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Studies on factors affecting the evolution of agroecosystems in the Dakotas

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by

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DEDICATION

To my mother

TABLE OF CONTENTS

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ABSTRACT

This dissertation combines remote sensing and applied economics tools to study land use conversions in North Dakota and South Dakota that are tied to this region's overall socio-economic welfare. Specifically, the region's corn and soybeans cultivation expanded significantly over the past decade replacing the region's grasslands and grain crops. In paper I, we estimate the localized impacts of the advent of corn-based ethanol plants on the Dakotas' corn acreage. We implement a Difference-in-Difference framework through more flexible assumptions as the Parallel Paths assumption of the standard model fails to hold. We find strong trends in the Dakotas' corn acreage over the past decade, but surprisingly some ethanol plants were found to have a negative impact on local corn acreage. In paper II, we evaluate crop competitiveness due to heterogeneous weather impacts on crop yields, and then test whether annual weather fluctuations explain land allocations among the Dakotas' major land uses. Our integrated framework suggests that annual weather variability is an important determinant of regional land use decisions. Under the A1B emissions scenario of climate change, we find that the yields of all of the Dakotas' major crops will decline by 2031-2060 relative to 1981-2010, leading to lower (higher) spring wheat (alfalfa) acres in Eastern (Western) Dakotas. In paper III, we develop and implement a satellite image-processing algorithm to estimate historical land use acres using raw Landsat sensor data, thereby extending the existing Cropland Data Layers back to 1984 in eastern Dakotas. We demonstrate that the availability of a longer time-series is useful as the rate of land use change may differ among different time-spans. In paper IV, we evaluate the cost-effectiveness of grassland conservation easements when spatial spillovers are present among

private landowners. We first develop a conceptual model to incorporate social spillovers in evaluating the role of easements in inhibiting grassland conversions. We empirically test whether social spillovers are present by estimating hazard rates of conversion as a function of neighborhood density of grasslands and easements. Our findings suggest that easements are strategic complements to existing grasslands in preventing grassland conversions in the Dakotas.

CHAPTER 1

GENERAL SUMMARY

Recent evidence suggests a significant shift in the agro-ecosystems of North and South Dakota. The region's grasslands are subject to intensive cropping, especially for corn and soybean cultivation. The Dakotas are rural states and these grasslands are a valuable ecological, agronomic and economic resource to this region. Grasslands generate ecosystem services by sustaining the region's wetlands that provide for a waterfowl breeding habitat. The grasslands have also supported livestock production on the region's drought-prone and marginal lands.

Although the Dakotas' grasslands are an important natural resource these are largely under private ownership, and so the regional land use changes can be viewed as an aggregate of the private land use decisions. These decisions are impacted by higher commodity prices, technological advancements, climate change, infrastructure, and agri-environmental policies. The spatial and temporal extent of Dakotas' grassland conversions is well characterized in the literature but formal analyses that establish causal relationships that identify factors of these conversions are lacking. Identifying factors that affect land use changes in this region is important for this region's socio-economic well-being as grassland conversions reduce ecological output and intensive cropping on these marginal croplands can lead to more frequent crop failures.

This dissertation combines applied economics methods and remote sensing tools to identify the factors of large-scale land use conversions in the Dakotas. Emphasis is placed on the impact of ethanol plants, crop competitiveness due to technological advancements and climate change, strategic land use decisions and conservation easements acquisition. In addition, we design and implement an image processing algorithm that characterizes historical land use using satellite sensor data back to 1984. The outcomes should be of interest to the policy-makers concerned with enhancing the Dakotas' ecological output. The findings are relevant to the region's biofuels, food crops and livestock production, and grassland conservation efforts.

In the first paper, we study the role that ethanol plants play in the grassland conversions of North and South Dakota. Since all of the Dakotas' ethanol plants are corn-based facilities we conjecture that higher accessibility to these demand terminals would lower transportation costs and incentivize higher corn production in their locality. We implement a quasi-experimental setting and utilize the spatial locations of ethanol plants to evaluate their impact on local corn acreage. In particular, we utilize the Difference-in-Difference (DID) estimation strategy in conjugation with Propensity Score Matching to control for the endogeneity due to the plants' location. We extend the standard DID model to incorporate flexible trends since the fundamental identifying assumption of the standard DID fails to hold. I find that although evaluating localized treatment effects is plausible but identifying them is challenging for this study.

In the second paper, we present a new integrated framework to analyze climate change impacts on regional agricultural productivity and private land use decisions. We implement our framework to demonstrate the agricultural impacts of climate change on recent land use transitions in the Northern Great Plains. We first estimate a yield-weather relationship for all of the region's major crops, while incorporating novel extensions to the commonly implemented yield-weather model. Specifically, we incorporate trend-weather and soil-weather interaction terms, and differentiate between the detrimental impacts of isolated and consecutive heat events on yields. We further estimate yield-weather elasticities to evaluate asymmetric productivity impacts of weather across crop types. We then utilize a non-linear system of multinomial logistic models to identify the role of weather-driven crop yields on observed land use shares, including the grass shares. We find evidence that weather-driven returns determine regional land use allocations. We finally evaluate the medium-term land use implications of the A1B climate change scenario by 2031-'60, relative to 1981-2010.

In the third paper, we design and implement a robust satellite image processing algorithm to identify historical land uses in South Dakota and North Dakota since 1984. We identify historical land allocations to five major land uses in the region: corn, soybeans, wheat, alfalfa, and grass. We contribute by extending the narrow time-window of publicly-available Dakotas' Cropland Data Layer (CDL) imagery that would facilitate a longer time-series to better document regional land use changes. We also summarize land use trends for this region and find that the restricted data availability due to CDL tends to exaggerate the rate of land use change across crop and non-crop categories.

In the fourth paper, we analyze the cost-effectiveness of a conservation policy for grassland protection when localized spillovers are present in grassland conversion decisions. We focus on the permanent grassland conversions in eastern North Dakota during 1997-2015. Our spatio-temporal analysis suggests that the region's existing croplands and grasslands occur as large, contiguous tracts where permanent grass conversions occurred in proximity of the crop-intensive areas. We conjecture that localized spillovers exist in this region's land use decisions and present a game-theoretic framework of binary choices to evaluate easement allocations when strategic complementarities exist among private landowners. Our analytical findings suggest that easements acquired as contiguous tracts and on lands that provide weak cropping incentives, e.g. poor soils, are relatively more cost-effective. We empirically validate our conjecture of localized spillovers by employing a duration modelling framework. We find that higher grass density inhibits the risk of conversion in its locality, and that easements are strategic complements to higher grass acres with regards to inhibiting conversion risks.

CHAPTER 2

ROLE OF ETHANOL PLANTS IN DAKOTAS LAND USE CHANGE: INCORPORATING FLEXIBLE TRENDS IN THE DIFFERENCE-IN-DIFFERENCE FRAMEWORK WITH REMOTELY-SENSED DATA

(PAPER I)

by

Gaurav Arora, Peter T. Wolter, Hongli Feng and David A. Hennessy

ABSTRACT

The focus of this study is the Dakotas' recent land use transitions from grass to corn and soybean cultivation. Recent literature has extensively characterized these land use changes and related concerns. However, formal analyses to understand the factors underlying these conversions are lacking. We study the role of Dakotas' ethanol plants in these land use changes. We construct a spatially delineated dataset and implement a Difference-in-Difference (DID) model in conjunction with Propensity Score Matching to estimate the impact of a corn-based ethanol plant on nearby corn-acres. We hold the advent of an ethanol plant to be the treatment and estimate the treatment effects for each ethanol plant based on the parallel paths assumption that is standard for the DID methods. We find that effects vary by ethanol plants and so we view as inappropriate the single point estimates for all ethanol plants in a region that are usually provided in the literature. Surprisingly, we find insignificant positive, and significant but negative ethanol plant impacts on local corn-acres. Negative estimates are hard to reconcile with the economic incentives due to ethanol plants. We also find intensified corn production and reduced corn-soy rotations due to the ethanol plants. Furthermore, based on placebo tests and pre-treatment trends in corn acres, we find that the identifying parallel paths assumption of the standard DID model does not hold. We incorporate differentiated trends into the DID framework through more flexible assumptions. To validate the flexible assumptions due to differentiated trends, we implement a spatial placebo and find that estimating identified localized treatment effects in this study is challenging. The estimated treatment effects are identified for only two out of the four ethanol plants in North Dakota. The identified treatment effects on local corn acreage are found to be positive for one plant and negative for the other. In light of economic incentives provided by the establishment of an ethanol plant, the negative treatment effect is puzzling.

