybean and cotton during 1950-2005 revealed non-linear temperature impacts on crop yields (Schlenker and Roberts 2009). Typically, marginally higher temperatures enhance yields up to a threshold, beyond which heat generated from higher temperatures is detrimental to yields (Thompson 1975). Similar findings were reported by Cabas et al. (2010) for maize, soybean and winter wheat yields for Ontario, Canada during 1981-2006.

This literature has since advanced to account for spatial adaptation to warming in maize (Butler and Huybers 2013), the effect of CO_2 fertilization on yields (Attanavich and McCarl 2014), adoption of genetically-engineered maize and soybean seeds (Xu et al. 2013, Lusk et al. 2018, Ortiz-Bobea and Tack 2018), impacts of extreme weather events on maize and soybean yields (Massetti and Mendelsohn 2016), and the impact of warming on yield variance (risk) leading to higher insurance premiums and subsidy projections by 2100 (Tack et al. 2018). Field-trials of U.S. wheat varieties have revealed that newer seed varieties exhibit less resistance to yield reduction from extreme spring-time temperatures (Tack et al. 2014, 2015). Liang et al. (2017) inferred that the negative climate effects would outweigh the net technological gains in U.S. agriculture to decrease its total factor productivity (TFP) to 1980-levels before the year

2050. Ortiz-Bobea et al. (2018) found that the agricultural TFP of the Midwestern United States region has become more sensitive to hotter temperatures since the 1980s.

Flexible yield-weather models that estimate the long-run adaptability of cropping systems (Moore and Lobell 2014; Liu et al. 2016; Davenport et al. 2018) have found yields to be less sensitive to warming in colder regions, e.g., for maize in the north-western portion of the U.S. Corn Belt (Butler and Huybers 2013) and for wheat in Europe (Liu et al. 2016). So, relocating cropping to less central latitudes would be a viable adaptation response to the detrimental yield impacts of global warming. Several studies have also modelled cropland use change as a function of weather, crop and livestock returns, and government payments (Kaminski et al. 2013; Mu et al. 2013; Rashford et al. 2016; Cho and McCarl 2017; Mu et al. 2017; Mu et al. 2018).

Kaminski et al. (2013) estimated a structural model to assess climate impacts on Israel's cropland use changes during 1992-2001. The authors specified a parametric crop production technology and estimated its parameters as a function of weather. The resulting weather-driven yields provided crop-specific profit expectations, which were then utilized to estimate cropland use shares as a function of own-profits. Mu et al. (2013) and Mu et al. (2018) estimated reduced-form models of U.S. crop and pasture land allocation as a non-linear function of weather during 1987-2007 and 1982-2012 respectively. Rashford et al. (2016) and Cho and McCarl (2017) estimated similar land use models for multiple crops during 1982-'97 and 1970-2010 respectively. Mu et al. (2017) developed a two-stage quinquennial land use model for crop and livestock production in the U.S. counties during 1978-2012. They first estimate crop and livestock returns as a function of inter-annual weather variations. These predicted returns were then used to model land use shares along with 30-year-averages of precipitation and degree-days.

Building on the existing literature, our paper seeks to contribute to understanding linkages between climate change and agriculture. Specifically, we posit intra-regional land use switching among crop and non-crop uses as an adaptation strategy to differential crop productivity impacts of annual weather fluctuations when total cultivable acreage is fixed. A two-step modeling framework is developed where the inter-crop differences in the effect of weather on yields and profits drive land use share decisions. Our approach is quite close to that in Kaminski et al. (2013). That paper estimated the parameters of a presumed crop technology as a function of weather while we first estimate a reduced-form crop-specific yield-weather relationship. A major difference is our emphasis on incorporating the differential crop yield impacts of weather fluctuations. Moreover, we include both own- and cross-crop profits in land use share regressions, where the authors only used own-crop profits to estimate cropland use shares.

Although Mu et al. (2017) also implemented a two-step procedure to estimate land use decisions their approach differs considerably from ours. The authors estimated land use shares as a function of the farmers' expected weather (30-year averages) and expected land use returns. The expected land use returns were estimated in the prior step using *actual* weather fluctuations during each year's growing-season. However, these inter-seasonal weather outcomes are unknown to the farmers at the start of the growing season while making land use decisions. Instead, we construct crop profits as a function of *expected* yields that are dependent on the weather information available to farmers at the time of each year's planting date. These expected profits then drive land allocation decisions. Our approach explicitly accounts for how weather affects land use changes through differentiated productivity impacts across crop-types.

The article proceeds by outlining the underlying methodology, followed by a description of our study region. We then present the estimation results and conclude with a brief discussion.

2 Methods

2.1 Overview

Figure 1 provides an outline of this study's underlying integrated conceptual framework. The first step is a set of yield-weather regressions for all major crops in a region. Yields are the dependent variable while weather, soils and annual productivity trends are controls. We also control for policy shocks and include several innovations to the existing yield-weather models. Specifically, we introduce differentiated impacts of the single-day and consecutive heat events, as well as trend-weather and soil-weather interactions. The trend-weather interaction terms will evaluate how the impact of weather stressors on yields has evolved over time, while the soil-weather interactions will account for how deficient soils affect the yield impacts of detrimental weather. Kaminski et al. (2013) also used the soil-weather interactions to estimate a structural land use model. In addition to these innovations in the yield-weather model we estimate the unit-less yield-weather elasticities to compare the impact of weather outcomes across crop-types.

In the second step, we combine crop-specific weather-driven yield predictions with price and cost information to calculate crop profits, which are then included as independent variables in regional cropland allocation models. The advantage of our two-stage specification is that it links land use decisions to how weather generates productivity shocks for individual crops as informed by the yield-weather model. Our modelling strategy differs from earlier studies by explicitly articulating the pathway through which weather impacts land use change.

Finally, we employ downscaled regional weather predictions from multiple global climate models to provide future yield and land use forecasts. We apply our integrated model to study county-level land use changes in the non-irrigated agroecosystems of the U.S. Northern Great Plains. This region has been experiencing dramatic land use changes in recent years in terms of grassland losses and cropland expansion due to changes in economic and climate conditions.

2.2 Yield-weather model

We estimate the following yield-weather model with crop-specific yields, $Y_{i,t}$, in county *i* and year *t* as dependent variables:

$$\begin{aligned} Y_{i,t} &= \beta_0 + \sum_{n\in\Omega} \beta_1^n D_n \times (t - n) + \beta_W W_{i,t} + \beta_{WETSD} WETZ_{i,t} \times SD_{i,t} \\ &+ \beta_{DRYSD} DRYZ_{i,t} \times SD_{i,t} + \beta_{Qd} Q_i^{dry} \times W_{i,t} + \beta_{Qw} Q_i^{wet} \times W_{i,t} + \beta_{tW} t \times W_{i,t} + \sum_i \nu_i c_i + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

Equation (1), hereafter eq. (1), is estimated separately for each crop-type, i.e., maize, soybean, spring wheat and alfalfa. Here the indicator variable D_n, defined as $D_n = 1$ whenever $t \geq n$ and $D_n = 0$ otherwise, is interacted with *t* to specify a continuous, linear spline. Knots, n, at point set $\Omega = \{1965, 1980, 1995\}$ capture potential shifts in yield trends every fifteen years due to better technology, improved land management, and exogenous policy change. We ruled out decadal knots in favor of a fifteen-year knot set based on degrees-of-freedom adjusted goodness-of-fit (F-test). The fifteen-year knots have appeal because the expansion in use of artificial fertilizer ceased circa 1980, the era of genetically modified maize and soybean commenced in 1996 and policy inhibitions to land use change were removed with the implementation of 1996 Freedom-to-Farm Act (Gardner 2002, Ch. 2, pp. 22-26). Quantities Q_i^{dry} and Q_i^{wet} are soil deficiency variables that represent dry/shallow soils and wet/poor-drainage soils, respectively. The soil deficiency information is appended as "subclass" to the commonly used Land Capability Classification (LCC) provided by National Resource Inventory. The LCC system ranks soils in categories 1-8 in the ascending order of their intrinsic limitations and required management costs for agricultural production. Variable c_i represents county-level fixed effects.

Vector $W_{i,t} = \{GD_{i,t}, SD_{i,t}, DRYZ_{i,t}, WETZ_{i,t}\}$ captures a concave yield response to weather outcomes: heat stress and moisture deficiency. We aggregate daily minimum and maximum temperatures from weather stations into threshold-based seasonal heat exposure variables using a min-max interpolation[1]. The beneficial degrees are summed over the growing-season to obtain growing degree-days (*GD*s) while harmful degrees are summed into stress degree-days (*SD*s) (*SI*, eq. S1). A two-step strategy is utilized to identify *GD* and *SD* thresholds for each crop. A step-function is estimated by regressing crop yields on each 1-degree Celsius bin having controlled for quadratic trends and precipitation (*SI*, Figure S2-S5), as also implemented by Schlenker and Roberts (2009). This initial guide to the thresholds is then refined using regression loops with intent to maximize the fit of the 'full' model in eq. (1).