Introduction and Motivation

Recent research suggests significant land use transitions in North and South Dakota, where grasslands have been lost to corn and soybean cultivation. We analyze the role of ethanol plants in the growth of the Dakotas' corn/soy acreage over the past decade. The U.S. ethanol industry boomed after the introduction of the Renewable Fuels Standard in the Energy Policy Act of 2005. In 2015, about 215 ethanol plants were operational in the country. Existing economic analyses have established *regional* impacts of ethanol plants on farmland values, local corn prices and land use. We investigate *localized* impacts of ethanol plants on the Dakotas' land use changes. Our view is that these plants would acquire corn locally to reduce transportation costs towards ethanol production, and would encourage local corn production by offering higher per bushel prices to nearby growers.

The eastern Dakotas contain a major portion of the U.S. Prairie Pothole Region (PPR), which encompasses most of the country's remaining native grasslands. The prairies support the region's wetlands that provide nesting habitat for waterfowl and other avian species. The grasslands also store excess atmospheric carbon and reduce soil erosion. Dakotas' soils are dry, erosive, and prone to highly variable biomass outputs. Historically, brasses have sustained livestock production on these marginal soils. Traditionally, wheat has been the predominant crop due to its tolerance towards these marginal soils. The recent land use changes in the Dakotas towards intensified crop production raise many ecological, environmental, agronomic, and economic concerns.

The ecological concerns arise due to loss of native prairie and drying up of regional wetlands that threaten the local waterfowl population. Intensified cropping raises agronomic concerns of reduced soil quality due to increased erosion, reduced water holding capacity of the soils and lower productivity. Erosion due to intensified row cropping practices, especially corn, also pollutes regional water streams. Loss of stored carbon from uprooting native grasses adds to environmental impacts of these conversions. The economic concerns are tied to the reduced ecosystem services through loss of native prairie and game species, and frequent crop failures due to the region's erosive soils. Further, fewer opportunities for livestock production remain as row cropping intensifies on more productive soils. Also, higher corn and soybean cultivation would tailor the socio-economic structure of the region towards more crop-based infrastructure, thereby making crops even more attractive to farmers.

Many studies have analyzed the spatial and temporal extent of cropland expansions that displaced grasslands, including the Dakotas' native prairies (discussed hereinafter). The Dakotas have added the most new cultivated land in the United States after 2006 with significant grassland conversions. Relevant studies also point towards the potential role of various physical and market-related conversion factors, along with the potential role of agricultural and environmental policy. Although the Dakotas' land use changes are well characterized, a formal causal analysis to understand what drives these changes is absent. We extend this literature by formally establishing the causal impacts of ethanol plants on local land use changes in these states. All of the Dakotas' ethanol plants are corn-based. Hence, we ask how the advent of an ethanol plant affects corn plantings in its proximity.

Understanding the role of ethanol plants towards grassland conversion is relevant since these grasslands are a public resource largely under private ownership. Therefore, the observed land use changes are essentially an aggregate outcome of the localized private decisions by individual landowners. The private land use decisions are potentially driven by the changing climate, evolving technology, the local business environment, infrastructure, commodity prices, and government payments towards conservation and crop insurance. For example, Claassen et al. (2011) suggest that federal crop insurance subsidies have intensified cropping practices by reducing related financial risks. Ethanol plants, the focus of this study, also reduce production risks as they enhance corn demand in their locality that potentially incentivizes grassland conversions towards corn cultivation.

There are 19 ethanol plants in the Dakotas (four in ND and fifteen in SD) with a combined capacity of 1,386 million gallons per year (mgy, 363 mgy in ND and 1,023 mgy in SD), accounting for about 9% of the total U.S. ethanol production capacity. Most of the Dakotas' ethanol plants started operations during 2006–08, which coincides with the observed rapid land use conversions outlined in the pertinent literature. We expect the ethanol plants to influence localized land use changes and hence modelling those rather than aggregate, regional-level decisions is more relevant. We present a unique research design that utilizes spatially-delineated data and implements a quasi-experimental setting to evaluate the impact of ethanol plants on local corn acreage. We now provide a brief summary of the many land use change studies that have characterized the recent grassland conversion in this region.

Wright and Wimberly (2013) used the U.S. Department of Agriculture (USDA) Cropland Data Layer (CDL) database to summarize spatial conversions from grass to corn and soybean between 2006 and 2011 in the U.S. Western Corn Belt (WCB), spanning North and South Dakota, Nebraska, Iowa, and Minnesota. The Dakotas experienced the most grassland conversions with 271,000 hectares lost to cropping out of the 528,000 hectares in all of WCB. Higher commodity prices and increased biofuels production were attributed as potential drivers for such land use changes. The spatial characterization of land use changes in these two states revealed a westward expansion of the Corn Belt toward the Missouri River. Lark et al. (2015)

asserted that the Dakotas added the most new cultivated land in the United States during 2008–12, predominantly east of the Missouri River. However, northwestern and southeastern North Dakota experienced contraction of croplands during this period. Lark et al. present a long-term trend analysis using the U.S. Geological Survey (1972–2002) to evaluate conversions on native grasslands. The Dakotas stood out with the highest conversion rates on lands previously attributed to native grasses. In addition, soybeans (wheat) was found to be the first crop planted upon conversion east (west) of the Missouri River.

Johnston (2014) provided a longer-term perspective on cropland expansion in the Dakotas, utilizing USDA National Agricultural Statistical Service (NASS)'s state-level crop acreage data (1980–2011) and the CDL data (2006–12). The corn/soy acreage almost tripled between 1980 and 2011, where these crops accounted for only 5% of the Dakotas' agricultural acreage in 1980. The probability of corn/soy being re-planted to corn/soy increased from 68% in 2006–07 to 80% in 2011–12. The corresponding probability for grasslands decreased from 81% in 2006–07 to 74% in 2011–12. Corn and soybeans were also found to replace wheat and small grain crops that were historically dominant due to their tolerance for the local climate. Johnston attributed technological advancements (i.e., drought/cold-resistant corn and soybean varieties) as potential drivers of such land use transitions.

A study by Stephens et al. (2008) estimated the probability of grassland conversion conditional on amounts of surrounding grasslands, slope, and soil productivity. The annualized grassland loss in the Dakotas' Missouri Coteau region was estimated to be 0.4%, which amounts to 36,450 hectares during 1989–2003. However, they found that the probability of conversion varied across the lands of high biological value (amenable to waterfowl breeding). Stephens et al.

recommended that conservation policies should be targeted specifically to the lands with higher conversion probability, conditional on their location and soil quality attributes.

This paper is subdivided into several sections. We first motivate the economic incentives that theoretical considerations suggest should motivate land use conversion in the proximity of ethanol plants. A literature review of the relevant findings on the impacts of ethanol plants from earlier studies is then discussed. Our data section discusses how we constructed a spatially delineated dataset for this analysis and provides a detailed explanation of the relevant variables. The methodology section presents our research design, the Differences-in-Difference (DID) model in conjunction with Propensity Score Matching and an extension of the DID to include flexible trends. Section 4 provides estimation results for each ethanol plant and lastly we conclude with some discussions.

Economic Motivation

Consider a representative farmer's dual profit function, $\pi(p-t(x))$, that depends on the difference between the market price of corn and its transportation cost $t(x)$. The transportation cost is a function of the distance between a representative farmer and the demand terminal for corn (x). To motivate the economic incentives due to proximity of these ethanol plants, we compare the pre- and post-ethanol plant trends in corn basis for counties that house these plants in North and South Dakota (see figure 1). Basis is the difference between the local price and the futures price of a commodity. Basis accounts for the transportation costs, and thus a higher corn basis in the post-ethanol plant years should be tied to the reduced transportation costs in the plant's proximity. Figure 1 shows a steeper basis trend after 2008 when compared to before 2006 (i.e., corn basis was higher in the post-plant years in those counties that housed ethanol plants).

Therefore, we conjecture a positive and statistically significant impact of ethanol plants on local corn acreage.

Literature Review

Earlier attempts to assess the impacts of ethanol plants involved an indirect evaluation of land use change by way of analyzing impacts on local corn prices and farmland values. In more recent years, studies have considered the direct impact of ethanol plants on corn acres as a measure of land use change. We provide a brief review of analyses involving grain prices and farmland values, followed by a detailed review of the analyses of impacts on land acreage because these are of direct relevance to our inquiry.

Miao (2013) has evaluated the proportion of corn acreage for the Iowa counties in response to the location, capacity, and ownership of ethanol plants. He utilized a county-level panel data set from 1997 through 2009, and applied the Arellano-Bond generalized method-of-moments estimator to estimate the effect of ethanol plants on land use shares in the region. The specialized estimator attempts to control for the endogeneity of ethanol plants and for corn-soybean rotations by including a lagged dependent variable (that is, proportion of corn acreage). He found a positive and significant impact of ethanol plants on intensity of corn production in Iowa. He also found that, all else equal, locally owned ethanol plants have twice as strong an effect on local corn acreage as their non-locally owned counterparts.

Motamed et al. (2016) used a grid-level spatially-delineated dataset to estimate a non-linear response of the refining capacity of ethanol plants in each grid-cell's neighborhood on its corn acreage in the U.S. Midwestern states: ND, SD, NE, MN, WI, IA, KS, OK, MI, IL, IN, OH. They utilized a panel regression model where the dependent variable is corn acreage on 10km X 10km land parcels during 2006–10. They corrected for the endogenous ethanol plant locations and neighboring land use by utilizing the length of railroads within each grid cell as an instrument for refining capacity. They found a significant increase in corn acres in grid cells with higher ethanol refining capacity in their neighborhood, but the effect dampened over the years. Motamed et al. (2016) built upon an earlier study by Motamed and McPhail (2011) that models regional corn acreage on the proximity to nearest ethanol plants. In the 2011 study, the covariates were distance to the nearest grain elevators and ethanol plant, the plant's capacity, cash bids at the nearest grain elevator and a soil productivity index. The instruments for each parcel's distance from the nearest ethanol plant were the distance from the nearest interstate ramp, primary/secondary roads and water ports. This analysis estimated that upon moving one percent closer to an ethanol plant corn acreage increased by 0.64% within their region of study.

Turnquist et al. (2008) measured the impact of ethanol plants on farmland acreage for the state of Wisconsin between 2000 and 2006. Although Wisconsin was reported to be losing farmland to other uses during this period, fallow or undeveloped acres were found to increase. The authors investigated the possibility that the fallow lands were reverted as croplands in proximity of the ethanol plants. The authors used municipality-level land use data and allocated 2-mile, 10-mile and 50-mile zones around the four operational ethanol plants during 2000–06. The differences between percentage changes in agricultural acreage (2000–06) across these zones evaluated the ethanol plant impacts in Wisconsin. The impact of ethanol plants on each of three zones' agricultural acreage was found to be statistically insignificant.

Mueller and Copenhaver (2009) analyzed the impact of two Illinois ethanol plants (Illinois River Energy Center (IRE) and Patriot Renewable Fuels (PRF)) on surrounding land use, as part of a larger study to deduce the impact of these plants on greenhouse gas emissions. They used satellite imagery and observed land use in corn supply regions for each plant in 2006, 2007, and 2008 to evaluate its impact. Defining these corn supply regions involved corn growers' surveys and inquiries from ethanol plants to judge the spatial extent of their corn suppliers. A 43-mile and a 23-mile circle was placed around IRE & PRF, respectively. The study concluded that ethanol plants had a weak influence on direct land use change in their vicinity, and inferred that higher yields supported increased exports and increased ethanol production.

Brown et al. (2014) utilized a spatial econometric regression framework to assess the land use decisions of farmers due to proximity to ethanol plants in Kansas. Using satellite imagery, they separately evaluated conversions from other cropland and non-cropland uses in 2007 to corn production in 2008 and 2009 on 5-acre parcels. The authors found that reducing parcel's distance to the nearest refinery by 1% significantly increased non-cropland (other cropland) conversion to corn acres by 5% (4%) in a county 25 miles away from the refinery and by 15% (11%) in a county 75 miles from it. However, their estimates may be biased due to likely endogeneity of ethanol plant locations. Stevens (2015) also utilized a spatially-explicit field-level dataset for IA, IN, IL and NE to estimate the change in probability of planting corn with proximity of the nearest ethanol plant between 2002 and 2014. He found a positive impact of the presence of an ethanol refinery only within its 30-mile radius, although not controlling for the endogeneity of plants' locations.

The literature lacks a consensus regarding impacts of ethanol plants on local grain prices and agricultural land values (Miao 2013), which can provide indirect evidence of ethanol plants on land use change. Examples in the context of farmland values are Zhang et al. (2012), Henderson and Gloy (2008) and Du et al. (2007). Zhang et al. (2012) used disaggregated parcel-level data for Western Ohio to evaluate the impact of increased biofuels demand. They conducted DID estimation on matched parcels to find increased farmland values in the vicinity of the ethanol plants at a time that witnessed a sharp dip in residential values. The study by Henderson and Gloy (2008) used a hedonic framework to find a positive impact of ethanol plants on agricultural land values in 2007. Zhang et al. (2012) have, however, criticized the hedonic framework due to its inability to correct for selection bias in plant locations. Du et al. (2007), on the other hand, rejected the hypothesis that ethanol plants significantly affect Iowa farmland cash rental rates. In the context of local grain prices, Katchova (2009), O'Brien (2009), and McNew and Griffith (2005) found a positive and significant impact of ethanol plants on local grain prices, whereas Lewis (2010) found that these positive impacts vary spatially. The author found significant impacts for MI and KS, and an insignificant impacts for IA and IN.

The above review suggests disagreement in the literature on the direct and indirect impacts of ethanol plants on local land uses. Moreover, most studies utilize aggregated county-level datasets. An issue with such aggregated datasets for a location-based analysis is worth considering. Including an indicator (or dummy) variable for the existence of ethanol plants as a regressor assumes its location to be central to its home county when this variable equals 1. It thereby assumes that the corresponding ethanol plant will not impact the counties neighboring its home county. However, as in the Dakotas, an ethanol plant is often located near the shared boundaries of two or three counties. Consequently, it is appropriate to use spatially delineated data as some studies do. However, the endogeneity due the ethanol plant's location was ignored by most of the earlier studies and may provide biased estimates of the impacts of ethanol plants.

We extensively utilize remote sensing tools that generate spatially delineated data with micro-resolutions of the researcher's choice. This article presents estimates of impact of ethanol plants using 500-acre plots as representative decision-making units.[1] This enables the evaluation of the effects of ethanol plants on a plant-by-plant basis, rather than by pooling county-level data for ethanol plants in an entire state or all of the Midwestern United States. Adopting a methodology that allows for analyzing impacts of individual plants enables fine-detail scrutiny of local conversion effects. This provides an alternative approach to validate the estimates of the impacts of ethanol plants on corn acreage arrived at from more aggregate methods.