Palmer's Z index, denoted as *Z* hereafter, accounts for evapotranspiration, soil's water storage capacity, and precipitation (Karl 1986). When compared with precipitation or a coarse precipitation-temperature interaction term, *Z* is more appropriate in capturing the impact of soil moisture availability for crop growth (Heim 2002). Monthly *Z* values are available for the U.S. climate divisions, where each climate division contains multiple counties and some counties overlap with multiple climate divisions. We calculate area-weighted county-level *Z* values and transform those to capture moisture stress from severe-to-extreme dryness ($Z \leq -2$, *DRYZ*) and severe-to-extreme wetness ($Z \geq 2.5$, *WETZ*) (*SI*, eq. S2). $WETZ \times SD$ and $DRYZ \times SD$ are included in eq. (1) to evaluate whether excessive (deficient) moisture conditions mitigate (aggravate) the detrimental yield impacts of *SD*s.

We incorporate several innovations to the commonly implemented yield-weather model (Thompson 1975; Schlenker and Roberts 2009; Butler and Huybers 2013; Xu et al. 2013). First, soil deficiency variables Q_i^{dry} and Q_i^{wet} (county *i* acreage of 'dry/shallow' and 'wet/poor

[1] The min-max interpolation method was adapted from Xu et al. (2013). Snyder (1985) proposed a sinusoidal interpolation method that was adapted by Schlenker and Roberts (2009) and D'Agostino and Schlenker (2016). A comparative analysis reveals that the outcomes of these two interpolation methods are similar and highly correlated (see SI, tables S1-S2 and Figure S1).

drainage' soils respectively) are interacted with $W_{i,t}$ to infer whether soil deficiencies aggravate the yield impacts of weather stressors. Q_i^{dry} and Q_i^{wet} are county-level variables; they provide a general inference on how soil quality impacts agricultural yields, but they do not vary by the crops grown on these soil types (see *SI* for details on soil data and relevant variables). Second, while stand-alone trends likely reflect temporal adaptations from the impact of newer technology or management practices on crop yields, we include trend-weather interactions to seek insights on how such innovations modified the yield impacts of weather stressors. To enable a direct interpretation of the interaction term coefficients we center variables at their respective means.

Third, differentiated yield impacts are estimated from isolated, single-day heat events and also from consecutive, two-or-more-day events. We disaggregate growing-season *SD*s into isolated or single-day events (SD^{1}), two-to-three-consecutive-days events (SD^{23}) and four-or-more-consecutive-days events (SD^{4+}). We normalize SD^{1}, SD^{23}, and SD^{4+} to allow a comparative analysis of coefficient estimates across these variables (see *SI*, eq. S3-S4 for details). In addition, we consider whether intra-season differences exist for weather impacts on yields by including weather outcomes separately for the 1st and 2nd halves of the growing season (see *SI* for details).

Finally, we evaluate yield-weather elasticities, i.e., percent change in crop yields due to a one percent increase in individual weather outcomes, to analyze the crop comparative advantage due to weather's differential yield impact across commodities. The main advantage of the elasticity measure is that it is normalized and is not affected by the specific units or scales of variables, and thus allow for meaningful comparisons of coefficients of weather indicators across crop-types.

2.3 Land use change estimation

A profit-maximizing land allocation occurs when the marginal returns from each unit acreage are equal across all land uses, including for crop and non-crop uses. Marginal crop returns depend upon yields that, in turn, depend upon weather and soils. Bad weather decreases crop yields, making the crop less profitable. Heterogeneous crop-specific yield impacts of weather will imply differential impacts on crop profits, causing higher acreage allocations to those crop-types that are comparatively better suited to changes in weather patterns.

Let the share of land allocated to use *u* in county *i* and year *t* be $s_{i,t}^{u}$, i.e., the ratio of *u*'s acreage to total county acreage. As is standard strategy for modelling land use shares (Wu et al. 2004; Rashford et al. 2011), we posit $s_{i,t}^{u} = f(X_{i,t};\beta^{u})$ where $X_{i,t} = \{(\pi_{i,t}^{u})_{u\in U},(G_{i,t}^{u})_{u\in U}\}$; $\pi_{i,t}^{u}$ and $G_{i,t}^{u}$ denote, respectively, per-acre profits and government payments received from use *u* for county *i* in year *t*. We express land use shares as multinomial logit functions that sum to one for all counties in each year while predicted shares lie between zero and one. That is,

$$s_{i,t}^{u}(X_{i,t};\beta^{u}) = \frac{\exp[\beta^{u}X_{i,t} + \varepsilon_{i,t}^{u}]}{\sum_{v\in U}\exp[\beta^{v}X_{i,t} + \varepsilon_{i,t}^{v}]};\ u,v\in U, \qquad (2)$$

where $s_{i,t}^{u}\in(0,1)\ \forall i,t$ represents the acreage share of land use category *u* and set U contains all distinct land use types. The system of equations in (2) is transformed into log-linear form by assigning a reference land use category *r*, normalizing with respect to this reference category, and then defining $\bar{\beta}^{u} \triangleq \beta^{u} - \beta^{r}$, $\bar{\varepsilon}_{i,t}^{u} \triangleq \varepsilon_{i,t}^{u} - \varepsilon_{i,t}^{r}$, and $U\setminus r \triangleq \bar{U}$ (*SI*, eq. S5-S7):

$$\log(s_{i,t}^{u}/s_{i,t}^{r}) = \bar{\beta}^{u}X_{i,t} + \bar{\varepsilon}_{i,t}^{u};\ u\in\bar{U}. \qquad (3)$$

Vector $X_{i,t}$ in eq. (3) comprises of per-acre crop profits and government payments. The per-acre crop profit is defined using predicted yields in eq. (1), i.e., $\pi_{i,t}^{u} = P_{t}^{u}Y_{i,t}^{u} - C_{t}^{u}$, meaning that the yield-weather response feeds into the land use model through weather-induced change in profit. P_{t}^{u} and C_{t}^{u} are, respectively, annual per-bushel crop price and per-acre production cost. The post-harvest prices and growing-season weather are not known at the time farmers make land use decisions. So we use annual crop futures prices as farmers' expectations of post-harvest prices and regional-level per-acre cost of production for each land use category. We provide a detailed description of output prices and production costs for our study region in a later section.

We control for the role of government payments in land use decisions by including insurance subsidy payments for each crop, disaster payments and other farming subsidies as covariates. Crop insurance helps mitigate crop failure risks, making it a relevant explanatory variable for land use in regions with limiting soils and variable weather. Land allocations are likely endogenous with government payments due to simultaneity between cropping decisions and choices that determine government payments. For example, a farmer's decision to buy crop insurance is tied to his crop-type and acreage allocation decisions, which are driven by the market prices of crops and respective inputs. As such we estimate a two-stage least squares (2SLS) land use shares model.

Step 1 implements a standard instrumental variable (IV) regression approach to estimate government payments that are otherwise likely to be endogenous with contemporary land use decisions (Feng et al. 2012). Specifically, government payments are modelled as a function of the following instruments: crop futures prices and farmers' subjective weather predictions ($\hat{W}^u_{i,t}$). Instruments are chosen such that they are correlated with the endogenous government payments but uncorrelated with the residual in land use regressions, conditional on the covariates. Futures prices and predicted weather are taken to be valid instruments because they capture expectations about post-harvest market-driven and weather-driven crop profitability, respectively. That is,

$$\hat{G}^u_{i,t} = \hat{\lambda}^u_0 + \hat{\lambda}^u_P P^u_t + \hat{\lambda}^u_{\hat{W}} \hat{W}^u_{i,t}, \qquad (4)$$

where $\hat{\lambda}^u_{\hat{W}} = [\hat{\lambda}^u_{GD}, \hat{\lambda}^u_{SD}, \hat{\lambda}^u_{DRYZ}, \hat{\lambda}^u_{WETZ}]$. Landowner expectation for each year's growing-season weather, $\hat{W}^u_{i,t}$, is modelled as an AR(4) process

$$\hat{W}^u_{i,t} = \hat{\phi}^u_o \mathbf{1} + \hat{\phi}^u_t t\mathbf{1} + \left[\sum_{l=1}^{4} \hat{\phi}^u_{W,l} \hat{W}^u_{i,t-l}\right]\mathbf{1}, \qquad (5)$$

where $\hat{\phi}^u_{W,l} = [\hat{\phi}^u_{GD,l}, \hat{\phi}^u_{SD,l}, \hat{\phi}^u_{DRYZ,l}, \hat{\phi}^u_{WETZ,l}]$, $\mathbf{1}' = [1,1,1,1]$ and $W_{i,t}$ is as defined earlier. We test for non-stationarity of weather variables to be sure that the eq. (5) least-squares predictors are meaningful. Eq. (S8-S9) and tables S3-S10 provide details on stationarity tests and estimation of $\hat{W}^u_{i,t}$. Although the AR(4) specification for predicting farmers' subjective weather expectation is somewhat arbitrary, we find the distribution of $\hat{W}^u_{i,t}$ to be similar for AR(3), AR(4) and AR(5) processes. Moreover, the prevalence of weather cycles (Schubert et al. 2004; Yang et al. 2007) makes the autoregressive specification appropriate for estimating farmers' weather expectations.

In step 2 we use the logit model to estimate the land use shares as a function of crop returns, including profits and predicted government payments from step 1, such that all major crops compete for fixed arable acreage in each county. Since common regressors may lead to contemporaneous correlation among residuals across the equations for different crops, we estimate land use shares using the seemingly-unrelated regressions (SUR) framework.

$$\log(s^u_{i,t} / s^r_{i,t}) = \sum_{v \in \bar{U}} \{\bar{\beta}^v_\pi \pi^v_{i,t} + \bar{\beta}^v_G \widehat{G}^v_{i,t}\} + \beta_{LCC} Q_{\%LCC \le 2,i};\ u, v \in \bar{U}. \qquad (6)$$

Note that eq. (6) is step 2 of the 2SLS model where the regressors are derived using predicted variables in eqs. (4) and (5), and the variable $Q_{\%LCC\le2}$, i.e., percent soils under the LCC categories 1 or 2. Apart from crop profits we control for grassland and other land use returns, i.e., the per-acre net returns from grazing, π^{cow}, per-acre rental returns from fallow lands, π^{fallow}, and per-acre returns from lands enrolled under the Conservation Reserve Program of US Department of Agriculture, π^{CRP}. Table 1 provides the definitions of covariates included in eq. (6).

Although model (6) links annual weather fluctuations with regional land use switches, some caveats remain. First, significant overlaps in crops' growing-seasons, similar weather requirements and highly correlated yield-trends post-1996 cause high multicollinearity among the crop profits as calculated using predicted yields. Second, crop rotations are not explicitly modelled. Rotations matter when studying responses to shocks (Hendricks et al. 2014; Kim and Moschini 2018) although their omission in county-level analysis is inevitable due to aggregation. Third, the crop-specific production costs data are spatially invariant, which is unrealistic. This is a tradeoff that comes with incorporating crop profits as a function of weather-induced yields. However, including county-level soil quality variable, $Q_{\%LCC\leq 2}$, in conjunction with spatially homogenous cost indicators would control for county-specific costs to some extent.

2.4 Simulating the climate change impacts on regional yields and land use

We consider climate change expectations under the Intergovernmental Panel on Climate Change's (IPCC) Representative Concentration Pathway (RCP) with 4.5 Watts/m^2 radiative forcing (650 ppm CO_2 concentration equivalent) in 2100, termed as RCP4.5 (IPCC 2014). The climate projections data were acquired from the 1/16th degree resolution grids of the Coupled Model Intercomparison Project Phase 5 (CMIP5) outputs in the General Circulation Models (GCM) archive, made available by the U.S. Geological Survey's Geo-Data Portal (GDP)[2]. Under the RCP4.5 scenario, global temperatures are likely to rise by [1.5^{o}C, 4.5^{o}C] by 2100 relative to 1850-1900 levels (IPCC 2014). We utilize daily weather projections from seven distinct climate models: CESM, CNRM, GFDL, GISS, HADGEM, IPSL and MIROC for the climate divisions during 2031-'55 relative to 1981-2005. The projections data were then matched to the counties contained in each climate division, and if a county overlapped with multiple climate divisions we

[2] Available at http://cida.usgs.gov/gdp/. Last accessed on 6/8/2019.

assigned an area-weighted average value for each weather outcome. Multiple model outputs are included because a definitive model has not emerged from the climate science literature, and variability in climate projections from different models can be significant (Burke et al. 2015).

To capture how future climate change will shift daily weather, we construct future weather projections by superimposing a change-vector, calculated from model-based daily climate projections data, onto historical station-level weather data. Daily climate projections data are not used directly because these are model-based simulations of interactions among physical systems of atmosphere, oceans, land, and ice, and are therefore non-random. Second, the non-random distribution of growing-season temperatures may differ across climate models.

To construct weather projections for 2031-'55 relative to 1981-2005, let $F_{k,y,m,d}$ represent the historical realizations of temperature/precipitation in climate division *k* on day *d* of month *m* in year *y*, and let $\tilde{F}_{k,y,m,d}$ be the model-based climate projections. Define $\Delta\tilde{F}_{k,y',y,m,d} = \tilde{F}_{k,y',m,d} -$ $\tilde{F}_{k,y,m,d}$ as the daily-shift in projected weather for every climate division *k* on the same dates except 50-years apart, i.e., $y' = y + 50$. A potential candidate for weather projections $F_{k,y',m,d}$ = $F_{k,y,m,d} + \Delta\tilde{F}_{k,y',y,m,d}$ leads to problematic outcomes, e.g., negative precipitation, which we mitigate by implementing 31-day moving average (MA) mean-shift operators. That is,

$$\text{a) } \Delta\tilde{F}^{MA(31)}_{k,y',y,m,d} = \frac{\sum_{\mu=-15}^{15} \Delta\tilde{F}_{k,y',y,m,d+\mu}}{31}; \qquad (7)$$
$$\text{b) } F^{MA(31)}_{i,t'} = F_{i,t} + \Delta\tilde{F}^{MA(31)}_{i,y',y,m,d}.$$

Recall that we utilize seven distinct sets of climate projections, and so eq. (7a-b) are evaluated for each projection set. To assess robustness, two other formulations of mean-shift operators are implemented, namely the monthly average and the annual growing-season (April-August) average (*SI*, eq. S10-S11). These alternative shift-operators provide similar inferences. We also project Z by modelling historical monthly Z values as a function of monthly weather variables (*SI*, eq. S12, Table S11). To compare historical (1981-2005) and projected (2031-'55) weather variables, we utilize the median value of the outputs from seven climate models, i.e., the fourth ranked observation among seven for every county on each day during 2031-'55.

Projected weather outcomes are utilized to predict individual crop yields during 2031-'55 relative to 1981-2005 conditional on soil quality and yield-trends. We multiply the historical weather variable's coefficient estimates in eq. (1) by weather projections, and use static trends at the 2005 level when comparing yields during 2031-'55 vs. 1981-2005. Static trends allow for consistent temporal yield comparisons because trend prediction to 2055 is speculative given the periodic technological breakthroughs that redefine crop agriculture. We estimate two types of errors in yield forecasts. The first is climate model uncertainty arising from yield predictions based on the seven climate model outputs. The other, called regression uncertainty, is out-of-sample forecast error when using the coefficient estimates of a historical regression. We follow Schlenker and Roberts (2009) and D'Agostino and Schlenker (2016) to compute bootstrapped errors (500 iterations) in yield forecasts by randomly excluding 10% years, re-estimating eq. (1), and calculating the difference between observed and predicted yields for the excluded years.

Finally, we feed our weather-conditioned yield forecasts into crop profit evaluations and then feed those profits into the land use shares regressions to arrive at the climate change effects on land use (see Figure 1). In addition, the weather projections are decomposed based on only-temperature (only-precipitation) change, holding precipitation (temperature) constant, which are followed by recalculating yield and land use projections, discussed hereafter.

3 Study Area

We implement our integrated model to study the role of changing weather patterns on land use transitions in two rain-fed cropping states of the U.S. Northern Great Plains: North Dakota (ND) and South Dakota (SD). The Dakotas exhibit substantial variability in soils and climate, and lie distant from any mountain or coastal effects. The five major regional land uses, i.e., maize, soy, spring wheat, alfalfa and grass, constitute more than 80% of the total county acreage for 111 out of 119 Dakota counties.[3] Soybeans were mostly cultivated in the eastern Dakotas (Figure 2a) and so there are no data for soybean yields in 65 (out of 119) counties, mainly lying west of the Missouri River. Figure 2b suggests that these states added the most maize and soybeans acreage during 1995-2016, up by 170% from 6.6 million acres to 17.7 million acres, which is a much greater change than over the entire Northern Great Plains (81%) or the United States (34%).