Data

We use remotely sensed data for land use and soil quality in the Dakotas from two main sources: the 'CropScape' portal of the USDA-National Agricultural Statistical Service's Cropland Data Layer (CDL) Program, and the Web Soil Systems portal of USDA-National Resource Conservation Service (NRCS).

USDA-Cropland Data Layer

CDL satellite imagery for South Dakota are available from 2006 to 2013 and for North Dakota from 1997 to 2013. CDL provides raster (pixelated) data for all contiguous U.S. states with different spatial resolutions, 56 m pixels for 2006–2009 and 30 m pixels for other years. To be able to compare land use statistics across different years we employ remote sensing tools, namely ERDAS Imagine and ArcGIS, and bring each year's imagery to a uniform spatial resolution of 500 acres. To achieve this, each year's raster image was first converted to vector form (pixels to polygons), and then overlaid onto a grid-plot with 500 acre-polygons. The grid

[1] We conducted our initial analyses at a much finer resolution (up to 160-acre plots). Aggregating the data up to 500 acres did not change our results significantly. However, higher aggregations suppress measurement errors from satellite imagery.

polygons are designated as representative decision-making land parcels with a unique identifier that are observed every year. Overall, our study sample includes approximately 104,000 parcels for North Dakota and 99,000 parcels for South Dakota.

USDA NRCS-Web Soil Systems

We retrieve tabular data for Land Capability Classification (LCC) and representative slope from the Soil Data Viewer application developed by NRCS. Soil Data Viewer provides detailed definitions for both these variables. Briefly, LCC groups soils into eight broad classes each representing impediments for cropping, with higher class codes assigned to more serious impediments. LCC classes I and II are well-suited for cropping, whereas LCC classes III and IV require additional management practices to be suitable for cropping, often restricting their use to pasture, rangeland or forests. LCC level V and worse have severe limitations that make them impractical for crop cultivation. Representative slope simply measures the average rise per unit run. The tabular data combines these soil attributes to geographically delineated and uniquely identified soil map units. To attribute soil quality for each of our representative land parcels, we calculate area-weighted LCC (*WLCC*) and slope (*WSLP*) variables. The area-weights are calculated as the proportion of each soil map unit's area within the 500-acre land parcels. See supplementary information for more information on data integration.

Ethanol Plants' Spatial Coordinates

The spatial coordinates of ethanol plants, ultimately used to determine treatment and control groups, were acquired by using the Google Earth application in conjunction with online maps of these plants made available on *Ethanol Producer Magazine*'s website. We conduct our analysis on all four ethanol plants in North Dakota and four out of 15 ethanol plants in South Dakota, listed in table 1 with spatial locations in figure 2. Choice of ethanol plants is driven by our methodology and land use data availability in South Dakota (2006-2013), to be discussed hereafter under 'Estimation Results'.

Methodology

Our objective is to quantify how the emergence of an ethanol plant affects local land use change. The detailed micro-level panel dataset for the Dakotas allows us to implement a quasi-experimental design to evaluate the impact of ethanol plants on land use patterns in their neighborhood. In this sense, we interpret the advent of an ethanol plant as the treatment where pre-and post-treatment year outcome levels are the observed land use patterns before and after it started operations, respectively.

To implement a quasi-experimental setting with ethanol plant as treatment, we first need to define treatment and control groups. The argument that a plant's location is potentially influenced by the opportunity for growing corn in its vicinity relates to minimizing costs of acquiring corn for ethanol production. An ethanol plant that procures most of its annually required corn from nearby areas saves on transportation and related logistical costs, and so is willing to compensate local suppliers. Therefore, in order to define our treatment and control groups, we assume that the related transportation costs are monotonic in the Euclidean distances between a land parcel and the ethanol plant, and that the grower bears at least some of these costs. In this scenario, a supplier/landowner located nearer to the ethanol plant has higher incentive to grow corn than one farther away, *all else equal*. Consequently, we choose to designate samples that lie closer to the ethanol plant as treatment samples and ones farther away as control (or untreated) samples.

Back-of-the-Envelope-Calculations: How Significant are Transportation Costs?

We support transportation costs, and thus Euclidean distances, as sensible treatment and control parameters with some empirical evidence. Consider transport-trucks with the carrying capacity of 1 ton (=39.4 bushels[2]) corn and a mileage of 134 ton-miles per gallon. The annual average cost of diesel was \$2.4–\$4 after 2005 (U.S. Energy Information Administration). O'Brien (2009) estimated the total transportation cost to be approximately four times the fuel cost, which is 0.20–0.28 cents as the fuel cost of transporting one corn bushel for one mile was 0.05–0.07 cents in the U.S. Hence, the maximum willingness to pay in order to incentivize a farmer located 50 miles closer to an ethanol plant would range between 10–14 cents per bushel of corn.

On the other hand, cash rents for croplands ranged between \$39–\$46.5 in ND and \$53–\$71.5 in SD from 2006–10 (USDA NASS Land Values Summary, 2006–10). Given the corn yields of 111–132 bushels/acre in ND and 97–151 bushels/acre in SD (USDA NASS Quick Stats, 2012), the average cropland rents for the Dakotas were between 30–73 cents per bushel of corn. Since the transportation costs are 14%–47% of the total cropland rental values, these should generate strong incentives for proximate landowners to engage in corn production.

Designating Treatment and Control Groups

An aspect of our research design that differentiates it from many other quasi-experimental studies is that our treatment is not exogenous. We designate the advent of an ethanol plant as treatment, which itself is a market outcome. The implication of this endogenous intervention is that we do not have exogenous control groups. Rather, our treatment and control

[2] Bushel/Ton Converter. www.agriculture.alberta.ca

groups follow the ‘rule of thumb’ that treated parcels are located nearer to the ethanol plant than their untreated counterpart.[3] This admits innumerable possibilities for treatment and control groups near each ethanol plant’s location and practically inexhaustible combinations that can be included for this study. It is, therefore, important to conduct robustness checks to seek the sensitivity of our treatment effects’ estimates among different combinations of treatment and control groups. We accomplish that by designating two treatment groups and two control groups for each ethanol plant (see table 2 for the schematics). The control groups are kept apart to ensure independence in robustness checks for each treatment group (see figure 3).[4]

Among the combinations of treatment and control groups, we conjecture that the treatment effects from the nearest treatment group and the farthest control group combination will be larger in size and more significant than the other comparisons. We present the regression results for this particular combination and compare it with others as a robustness strategy.

DID in conjunction with PSM

Given pre- and post-treatment periods, as well as treatment and control groups for each ethanol plant, we use the DID estimation strategy in conjunction with propensity score matching (PSM) to evaluate their role in land use conversion. Using the DID approach is reasonable since

[3] In some cases, we have two or more ethanol plants competing for corn from common land parcels. To analyze treatment effects for an ethanol plant in such cases we exclude parcels that are closer to other ethanol plants, irrespective of the parcels’ designated group.

[4] Due to spatial constraints, it is infeasible for all of the treatment and control groups to be non-overlapping. This is because having non-overlapping groups would require more space, which in turn would bring our groups closer to other nearby ethanol plants.

the location of an ethanol plant is endogenous to land use trends in its locality. The issue of endogeneity arises because Dakotas' ethanol plants are corn-based facilities and their location decisions could place them in regions with high corn production in pre-plant years or with high potential for corn production in the post-plant years. DID is intended to control for such endogeneity by estimating causal impacts as the difference between average temporal trends of land use acres across treated and untreated groups, assuming that, in the absence of the ethanol plant, land use in both these groups would evolve equivalently. This assumption of parallel trends requires treated and untreated land parcels to be alike, except for their proximity to the ethanol plant. That is, estimated treatment effects are unbiased if these land parcels are randomly assigned to the treatment and control groups, and we control for any within-group or across-group dissimilarity among them (other than the advent of an ethanol plant).