In addition, the eastern Dakotas are a part of the Prairie Pothole Region, at the Corn Belt's western margin, with soil and climatic limitations that have traditionally favored beef feeder cattle over crop production. Mixed-prairie grasslands provide valuable ecosystem services, e.g., wildlife habitat, pollination, carbon sequestration and less soil erosion (Gelfand et al. 2011; Otto et al. 2016). Increasingly, however, combined maize/soy acreage has displaced the area's grasses and small grains (Wright and Wimberly 2013; Lark et al. 2015; Wimberly et al. 2017).

We find that the regional yields fluctuate with weather conditions for all major crops. During our study period, the most prominent crop yield dips occurred during drought (1977, 1988, 2002, 2012) and flood (1979, 1993, 2006) years (*SI*, Figure S6). Growing- and stress-degree-days were calculated using the daily temperature data from 306 weather stations in ND and 397 stations in SD to estimate crop yields. All counties have at least one weather station. Variables *DRYZ* and *WETZ* were calculated using the monthly *Z*-values for the Dakotas' eighteen climate divisions

[3] Grass acres are calculated as county acreage less area under developed land, water, and cropland, including maize, soy, wheat, alfalfa, barley, dry beans, canola, oats, peas, rye, sorghum, sugarbeets and sunflower, acquired from USDA NASS Quickstat 2.0 portal.

(nine in each state). May-August (respectively, April-July) is designated as the growing-season for maize and soybeans (respectively, spring wheat and alfalfa).

In order to estimate the Dakotas' land use shares in eq. (2) we designated the major land use categories in set U, i.e., $u \in U \equiv \{m, s, w, a, g\}$, where m, s, w, a and g denote maize, soybeans, wheat, alfalfa and grass, respectively, and we have $s_{i,t}^{u} \in [0,1)$ and $s_{i,t}^{g} \in (0,1)\ \forall i, t$. Further, grass is designated as the reference land use category, i.e., $r = g$ and $\bar{U} = \{m, s, w, a\}$, to arrive at the modified land use shares equation model in eq. (6). The Great Plains have experienced extensive weather cycles in the past (Schubert et al. 2004; Yang et al. 2007) making the autoregressive specification in eq. (5) appropriate for estimating farmers' weather expectations.

To calculate per-acre crop profits, i.e., $\pi_{i,t}^{u}$, each crop's futures prices were used to represent the farmers' expectations of post-harvest prices. Specifically, we incorporate February (pre-planting) settlement prices of each year's December Futures contracts for maize (Chicago Board of Traders or CBOT), September contracts for spring wheat (Minneapolis Grain Exchange), and November contracts of soybeans (CBOT) (www.quandl.com). Where unavailable, as with alfalfa, we use contemporaneous local crop prices because we find these prices to be highly correlated with pre-planting futures prices for maize, soy and wheat in our study region (see *SI*, Figure S7). We acquire per-acre cost of production for maize, soybeans and spring wheat from the USDA Economic Research Service and per-acre cost for alfalfa from the FINBIN database hosted by the University of Minnesota. The grassland and other land use returns data, i.e., π^{cow}, π^{fallow} and π^{CRP}, were also acquired from the FINBIN database. The insurance subsidy payments for maize, soy and wheat; disaster payments, and other farming subsidies were acquired from the Environmental Working Group's Farm Subsidy Data (www.farm.ewg.org).

Yield-weather models were estimated for a longer time-window, i.e., 1950-2017, while the land use share models were estimated for the 1996-2016 period owing to the inavailability of government payments data for the Dakotas outside that timeframe. Missing acreage data for different crops across counties and years also meant missing yield values, which led to different observation numbers when estimating yields. Also, the land use shares were estimated in two sets: one including (east of the Missouri River) and one excluding soy shares (west of the River).

The National Climate Assessment of 2014 predicted that the Northern Great Plains will experience longer growing seasons and more frequent droughts/floods by 2050 relative to 1971-2000 (Shafer et al. 2014). Under the RCP4.5 scenario (IPCC 2014) this region's average annual temperature is projected to increase by 2.8^{o}C and annual total rainfall will be lower by 33% (down from 330 mm annually) between 1981-2005 and 2031-'55 (*SI*, tables S12-S15). The increased future temperatures would also lead to more negative Z values implying increased incidence of drought events (*SI*, eq. S12). Figure S8 shows that the distribution of the Dakotas' growing-season temperatures may differ across climate models (see *SI*).

4 Results

4.1 Evidence on yield-weather relationships for all crops

Table 2 presents the coefficient estimates for weather and soil-weather interaction terms in model (1) (see *SI*, Table S16 for full model). We find a consistent yield-temperature relationship for all four crops where the rate of decline in yields due to an additional SD is greater than the rate of increase in yields due to an additional GD. This is consistent with earlier findings for maize and soybean yields (Schlenker and Roberts 2009; Butler and Huybers 2013) which we now extend to wheat and alfalfa. We also find that heat stress from consecutive, multi-day events causes more damage to crop yields than that from isolated events (Table 2). Moreover, isolated heat events enhance yields for soybeans and spring wheat, similar to the toxicological concept called '*hormesis*' where low-doses of a toxic agent can stimulate growth.

DRYZ, or excess dryness, is found to be the most detrimental weather stressor for crop yields, as also reported earlier for maize and soybeans (Massetti and Mendelsohn 2016) and now extended to wheat and alfalfa. *WETZ*, or excess wetness, is harmful for spring wheat and maize yields but beneficial for alfalfa yields; however the effect is statistically insignificant for soybean yields. The non-decreasing *WETZ* impacts may be attributed to high water demand during the growing stages of alfalfa and soy plants. Furthermore, for all crops but spring wheat the adverse effect of excess moisture variable *WETZ* is mitigated by heat stress variable *SD*. $DRYZ \times SD$, which was included in symmetry with $WETZ \times SD$, also increases crop yields. Jointly these stressors impact yields less severely than the sum of their individual effects, where a failed crop might not be sensitive to further adverse weather. Soil-weather interaction terms indicate that dry/shallow (wet) soils aggravate the detrimental impacts of *DRYZ* (*WETZ*) on yields, although the effect is only weakly significant across crop-types (Table 2).

Marginal yield trends, representing year-on-year yield growth, were positive for all crops during 1950-2017, being strongest for maize and weakest for alfalfa yields (*SI*, Table S16). Spring wheat yields sustained very high growth trends commencing 1950 but were overtaken by maize yields circa 1970, where the development of hybrid maize seeds has supported strong yield growth since the 1930s (Griliches 1960; Olmstead and Rhode 2008). Interestingly, yield growth for all crops were dampened in the 1980s (*SI*, Figure S6) possibly due to the levelling-off of nitrogen fertilizer application rates by the early 1980s, where higher application rates had sustained high yield growth between 1950 and 1980. Maize yield trends improved after 1995, a phenomenon that may be due to more recent innovations in seed technology (Xu et al. 2013).

The trend-weather interaction terms reveal how weather's yield impacts evolved over time.

We find that the yield-enhancing effects of *GD*s have strengthened over time, while the adverse impacts of *DRYZ* have worsened (*SI*, Table S16). The improved yield impact of *GD*s might be attributed to seed technology innovations and early-season spring planting (Kucharik 2006, Choi et al. 2016) made possible by tillage practice and farm machinery advances. On the other hand, we find that the yield-reducing effects of excessive heat (*SD*s) have become more severe for maize and soybean and less severe for spring wheat over the years, while the interaction effect was statistically insignificant in the case of alfalfa. Our findings also suggest that the detrimental effects of *DRYZ* and *WETZ* have worsened over the years for all crop types. Urban et al. (2012) found higher mean temperatures to have increased maize yield variability in the Corn Belt region during 1980-2005. More recently, Ortiz-Bobea et al. (2018) reported that non-irrigated crop production in the U.S. had become more sensitive to summer temperatures between 1960 and 2004. By contrast, however, Yu and Babcock (2010) used only drought as a weather outcome in their yield-weather specification to conclude that maize yields had become more drought tolerant over time in the Central Corn Belt. We also find our model inferences to be unaffected upon controlling for spatial autocorrelation in errors (*SI*, Table S17).

Finally, we assess the impact of the individual innovations, i.e., soil-weather interactions, trend-weather interactions, and differentiated yield impacts of isolated and consecutive heat events, on the yield-weather model performance. We follow Schlenker and Roberts (2009) to estimate change in an out-of-sample root mean squared error (RMSE) due to each innovation from a baseline model where the trend-weather and soil-weather interaction terms are omitted from eq. (1). We randomly sample 58 out of 68 years for each county 500 times. We include each innovation, one at a time, into the baseline yield model and then compute the reduction in out-of-sample RMSE when compared to the baseline model. We find that upon including the trend-weather interaction terms in the yield-weather model for maize the RMSE reduction was ~3.83%. The Welch test (Welch 1947) confirmed this reduction to be statistically significant. The RMSE reduction due to the other two innovations was statistically insignificant. For soy, the RMSE reduction was 3.87% due to differentiated *SD*s, 1.57% due to trend-weather interactions and 1.43% due to soil-weather interactions, all statistically significant. The RMSE reduction was statistically insignificant due to all three innovations for spring wheat and alfalfa yields.

4.2 Crop Competitiveness and Land allocation among competing uses

Table 3 presents the estimated yield-weather elasticity, i.e., percentage change in yields due to a one percent change in corresponding weather variables when evaluated at variable means. Soybean yields were found to be the most responsive to a unit percentage increase in benevolent *GD*s (elasticity = 0.16), followed by maize (0.1), spring wheat (0.08) and alfalfa (0.05) during 1950-2017. Maize yields were the most responsive to the additional *SD*s (-0.08), followed by alfalfa (-0.07), spring wheat (-0.07) and soy (-0.04), while alfalfa yields were most responsive to the *DRYZ* (-0.06), followed by spring wheat (-0.05), maize (-0.04) and soybeans (-0.04).

To illustrate crop comparative advantage from elasticities, we note that decadal means of *GD*, *SD* and *DRYZ* experienced declining trends for all crops between 1971-'80 and 2001-'10. While *GD*s, *SD*s and *DRYZ* declined the most for soybeans (-17%, -55% and -55%, resp.) followed by spring wheat (-7%, -26% and -26%, resp.), maize (-4%, -26% and -23%, resp.), and alfalfa (-1%, -4% and -17%, resp.), *WETZ* increased the most for soy (129%), followed by maize (82%), spring wheat (37%) and alfalfa (27%) during this period (*SI*, Table S18). Overall, the weather changes over the period made soybeans less competitive as this crop is comparatively more sensitive to growing degrees and it experienced the largest decline in *GD*s.

The IV regressions for county-level government payments during 1996-2016 (*SI*, Table S21) reveal that higher crop prices are associated with lower per-acre non-insurance farm payments (including direct and counter-cyclical payments). However, higher crop prices can lead to higher insurance subsidy payments as the value of insured crop increases. *WETZ*s are positively associated with subsidy and disaster payments whereas *GD*, *SD* and *DRYZ* are weakly associated with government payments across crop-types. We expected that an increase in crop profits would induce higher acreage allocation to that crop and lower acreage allocation to its substitutes. However, crop rotations complicate such responses where maize is generally grown in sequence with soybeans and/or wheat. In the eastern counties (including soy shares), we find that higher maize profits enhance own acreage-share and reduce acreage for alfalfa and grass but also enhance acreage of soy and spring wheat (Table 4). Higher wheat profits imply more wheat and soy acres but fewer maize, alfalfa and grass acres. Higher alfalfa profits enhance share-allocation to all crops except for its own and grass shares. Also, corroborating earlier analysis (Feng et al. 2012), higher insurance subsidy payments were associated with higher crop acreage while disaster payments and farm subsidies were associated with lower crop acreage.[4]

We conducted a block bootstrap estimation of our sequential framework of multi-crop equations (yields, government payments and land use shares). Climate divisions were designated as spatial blocks and a total of 1,224 (18 climate divisions x 68 years) unique climate division-year pairs were resampled 500 times. The mean and standard deviation of the coefficients in our integrated framework were evaluated across the iterations. We found the bootstrapped estimates

[4] A weak instrument test failed to reject weak instruments for disaster payments implying that its coefficients might be biased and have large standard errors (*SI*, Table S22). However, the overall land use shares model specification was robust to including or excluding this variable. We also failed to reject the over-identifying restrictions for the spring wheat shares model, meaning that the excluded instruments might be correlated with regression errors and the model mis-specified with regards to those instruments (*SI*, Table S23).

to be quite similar to those reported in tables 2-5 (see *SI*, tables S24-S27 for details).

4.3 Impacts of Climate Change: Crop yield loss and land use change

To evaluate the implications of climate change we compare average yields from using projected and historical weather outcomes, holding trend yield fixed at 2005 (t = 56), in model (1). The fixed yield trends allow us to provide change estimates that avoid speculative assertions about future technological or policy innovations that could disrupt current yield growth trends. We find that soybean yields would decline by almost 33%, followed by maize (44%), spring wheat (50%) and alfalfa (64%) by the 2031-'55 period relative to 1981-2005 (Figure 3). The alternative yield-weather model specification with decomposed *SD*s provides similar yield-loss estimates for soybeans (31%), maize (40%) and spring wheat (47%), and a relatively smaller loss for alfalfa (50%) (*SI*, Figure S10)[5]. The projected Z values (*SI*, eq. S12, Table S14), as mentioned earlier, suggest extreme dry conditions in the future to be driving these yield reductions. Yield losses in the U.S. were previously reported to be 30%-82% for maize, soy and cotton by 2049 (Schlenker and Roberts 2009) and 40% for wheat under a 4^{o}C warming scenario (Tack et al. 2015).

To evaluate climate-driven land use impacts for the Dakotas we compare land use share estimates from projected and historical weather-induced crop returns, holding all else constant. Here we presume trends to continue until 2055 in eq. (1), i.e., t = 1 in 1950 and t = 106 in 2055 in order to inquire into whether the contemporary rate of yield growth trends would mitigate reduced net crop returns and acreage loss due to the climate-driven yield losses reported in Figure 3. Figure 4 shows that in the eastern Dakotas, which includes soy acres, grass acreage would increase by up to 23%, replacing maize, soybeans and alfalfa acres. Spring wheat acreage

[5] We restrict spring wheat and alfalfa yield forecasts to zero for years in which these are projected to assume a negative value.

is projected to increase by up to 54% in the south-eastern counties in the Dakotas, reversing the trend of increasing maize and soybean acres in the region during 1995-2016 (Figure 2b). High input costs for maize imply lower maize profits when compared with wheat, even though the projected climate change impact on maize yields is likely to be relatively less severe (*SI*, Figure S11). In the west, which excludes soy acres, grass acres are expected to replace crop acres where the expected acreage reduction is up to 22% for spring wheat, 18% for maize and 7% for alfalfa. As mentioned in Subsection 2.5 above, we evaluate the out-of-sample forecast error for the Dakotas' crop yields when using the coefficient estimates of a historical regression. The average out-of-sample forecast error is found to be 3.5 bushels/acre for soybeans, 4.8 bushels/acre for spring wheat, 12.5 bushels/acre for alfalfa and 15.8 bushels/acre for maize yields.

We also evaluate the climate change impacts on land use change from the alternative yield-weather model that includes decomposed *SD*s as regressors. Most projections are quite similar, except for alfalfa (resp. wheat) acres that are now projected to increase (resp. decrease) in the eastern Dakotas (*SI*, Figure S12). Overall climate change is likely to induce fewer cropland acres and more grass in the Dakotas, leading us to infer that negative climate effects on yields outweigh the present-day growth rate in yield trends. Bear in mind that our acreage projections are mediated solely through climate change and do not account for any future technological or policy interventions, or national/global adaptations of present-day production systems.

Climate change imposes combined heat and moisture effects on land use. We decompose the combined effects (Figure 4) into a temperature-only scenario holding precipitation constant (*SI*, Figure S13), and a precipitation-only scenario holding temperature constant (*SI*, Figure S14). While the implications of the temperature-only scenario are well in-line with the combined effects, the precipitation-only scenario provides contrasting projections including reduced grass acres in the eastern Dakotas and more maize/soy acres in the south-eastern counties of SD. Therefore, the combined land use change predictions seem to be driven mainly by temperature.

Our prediction that spring wheat acres will increase in some of the Dakotas' counties is in line with Rashford et al. (2016). However, Rashford et al. (2016) and Mu et al. (2017) also projected that climate change would lead to pastureland loss to cropping, which is in contrast with our projection that in future grass will increase in most counties. This divergence in predicting acreage may be, at least partially, due to our more articulated land use shares model. By contrast with these earlier studies we mediate climate effects on land use through non-linear yield-weather relationships.

5 Conclusion

Regional agriculture is vulnerable to adverse weather patterns, including more frequent heat events and less frequent rainfall events. One adaptation strategy is intra-region land use switching to sustain crop profitability. We assess the climate change impacts on regional crop yields and land use transitions. There exists a vast literature on the projected agricultural impacts of climate change. Our study has contributed to this literature by estimating crop comparative advantage due to climate change and how regional land use changes in response to the differential productivity impacts of climate change across different crop-types.

In the process we incorporate innovations to the existing yield-weather models that are shown to have economic as well as statistical significance in improving model performance. Specifically, we estimate the differentiated impact of the single-day and consecutive heat events; assess the evolution of yield tolerance to weather stressors over time; and evaluate whether deficient soils aggravate the yield losses caused by detrimental weather. In addition, we develop an autoregressive model for estimating the inter-annual weather expectations of farmers that are tied to the occurrence of weather cycles in the past.