We seek to ensure random assignment of land parcels to each group by utilizing the PSM strategy, thereby conditioning treatment selection on the observed the soil quality. Soil quality is central to the land use decisions, and would potentially influence ethanol plants' location choice toward regions with land attributes favoring corn production. Local infrastructure such as road and rail connectivity also potentially affects ethanol plants' location choice. We tend to choose, at least for some ethanol plants, our treatment and control groups along or parallel to an interstate highway so that the Euclidean distances from ethanol plants appropriately differentiate access to infrastructure across land parcels. It is noteworthy that while PSM controls for selection on observables, the DID estimation approach controls for selection on unobservables through individual and trend fixed-effects in the regression framework (List et al. 2003).

Identifying treatment effects from the DID model

The Parallel Paths Assumption (PPA) is fundamental to identifying the treatment effects that are estimated in DID models. To illustrate this point briefly, consider a representative land parcel i with $C_{i,t}$ as its corn acreage at time period t. We introduce binary variables d_i and δ_t to designate treatment/control groups and pre-/post-treatment periods respectively. So $d_i = 1$ for treated parcels and equals 0 otherwise while $\delta_t = 1$ for time periods after the advent of an ethanol plant and equals 0 otherwise. Further, denote $t^-(t^+)$ as the set of pre-treatment (post-treatment) time periods with t_0 as the treatment year.[5] Intuitively, to evaluate a treatment effect for treated parcel i's corn acreage we would compare the outcome levels with and without ethanol plant in the post-treatment era, that is $C_{i,t}$ with $t \in t^+$.[6] Consequently, the average treatment effect for the treated (ATT) equals $E[C^T_{i,t^+} - C^U_{i,t^+} \mid d_i = 1]$, where superscript T(U) denote presence (absence) of the plant. The issue, though, is that the outcome levels absent an ethanol plant (i.e., the treatment) in the post-treatment years are unobserved. The DID approach seeks to overcome this issue by assuming that treated and control parcels would follow *parallel land use trends* if the ethanol plant had not emerged at t. This PPA assumption is expressed as

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[5] For example, the Red Trail Energy ethanol plant that was established in 2007, so $t^- =$ $\{1997, 1998, ..., 2006\}$ and $t^+ = \{2008, 2009, ..., 2013\}$.

[6] We present the model for corn acreage. An extension for combined corn and soy acreage follows by changing the notation from $C_{i,t}$ to $CS_{i,t}$.

(1) $$E[C^U_{i,t^+} - C^U_{i,t^-} \mid Z, d_i = 1] = E[C^U_{i,t^+} - C^U_{i,t^-} \mid Z, d_i = 0],$$

In equation (1) superscript U signifies no treatment (both groups stay untreated) and Z is the set of observable covariates for each land parcel. If (1) holds then ATT is computed as

(2) $$ATT = E[C_{i,t^+} - C_{i,t^-} \mid Z_i, d_i = 1] - E[C_{i,t^+} - C_{i,t^-} \mid Z_i, d_i = 0]$$

Thus, the PPA is key to identifying the estimates of treatment effects and in the event that this assumption fails the estimates of ATT are meaningless. In order to provide comparisons such that PPA is most likely to hold, we restrict our sample for estimating treatment effects to one where the conditional probability of treatment (or propensity score, PS) for each untreated parcel is close ‘enough’ to its treated counterpart. This method is usually known as PS matching.

Propensity Score Matching

To estimate a conditional probability of treatment for each land parcel in treatment and control groups of an ethanol plant, we utilize a logistic regression. The probability of treatment is regressed upon the area-weighted soil quality variables, *WLCC* and *WSLP*, in their quadratic form. That is,

(3) $$P(d_i = 1) = \frac{\exp(\alpha_0 + \alpha_1 WLCC + \alpha_2 WLCC^2 + \alpha_3 WSLP + \alpha_4 WSLP^2)}{1 + \exp(\alpha_0 + \alpha_1 WLCC + \alpha_2 WLCC^2 + \alpha_3 WSLP + \alpha_4 WSLP^2)},$$ where

$\alpha_0, \alpha_1, \alpha_2, \alpha_3$ and α_4 are regression coefficients. The justification for a quadratic functional form lies in minimizing the *Akaike Information Criterion* (or maximizing the *log-likelihood*) relative to the linear and cubic forms. The estimated probability of treatment, $P(d_i = 1 \mid X_i^a)$ with X_i^a = $\{WLCC, WLCC^2, WSLP, WSLP^2\}$, is then used for matching treatment and control groups. The PS estimation results are summarized in table 3. We find these soil quality based models to significantly explain the probability of treatment in each case.

The logistic regressions that estimate the PS find that land parcels in the vicinity of ethanol plants may have higher LCC and/or be steeply sloped, not particularly suitable for corn production. Both *WLCC* and *WSLP* exhibit decreasing marginal returns in all cases. Higher treatment probability for parcels with relatively poor soil quality suggests that the ethanol plants may consider factors like lower land values and/or access to infrastructure (near a highway or a rail line) towards their location decisions. However, we cannot differentiate land values and infrastructure across land parcels at the fine spatial resolution of this study. The spread of estimated PS between 0 and 1 (figures 4–9) can measure whether our model specification explains the treatment probability reasonably well. A massing of estimated probabilities at extreme values (e.g., panels A and C in figures 4–9) indicates more variables are needed to reasonably explain PS in those cases. A constrained availability of variables that estimate the PS recommends caution while interpreting our treatment estimates.

We implement a one-to-one nearest-neighbor propensity score matching algorithm and include only those treated parcels for which there exists an untreated parcel whose PS lies within a pre-assigned radius (absolute difference between PSs) of each corresponding treated parcel's score. The choice of this radius involves a trade-off between bias and efficiency of treatment effects. A smaller radius will yield more similar land parcels in both groups reducing bias in estimated treatment effects but at the same time a smaller sample that entails higher variance.[7]

[7] We implement the PSM algorithm developed by Fraeman (2010), which optimizes the sample size in two steps. First, it searches for all possible matches to each treated sample within the pre-assigned radius and then, while assigning matches to these treated parcels, it prioritizes those

Post-matching heterogeneity in the distribution of soil quality variables among treated and untreated groups may potentially bias our treatment effects' estimates (Heckman et al. 1997). We report treatment effects calculated using samples from a pre-assigned radius or caliper of range [0.0001, 0.01]. The assigned calipers vary by ethanol plants and are chosen such that the post-matching samples are balanced while maximizing the number of observations in each case. The term "balanced" refers to ensuring a homogeneous distribution of these covariates across treatment and control groups. We find that reducing the pre-assigned radius yields higher balance across the two groups used for estimating treatment effects.

We follow Caliendo and Kopeinig (2008) to examine whether or not post-matching samples are balanced and to assess the matching quality. We conduct t- and F-statistics to test for equivalence of *WLCC* and *WSLP* means and variances across matched treated and untreated samples for each ethanol plant (Rosenbaum and Rubin 1985). Further, we test the joint-significance of *WLCC* and *WSLP*, in quadratic form, when estimating $P(d_i = 1)$ on the matched samples. This test rejects the joint-significance of these covariates, indicating no systematic differences in their distribution across treatment and control groups that could explain underlying variations in propensity scores (Dehejia and Wahba, 1999). The matching performance based on the mean and variance of the soil quality parameters across matched treatment and control groups and their corresponding calipers is presented in Table 4.

with the least number of matches from the first step. The SAS code that implements this algorithm is published in Fraeman (2010).