We apply our framework to assess the climate change impacts on crop yields and land use change in the U.S. Northern Great Plains, where we consider all major land uses in the area, including grass. We have not sought to account for market implications of climate change because commodity prices are determined at the global level. While several findings emerge it is particularly encouraging that alfalfa yield estimates, a legume usually grown for forage, are largely consistent with those for row crops. This suggests promising possibilities for extending existing yield-weather model frameworks to studying non-row crop categories.

Our main conclusion is that climate change in our study region, while to the absolute disadvantage of all the main crops, will provide grass-based agriculture with a comparative advantage. Other effects fixed, climate change may reverse the observed cropland expansions of the recent past in this region. We do not suggest, however, that grasslands will become more productive in delivering agricultural or ecological outputs. Although the study's implications are specific to the region, our analysis demonstrates the importance of climate change in altering intra-region crop competitiveness, thereby resulting in changes in the region's agroecosystem.

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Figures

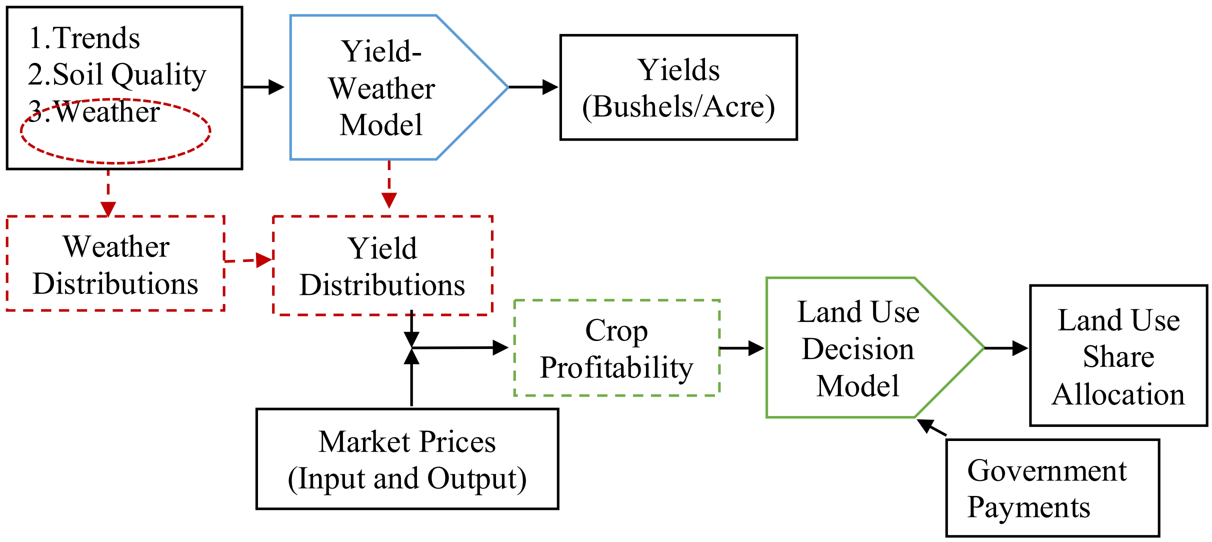

Figure 1. Conceptual framework to assess climate change impacts on regional crop yields and land use.

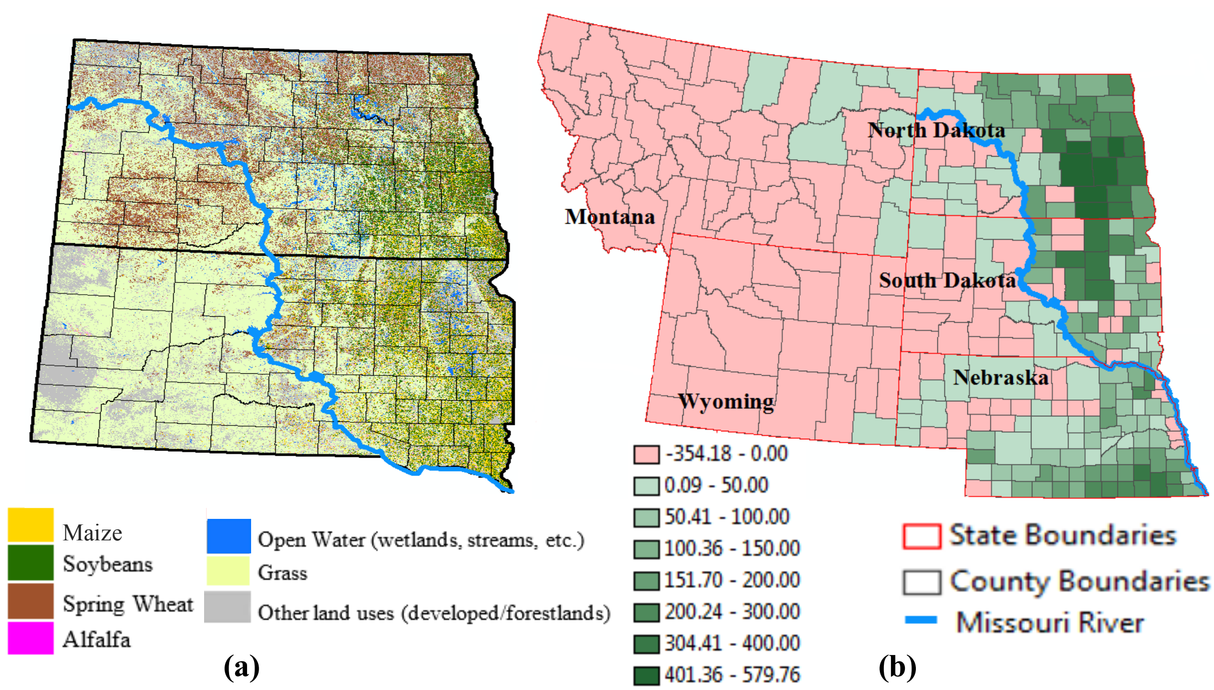

Figure 2. (a) 2006 Land Use in the Dakotas (Cropland Data Layer, USDA NASS). The color legend represents various land use types in the region. (b) Change in maize and soybeans acreage in the U.S. Northern Great Plains states between 1994-95 and 2015-16 (USDA NASS Quickstat 2.0). The ranges in the color legend represent the acreage change under maize/soy per thousand county acres.