Standard DID estimation summary and moving towards flexible trends in DID

In the DID regression framework using matched samples, we further control for pre-treatment land use decisions as an opportunity to convert to corn. To illustrate, if a land plot was entirely in corn during pre-treatment years, it will not reveal any treatment effect due to the lack of scope for conversion. In addition, even if the land was predominantly under wheat (or grass) in the pre-treatment year, the opportunity to convert comes with switching or conversion costs, respectively. Further, in recognition of the fact that farmers usually grow corn and soybean in rotation, we evaluate treatment effects for corn as well as the combined acreage of corn and soy as our dependent variables. See supplementary information for detailed estimation results of the standard DID model in conjunction with PSM.

We find positive, negative as well as statistically insignificant treatment effects on corn acres due to ethanol plants. The negative treatment effects are both surprising as well as hard to reconcile with the empirical evidence of incentives for corn production on land parcels in the vicinity of these ethanol plants. To further investigate the validity of such treatment estimates, we designate temporal placebos, per Figure 10, and estimate ATT for these falsified treatments. Ideally, a false treatment should yield zero treatment effects but our estimates, shown in Table 5, show that the standard DID framework yields non-zero treatment effects even though there was no treatment. Such placebo tests point towards an imperfect matching strategy or an inability to control for all the factors that affect growth of corn acres in our regressions.

An implication of imperfect matching is visualized in Figure 11, where we find non-parallel pre-treatment trends for matched treatment and control groups in the case of North Dakota plants. This means that corn acres were not evolving equivalently among treatment and control groups even when the treatment was absent. Non-parallel trends during pre-treatment periods contradict the PPA, and thus the ATT estimates of a standard DID model do not represent the treatment effects due to ethanol plants. We follow Mora and Reggio (2012) to incorporate these differentiated trends between treatment and control groups into a fully-flexible DID model. We also formally test and reject the PPA using this fully-flexible DID model below.

Incorporating Flexible-Trends into the standard DID framework

The differentiated or non-parallel pre-treatment trends across treatment and control groups in Figure 11 invalidate the PPA. We incorporate such trends into the standard DID framework through more flexible assumptions. To illustrate, we develop a special case of a fully-flexible DID model in an appendix. This special case is based on the non-parallel trends in corn acreage across treatment and control groups in the pre-treatment years (see figure 12(a), in green).[8] However, the corn acres could potentially vary for each pre-/post-treatment period as found earlier in Figure 11. A generalized version of the differentiated corn trends is visualized in Figure 12(b) and such trends are incorporated into a fully-flexible DID model.

Reber (2005) assesses the impact of court-ordered desegregation plans for schools on school enrollments in the U.S. through a flexible DID framework.

A fully-flexible DID model by Mora and Reggio (2012) is as follows:

$$C_{i,t} = \beta_0 + \sum_{\tau=T(i)+1}^{T(l)} \beta_\tau I_{[t=\tau]} + \beta^d d_i + \sum_{\tau=T(i)+1}^{T(l)} \beta_\tau^d \times I_{[t=\tau]} \times d_i + Z'_{i,t}\beta_z + \varepsilon_{i,t}, \quad (4)$$

where $T(i)$ is the first pre-treatment period and $T(l)$ is the last post-treatment period. The model in equation (4) captures flexible time-trends for pre- and post-treatment periods and allows them

[8] The special case is hoped to facilitate a smooth transition for readers from the standard DID model with failed PPA to a fully-flexible DID model.

to differ between treatment and control groups, thus capturing a fully-flexible situation, as in Figure 12(b). The model's advantage is that it calculates time-varying treatment effects, which in turn can potentially allow for differentiating between short-run and long-run impacts of the advent of an ethanol plant on the near-by corn acreage. Note that, unlike Mora and Reggio (2012), we include a vector of controls $Z_{i,t}$ in our regression equation (4). $Z_{i,t}$ consists of lagged soybean ($S_{i,t-1}$), wheat ($W_{i,t-1}$), and grass ($G_{i,t-1}$) acreage at time t for each parcel i. The variables are intended to control for the differentiated opportunity cost of growing corn on lands that were attributed towards soybean, wheat, and grass in the previous period. The treatment effects estimator from equation (4), denoted as $ATT'(s,n\,|\,Z_i)$, is given as

(5) $$ATT'(s,n\,|\,Z_i) = \Delta^{n-1} ATT(s\,|\,Z_i) = \Delta_s \Delta^{n-1} \beta^{d}_{t^*+s}$$ [9]

The term s refers to the s^{th} year after the last pre-treatment year t^* and the term n refers to a parallel (n^{th}-order)-differences assumption that identifies $ATT'(s,n\,|\,Z_i)$. $ATT'(s,n\,|\,Z_i)$ is defined as the n^{th}-order treatment effect s periods ahead of the last pre-treatment period (t^*). It is evaluated by comparing the $(n\text{-}1)^{th}$-order difference (Δ^{n-1}) in outcomes at period s relative to its counterpart at t^* across treatment and control groups. As discussed in the appendix, the parallel (n^{th}-order)-differences assumption can be written mathematically as:

(6) $$E[\Delta_s \Delta^{n-1} C^{U}_{i,t^*+s}\,|\,Z_i, d_i = 1] = E[\Delta_s \Delta^{n-1} C^{U}_{i,t^*+s}\,|\,Z_i, d_i = 0] \;\forall\; s \in \{1, \ldots, T(l) - t^* - 1\}.$$

For $n = 1$ equation (6) reduces to a parallel paths assumption. For $n = 2$ equation (6) reduces to a parallel (1st-order) differences or parallel growth assumption. Note that the parallel growth

[9] See Theorem 3 in Mora and Reggio (2012)

assumption is specific to each s^{th} post-treatment year. The parallel growth requires that the difference between corn acres in $s-1$ and s post-treatment years must be equal among treatment and control groups in the absence of a treatment. Also, $ATT'(s,2|Z_i)$ is similar to the Differences-in-Differences-in-Differences (DDD) estimator since we are comparing two-period differences in corn acres, rather than absolute acres, to compute treatment effects. For $n>2$, we move on to higher order differences. For example, $n=3$ implies a Δ^2 $(=(1-\mathrm{L})-(\mathrm{L}-\mathrm{L}^2))$ operator on s-periods ahead outcome variable in equations (5) and (6). It is clear that we require at least three pre-treatment years to estimate $ATT'(s,3|Z_i)$. In this sense, parallel (n^{th}-order) differences would require at least *n* pre-treatment periods, and hence the higher order generalizations ($n>2$) could not be implemented for the South Dakota plants due to data inavailability. It is interesting to note that the treatment effects can differ in size, sign, and interpretation based on the choice of n^{th}-order identifying assumption. However, these assumptions can be tested for equivalence using the coefficient estimates of the fully-flexible model. Testing the equivalence between parallel (n^{th}-order) and parallel ($n-1^{th}$-order) difference assumptions is similar to testing for the null hypothesis: $\Delta^{n-1}\beta^d_{t^*}=0$ such that $n<T(l)-t^*$.

As mentioned earlier, the PPA can be formally tested using coefficient estimates of the fully-flexible DID model. This is because the standard DID is a special case of the fully-flexible model (*n* = 1) and so the PPA is also a special case of the family of identifying assumptions in equation (6). To test whether the PPA holds we can simply test the null H_o: $\beta^d_t=0\ \forall\ t\le t^*$. This null hypothesis requires that the treatment effect in each pre-treatment year be zero. In the event that we have perfectly matched treatment and control groups, the PPA is equivalent to the above null hypothesis in the pre-treatment years. The H_o is rejected for each North Dakota ethanol plant (see Table 6) as indicated by the non-parallel pre-treatment trends earlier.