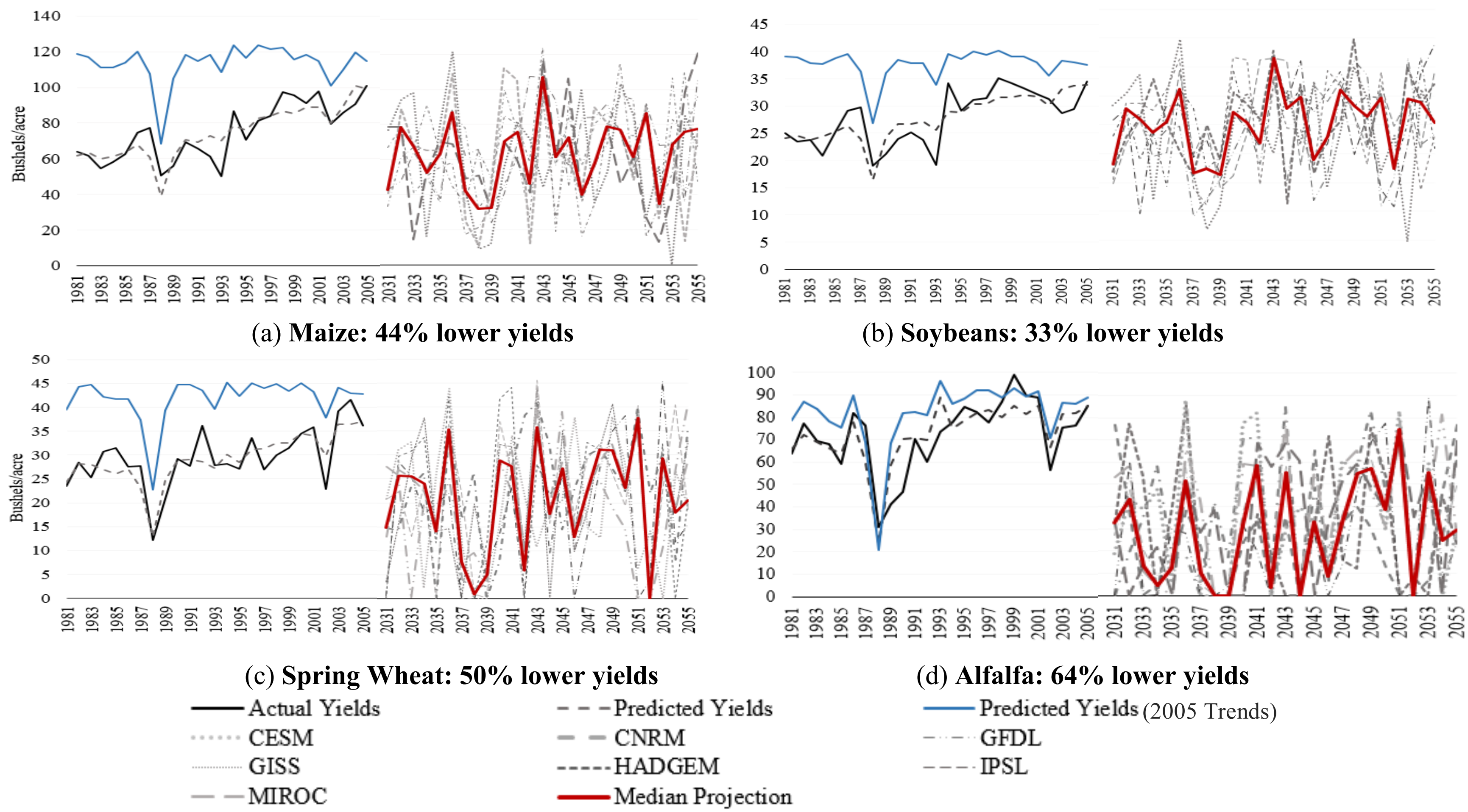

Figure 3. Historical (1981-2005) vs. Projected (2031-'55) Yields. Each year's crop yields in the above graphs are calculated as an average of all counties in North Dakota and South Dakota. Hashed representations of projected yields are from RCP4.5 emissions scenario from seven GCMs, namely CESM (Community Earth System Model), CNRM (Center National de Recherches Météorologiques (France)), GFDL (Geophysical Fluid Dynamics Laboratory), GISS (Goddard Institute of Space Studies), HADGEM (Hadley Global Environment Model), IPSL (Institut Pierre-Simon Laplace (France)) and MIROC (Model for Interdisciplinary Research on Climate). Median projection in a given year is calculated by taking the median yield value of the yield projections from each of seven climate model outputs in each county and then taking the average across counties. We restrict spring wheat and alfalfa yield forecasts to zero for years in which these are projected to be negative values.

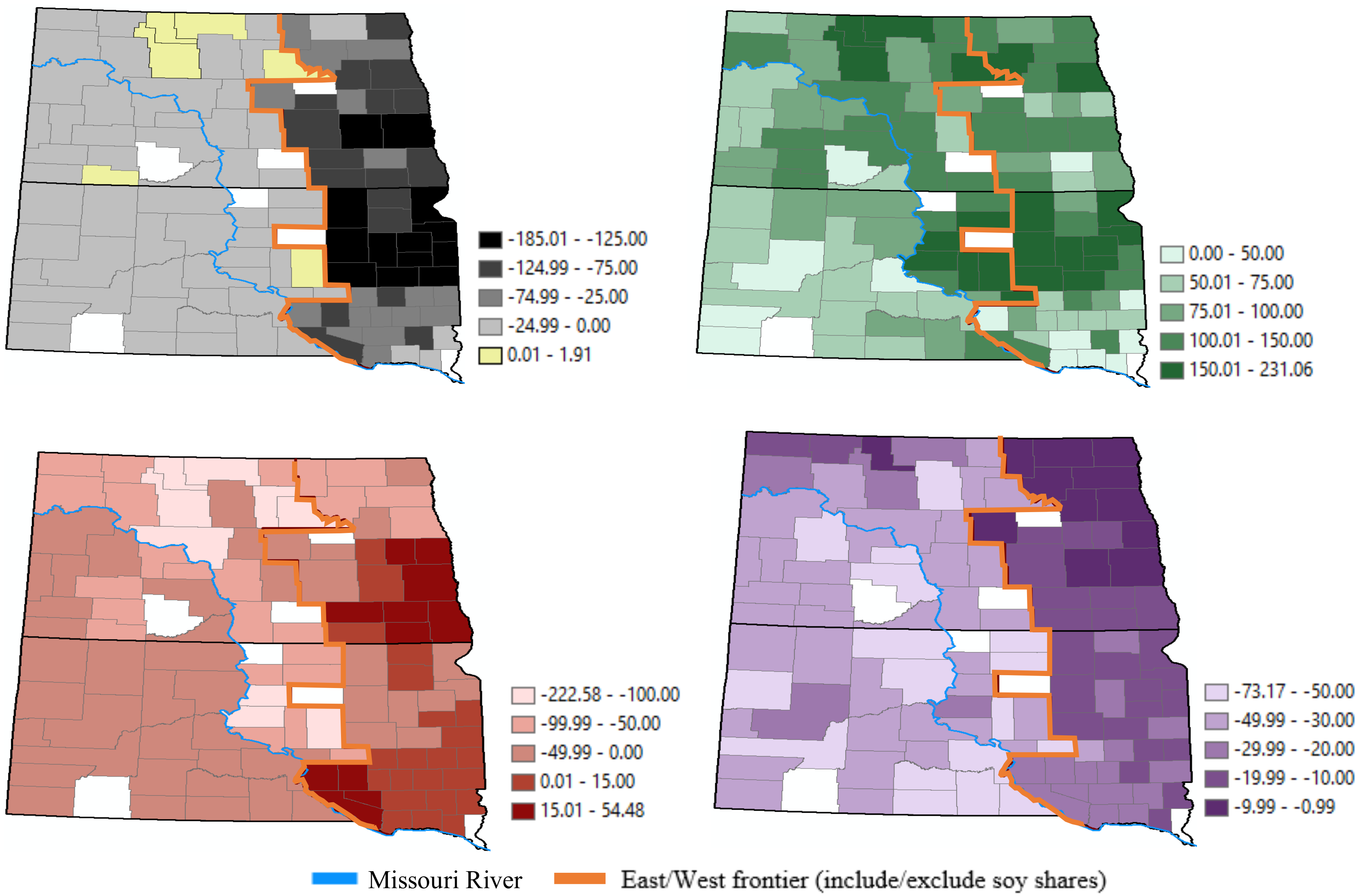

Figure 4. Climate-driven acreage changes by 2031-'55 relative 1981-2005. Land use change ranges in each panel are in acres per thousand county acres. The white colored counties represent missing yields for at least one crop in all years.

Tables

Table 1. Variable descriptions and summary statistics

Variable	Description	Mean	Std. Dev.
Variables used in the yield-weather model (1950-2017)			
Y^m	Maize yields (bushels per-acre).	61.9	39.4
Y^s	Soybean yields (bushels per-acre).	25.6	11.0
Y^w	Spring wheat yields (bushels per-acre).	25.4	12.0
Y^a	Alfalfa yields (tonnes per-acre).	1.8	0.8
GD^m	Growing degree-days for maize (April-July).	974.9	433.1
GD^s	Growing degree-days for soybeans (April-July).	1113.3	520.8
GD^w	Growing degree-days for spring wheat (May-August).	723.7	311.8
GD^a	Growing degree-days for alfalfa (May-August).	753.8	343.8
SD^m	Stress degree-days for maize (April-July).	30.1	39.5
SD^s	Stress degree-days for soybeans (April-July).	12.4	19.6
SD^w	Stress degree-days for spring wheat (May-August).	42.2	51.2
SD^a	Stress degree-days for alfalfa (May-August).	39.8	48.8
Q^{dry}	Percent land cover under dry/shallow soils.	8.9	7.4
Q^{wet}	Percent land cover under wet/poor-drainage soils.	6.2	7.9
Variables used in the 2-SLS land use shares model (1996-2016)			
s^m	Land use share for maize.	0.1	0.1
s^s	Land use share for soybeans.	0.1	0.1
s^w	Land use share for spring wheat.	0.08	0.09
s^a	Land use share for alfalfa.	0.04	0.03
s^g	Land use share for grass.	0.6	0.3
π^m	Maize profits ($ per-acre).	169.0	119.4
π^s	Soy profits ($ per-acre).	194.0	109.1
π^w	Spring wheat profits ($ per-acre).	117.3	83.4
π^a	Alfalfa profits ($ per-acre).	72.6	46.0
π^{cow}	Per-acre returns from cow-herd grazing ($).	72.5	27.0
π^{fallow}	Per-acre rental returns from fallow lands ($).	56.4	16.1
π^{CRP}	Per-acre rents received for conserving land under CRP ($).	10.7	7.0
$G^c_{ins.subsidy}$	Per-acre subsidy payment received for maize crop ($).	3.31	4.9
$G^s_{ins.subsidy}$	Per-acre subsidy payment received for soybean crop ($).	1.9	2.7
$G^w_{ins.subsidy}$	Per-acre subsidy payment received for wheat crop ($).	1.8	2.5
$G_{dis\text{-}pay}$	Per-acre disaster payments ($).	2.2	3.7
$G_{farm\ subsidy}$	Per-acre farm subsidy, e.g., counter-cyclical payments ($).	9.6	10.3
$Q_{\%LCC\leq 2}$	Percent land cover under soils of LCC category 1 or 2.	0.4	0.2

Notes:

1. The summary statistics are averaged across the 119 Dakota counties.
2. To define the variable π^{cow}, the per-cow returns from grazing were converted to per-acre returns by assuming that on-average each cow grazes on four acres (Wang 2015).