Multiple pre-treatment years are available for the four North Dakota ethanol plants. So the fully-flexible DID model can be implemented for these plants. However, an opportunity to implement multiple assumptions and estimating corresponding treatment effects for each case comes with the challenge of choosing among these estimates. We restrict our analysis to $n = 2$ as it is the least complex model that does not impose the PPA. That is, we compare difference in growth of corn acres between treatment and control groups rather than the difference in absolute acres, to assess treatment effects. We will conduct a spatial placebo to validate our treatment estimates, to be discussed later.

Estimation Results: The Fully Flexible DID Model

Econometric Considerations

The econometric considerations when estimating equation (4) are discussed here. First, we include lagged variables for the three major transitioning land use types other than corn (i.e., wheat ($W_{i,t-1}$), soy ($S_{i,t-1}$), and grass ($G_{i,t-1}$)). Since the lagged variables may impact the evolution of corn acres alongside the ethanol plants, excluding them may confound the treatment estimates through omitted variable bias. The coefficient estimates to these variables would also capture differentiated costs of conversion to corn from three different land use types. [10] Second, we compute heteroscedasticity-consistent standard errors by stratifying our panel by designating

[10] Although the lags primarily control for the opportunity to grow corn in these rural states, they also capture a negative correlation among $C_{i,t}$ and $C_{i,t-1}$ since corn, soy, wheat and grass are the major land uses under transition.

each land parcel as an individual cluster. This transforms the variance-covariance matrix into a block-diagonal with each block corresponding to an individual land parcel.

A point estimate of the average treatment effect on the treated, based on the parallel growths assumption (i.e., $n = 2$), at each post-treatment period $t^* + s$ can be written as

$$
\begin{aligned}
ATT'(s,2 \mid Z_i) = \Delta ATT(s \mid Z_i) &= \Delta_s(\beta^d_{t^*+s} - \beta^d_{t^*+s-1}) \\
&= (1 - L^s)(\beta^d_{t^*+s} - \beta^d_{t^*+s-1}) \\
&= (\beta^d_{t^*+s} - \beta^d_{t^*+s-1}) - (\beta^d_{t^*} - \beta^d_{t^*-1}).
\end{aligned} \tag{7}
$$

And a sample estimate of the variance of this point estimate can be computed as:

$$
\begin{aligned}
Var(ATT'(s,2 \mid Z_i)) = &Var((\beta^d_{t^*+s} - \beta^d_{t^*+s-1}) - (\beta^d_{t^*} - \beta^d_{t^*-1})) \\
= &Var(\beta^d_{t^*+s}) + Var(\beta^d_{t^*+s-1}) + Var(\beta^d_{t^*}) + Var(\beta^d_{t^*-1}) \\
&- 2Cov(\beta^d_{t^*+s}, \beta^d_{t^*+s-1}) - 2Cov(\beta^d_{t^*}, \beta^d_{t^*-1}) - 2Cov(\beta^d_{t^*+s}, \beta^d_{t^*}) \\
&+ 2Cov(\beta^d_{t^*+s}, \beta^d_{t^*-1}) + 2Cov(\beta^d_{t^*+s-1}, \beta^d_{t^*}) - 2Cov(\beta^d_{t^*+s-1}, \beta^d_{t^*-1}).
\end{aligned} \tag{8}
$$

For each of the four ethanol plants in North Dakota we present the coefficient estimates from the regression equation (4) in Table 6 and $ATT'(s,2 \mid Z_i)$ in Table 7.

Estimation of Treatment Effects

The fully-flexible DID model estimates year-specific treatment and time effects unlike the standard DID, which estimates a single treatment and trend effects between aggregated pre- and post-treatment years (see supplementary information). However, we find differentiated opportunities for growing corn on land parcels previously planted with wheat and grass, in line with the standard DID estimation. We also include lagged soy acres and find its coefficient in Table 6 to be always positive, although significant for TE and HRE, reflecting the usual cropping pattern of corn-soy rotations. The negative and significant coefficients for $G_{i,t-1}$ in all cases likely reveal high initial costs of land preparation to convert from grass to corn. Lagged wheat acres, on the other hand, are found to be positive and insignificant for BF and RTE as well as negative and significant for TE and HRE. The opportunity cost of converting from wheat to corn is lower than grass to corn, as reflected by the respective coefficients in all but one case. This is likely due to significant differences in cost of conversion.

The year-specific time dummies are interestingly higher in the post-treatment years than the pre-treatment years. This implies that the role of trend-related effects alone in driving increased corn acres in the vicinity of the North Dakota ethanol plants has been significant, irrespective of the treatment or control groups. Finally, turning to the year-specific treatment estimates, through interaction between time dummies and the treatment dummy, we still find negative (but insignificant) coefficients for BF that are hard to reconcile with economic incentives arising from transportation costs and increased local corn basis. Since the assumption of parallel paths is formally rejected, i.e., $\beta_t^d \neq 0 \; \forall \; t \leq t^*$, the year-specific coefficients on our time dummies interacted with treatment do not identify the ATT. However, comparing the size, sign and significance of the time-specific coefficients, with and without interacting with the treatment dummy, across the four ethanol plants, it is clear from Table 6 that we are dealing with four different dynamic systems. Based on these findings, we infer that point estimates of impact across many ethanol plants in a region, as usually reported in the literature, is problematic.

As discussed earlier, we estimate the impact of ethanol plants as $ATT'(s,2 \mid Z_i)$, which compares the growth of corn acres among treatment control groups over time. While the PPA based treatment estimates (although not identified) found declining absolute corn acres for three out of four ND ethanol plants, the parallel-growths-assumption-based estimates find increased growth in corn acres for two ethanol plants: RTE and TE. Whereas HRE was found in earlier estimates to increase the level of absolute corn acres locally, its presence is found to significantly decrease growth in local corn acres. BF is found to decrease absolute corn acres as well as growth in corn acres. Negative treatment effects, whether based on the PPA or the parallel growths assumption, are not supported by the economic incentives due to their presence.

In order to contrast our results with the existing regional-level analyses we pool the data for all four cases in North Dakota. We designate 2006–08 as treatment period so that the last pre-treatment year (t^*) is 2005 and the post-treatment years are 2009–13. We cannot discern a significant uniform impact due to the North Dakota ethanol plants, as opposed to the positive impact for all of the U.S. Midwest ethanol plants by Motamed et al. (2016). Motamed et al. (2016) do recognize the potential differences due to plant-level impacts but estimate a uniform impact for the region. We disagree with this single, regional-level point estimate as our plant-by-plant analysis suggests positive and negative impacts that are not reflected in the 'pooled' case.

Placebo test

We need to validate the parallel growths assumption so that the new $ATT'(s,2|Z_i)$ estimates can be trusted. Unlike the PPA, the flexible parallel $(n^{th}\text{-order})$-assumptions are specific to each post-treatment period, s. This feature allows these assumption to hold only for a subset of post-treatment periods. In this scenario, however, we can trust the treatment estimates only for the post-treatment periods where the corresponding assumption is valid.

We utilize a spatial placebo instead of the temporal placebos to validate the parallel $(n^{th}\text{-order})$-assumption that is specific to every s^{th} year ahead of the t^*. Since the temporal placebos are specified for a subset of years (utilized in case of standard DID, Figure 10) they cannot validate the new assumptions for all post-treatment years. In case of the standard DID, we aggregated pre- and post-treatment years and thus the PPA was not specific to any post-treatment year. This allowed allocating specific time periods as falsified treatment years (i.e., the temporal placebos) before or after the advent of an ethanol plant. We designate a spatial placebo (S.P.) that is a dummy ethanol plant (a point coordinate) in north-eastern North Dakota.