Table 2. The yields-weather regression model. Dependent Variable: Yields (bushels/acre)

	Maize		**Soybeans**		**Spring Wheat**		**Alfalfa**	
Variable	I	II	I	II	I	II	I	II
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]
SD	-0.163[a]		-0.069[a]		-0.058[a]		-0.104[a]	
SD^{1}		-0.086		0.183[a]		0.038		-0.316[a]
SD^{23}		-0.255[c]		-0.248[a]		0.033		-0.297[b]
SD^{4+}		-2.072[a]		-0.452[a]		-1.538[a]		-2.677[a]
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]
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]
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*

Notes
1. Models I and II represent estimation results with composite *SD*s and decomposed *SD*s respectively.
2. Decomposed *SD*s, i.e., SD^{1}, SD^{23}, and SD^{4+} represent isolated or single-day events, consecutive two-or-three-day events, and consecutive four-or-more-day's events, respectively.
3. 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.
4. Coefficient estimates for yield trends and trend-weather interaction terms were excluded from Table 2 to save space. See Table S16 in supplementary information for full results.
5. All models include county fixed effects which are not presented in the table.

Table 3. Yields-weather elasticities (Crop Competitiveness), with standard errors in parentheses.

Variable	Maize	Soybeans	Spring Wheat	Alfalfa
GD	0.10 [a]	0.16 [a]	0.08 [a]	0.05 [a]
	(0.015)	(0.016)	(0.013)	(0.016)
SD	-0.08 [a]	-0.04 [a]	-0.07 [a]	-0.07 [a]
	(0.006)	(0.007)	(0.004)	(0.006)
DRYZ	-0.04 [a]	-0.04 [a]	-0.05 [a]	-0.06 [a]
	(0.002)	(0.002)	(0.001)	(0.002)
WETZ	-0.01	-0.002	-0.02 [a]	0.05 [a]
	(0.003)	(0.003)	(0.002)	(0.002)

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

Notes: Yield-weather elasticity (percent yield changes due to a one percent change in weather variables) is unit-less and comparable across crops, and is evaluated at the mean value of the weather outcomes.

Table 4. Marginal effects of the change in exogenous variables on land use shares for the eastern portion of the Dakotas *including* soybean shares. Standard errors (in parentheses) are calculated using the Delta method (Greene 2008, Ch. 4).

	Maize	**Soybeans**	**Spring Wheat**	**Alfalfa**	**Grass**
	Estimate	Estimate	Estimate	Estimate	Estimate
π^{c}	0.00002	0.0003	0.0005[a]	-0.0002[a]	-0.0006[a]
	(0.0001)	(0.0002)	(0.0001)	(0.00004)	(0.0002)
π^{s}	0.0004[a]	-0.001[a]	-0.002[a]	0.0003[a]	0.002[a]
	(0.0001)	(0.0002)	(0.0001)	(0.00006)	(0.0003)
π^{w}	-0.0005[a]	0.0006[a]	0.0006[a]	-0.0002[a]	-0.0005[b]
	(0.0001)	(0.0002)	(0.0001)	(0.00005)	(0.0003)
π^{a}	0.0007[a]	0.0007[a]	0.0002[b]	-0.00006	-0.001[a]
	(0.0001)	(0.0002)	(0.0001)	(0.00006)	(0.0003)
π^{cow}	0.0004[b]	0.002[a]	0.001[a]	-0.001[a]	-0.002[a]
	(0.0002)	(0.0004)	(0.0002)	(0.0001)	(0.0004)
π^{fallow}	0.0005	0.0009	0.002[a]	0.001[a]	-0.004[a]
	(0.0004)	(0.0007)	(0.0005)	(0.0002)	(0.0009)
π^{CRP}	-0.001[b]	-0.001	0.0005	0.0002	0.002
	(0.0005)	(0.0009)	(0.0005)	(0.0002)	(0.001)
$G^{c}_{ins.subsidy}$	0.084[a]	0.004	-0.034[a]	-0.002	-0.045[a]
	(0.004)	(0.006)	(0.0004)	(0.002)	(0.008)
$G^{s}_{ins.subsidy}$	-0.025[a]	0.064[a]	0.022[a]	0.007[a]	-0.058[a]
	(0.006)	(0.010)	(0.006)	(0.002)	(0.012)
$G^{w}_{ins.subsidy}$	-0.047[a]	-0.049[a]	0.052[a]	-0.007[a]	0.044[a]
	(0.003)	(0.005)	(0.003)	(0.001)	(0.006)
$G_{dis\text{-}pay}$	-0.004[a]	0.002	-0.004[a]	0.0002	0.005[b]
	(0.001)	(0.002)	(0.001)	(0.0005)	(0.003)
$G_{farm\ subsidy}$	-0.024[a]	-0.017[a]	-0.019[a]	-0.003	0.055[a]
	(0.003)	(0.006)	(0.003)	(0.001)	(0.007)
$Q_{\%LCC\leq 2}$	0.177[a]	0.299[a]	-0.031	-0.036[a]	-0.355[a]
	(0.024)	(0.043)	(0.026)	(0.011)	(0.053)
R^2	0.843	0.574	0.803	0.922	n/a
N	646	646	646	646	646

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

Notes:

1. These marginal effects were calculated using the expression in eq. (S7). The respective regression estimates are available upon request.
2. The R^2 value for grass acres is not included here as it is the reference category in the land use share regression. The marginal effects for this land use category are functions of the coefficients of the system's other four crops' acreages (see *SI*, eq. (7ii).

Table 5. Marginal effects of the change in exogenous variables on land use shares for the western portion of the Dakotas, *excluding* soybean shares. Standard errors (in parentheses) are calculated using the Delta method (Greene 2008, Ch. 4).

	Maize	Spring Wheat	Alfalfa	Grass
Variable	**Estimate**	**Estimate**	**Estimate**	**Estimate**
π^c	0.00005[a] (0.00001)	-0.0003 [a] (0.00007)	-0.0001[a] (0.00003)	0.0004[a] (0.00007)
π^s	-0.0001[a] (0.00002)	-0.0002[b] (0.00009)	0.0001[a] (0.00004)	0.0002[b] (0.0001)
π^w	0.00001 (0.00003)	0.0008[a] (0.0001)	0.0002[a] (0.00006)	-0.0010 [a] (0.0002)
π^{cow}	0.0003[a] (0.00004)	0.001[a] (0.0002)	-0.0004[b] (0.00008)	-0.0012[a] (0.0002)
π^{fallow}	0.0005[a] (0.00007)	0.003[a] (0.0003)	0.001[a] (0.0002)	-0.004[a] (0.0003)
π^{CRP}	-0.0007[a] (0.00009)	-0.002[a] (0.0004)	-0.0003 (0.0002)	0.002[a] (0.0005)
$G^c_{ins.subsidy}$	0.012[a] (0.0004)	-0.002 (0.002)	0.006[a] (0.0008)	-0.015[a] (0.002)
$G^w_{ins.subsidy}$	-0.002[c] (0.0008)	0.063[a] (0.004)	-0.006[a] (0.002)	-0.05[a] (0.004)
$G_{dis\text{-}pay}$	-0.001[a] (0.0002)	-0.002[b] (0.001)	0.002[a] (0.0005)	0.002 (0.001)
$G_{farm\ subsidy}$	-0.009[a] (0.0007)	-0.053[a] (0.003)	-0.005[a] (0.002)	0.061[a] (0.003)
$Q_{\%LCC\leq 2}$	0.054[a] (0.003)	0.348[a] (0.017)	-0.016[b] (0.008)	-0.346[a] (0.018)
R^2	0.966	0.898	0.915	n/a
N	780	780	780	780

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

Notes:

1. These marginal effects were calculated using the expression in eq. (S7). The respective regression estimates are available upon request.
2. The R^2 value for grass acres is not included here as it is the reference category in the land use share regression. The marginal effects for this land use category are functions of the coefficients of the system's other four crops' acreages (see *SI*, eq. (7ii).