We locate our S.P. in north-eastern North Dakota (Figure 2) for three reasons. First, to avoid competition in demand for corn from other ethanol plants. The nearest to our S.P. is Tharaldson Ethanol which is approximately 300 km away. Second, we did not locate our placebo in north-western ND so as to avoid competition for rails/roads infrastructure by the region's Bakken Shale industry. Third, we locate our S.P. such that it sits on ND State Highway 18, following the ethanol plants in our study that are usually situated on a major highway/railroad.

We designate treatment and control groups for our S.P. with 735 land parcels in all. We then match these constituent land parcels by estimating a treatment probability for each of these from equation (3) and utilize the nearest-neighbor matching algorithm as discussed earlier. We find that area-weighted LCC and slope, in a quadratic functional form, are jointly significant in estimating the propensity of treatment from a logistic regression. Lower LCC and higher slopes are found to increase a representative parcel's treatment probability. A matching caliper of 0.01 is found to yield a balanced panel with 180 land parcels and 17 years (1997–2013). This balanced sample is then used to estimate equation (4) separately for years 2006, 2007, and 2008 as treatment year designates. We run three separate regressions for each treatment year designate due to the time period-specific identifying assumptions of the fully-flexible model. So, placebo treatment estimates will correspond to TE for 2006; to RTE & BF for 2007; and to HRE for 2008. Since a placebo is a false treatment, we expect a zero impact on corn acres due to S.P. Non-zero estimates will invalidate the identifying assumption of the new ATT.

The estimation results for placebo regressions and corresponding $ATT'(s,2)$ are presented in Tables 8 and 9, respectively. We find that $ATT'(s,2)$ remains unidentified for

HRE and TE, but identified for RTE and BF (except for post-treatment years 2011 and 2013). This finding suggests that identifying localized treatment effects is challenging. Nevertheless, we can still infer upon the effects of ethanol plants on local land use using the regression estimates for RTE and BF. Note that even the placebo regressions find differentiated conversion opportunity costs from soy to corn, wheat to corn, and grass to corn.

Since the treatment effects remain unidentified for HRE and TE, we test the equivalence between the parallel (3rd-order) and (2nd-order) differences assumptions, and between the parallel (4th-order) and (3rd-order) differences assumptions. The results are presented in Table 10. We find that parallel (3rd-order) and (2nd-order) differences assumptions are not equivalent for HRE and TE. We evaluate $ATT'(s,3|Z_i)$ for these two ethanol plants and seek differences from $ATT'(s,2|Z_i)$, if any (see table 11). $ATT'(s,3|Z_i)$ and its variance are expressed as under:

(9) $$ATT'(s,3|Z_i) = (\beta^d_{t^*+s} - 2\beta^d_{t^*+s-1} + \beta^d_{t^*+s-2}) - (\beta^d_{t^*} - 2\beta^d_{t^*-1} + \beta^d_{t^*-2}).$$

(10) $$\begin{aligned} Var(ATT'(s,3|Z_i)) = {} & Var(\beta^d_{t^*+s}) + 4Var(\beta^d_{t^*+s-1}) + Var(\beta^d_{t^*+s-2}) \\ & + Var(\beta^d_{t^*}) + 4Var(\beta^d_{t^*-1}) + Var(\beta^d_{t^*-2}) \\ & - 4\cdot Cov(\beta^d_{t^*+s}, \beta^d_{t^*+s-1}) + 2Cov(\beta^d_{t^*+s}, \beta^d_{t^*+s-2}) - 4Cov(\beta^d_{t^*+s-1}, \beta^d_{t^*+s-2}) \\ & - 4Cov(\beta^d_{t^*}, \beta^d_{t^*-1}) + 2Cov(\beta^d_{t^*}, \beta^d_{t^*-2}) - 4Cov(\beta^d_{t^*-1}, \beta^d_{t^*-2}) \\ & - 2Cov(\beta^d_{t^*+s}, \beta^d_{t^*}) + 4Cov(\beta^d_{t^*+s}, \beta^d_{t^*-1}) - 2Cov(\beta^d_{t^*+s}, \beta^d_{t^*-2}) \\ & + 4Cov(\beta^d_{t^*+s-1}, \beta^d_{t^*}) - 8Cov(\beta^d_{t^*+s-1}, \beta^d_{t^*-1}) + 4Cov(\beta^d_{t^*+s-1}, \beta^d_{t^*-2}) \\ & - 2Cov(\beta^d_{t^*+s-2}, \beta^d_{t^*}) + 4Cov(\beta^d_{t^*+s-2}, \beta^d_{t^*-1}) - 2Cov(\beta^d_{t^*+s-2}, \beta^d_{t^*-2}). \end{aligned}$$

Observe that the sign of the higher-order treatment effects for TE and HRE is the same as earlier. These higher-order treatment effects (n = 3) are interpreted as change in rate of growth in corn acres due to the presence of an ethanol plant. However, the spatial placebo invalidates the identifying parallel (3rd-order) difference assumption. Hence, we now rely solely on HRE and BF to infer on the role of ethanol plants in North Dakota.

The treatment estimates for corn acres due to HRE and BF do indicate a potential shift in agricultural systems due to these ethanol plants, but are not conclusive on the direction of this shift. While HRE has caused a positive, insignificant growth in corn acres, BF is found to affect corn growth in a significantly negative manner. The negative growth in corn acres due to BF is not supported by the aforementioned economic incentives for corn production in its vicinity. We further investigate the negative treatment effects due to BF below.

To investigate the negative impact of Blue Flint on growth of corn acres in its locality, we designate alternative treatment and control groups to the east of BF and on the east of the Missouri River. Conducting this analysis with these newly designated treatment & control groups will also gauge the sensitivity and robustness of our treatment estimates. The originally designated treatment & control groups lie south of BF, but on the other side of the river than BF. [11]The alternative treatment and control groups are designated to the east of BF because a new ethanol plant, Dakota Spirit AgEnergy (administered by the Midwest Ag Energy Group, also the owner of BF), was established in June, 2015.[12] This new ethanol plant is located approx. 200 km east of BF and 100 km west of TE. A linear city model of supply would suggest existence of a supply-demand gap to the east of BF that led to the emergence of a new plant to bridge this gap. Out treatment effects will capture whether BF prompted an increase in corn acres among eastern

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[11] Both treated and control parcels to south of the BF need to cross a river bridge to reach the plant that leads Euclidean distance to be effectively much shorter than the actual distance (see table in Appendix). Therefore, the treatment effects from the alternative T & C groups should be weaker than their southern counterpart.

[12] See *http://www.midwestagenergygroup.com/dakota-spirit-agenergy*

land parcels. We estimate $ATT'(s,2|Z_i)$ for the alternative groups and present the estimation results in Tables 12 and 13.

The alternative treatment estimates for BF are in agreement with the treatment effects from original treatment and control groups. Although corn acreage to the east side of BF increased from 2008–2013 and accelerated in 2012 and 2013, BF seems to have played a counter-productive role as far as corn acreage is concerned.

Discussion and Conclusion

The Dakotas' grasslands are a valuable natural resource as they sustain livestock production and support a waterfowl breeding habitat on existing wetlands. However, the regional agricultural production significantly increased over the past decade and intensified cropping has displaced these grasslands. Alongside, most new corn-based ethanol plants started operations in the Dakotas between 2006 and 2008. This study seeks to understand the role of new ethanol plants on local corn acreage. We argue that the economic incentives due to ethanol plants are generated as reduced transportation costs and are more relevant at a local level. We utilize a unique research design to evaluate localized land use impacts for *each* ethanol plant rather than a uniform regional impact for all ethanol plants, as usually found in the literature.

We implement a quasi-experimental setting and utilize the DID estimation strategy to evaluate an ethanol plant's impact on local corn acreage, controlling for the endogeneity due to its location. The treated and untreated parcels are first matched on soil quality in order to ensure that the impact of soils on land use does not confound our DID treatment estimates. Use of DID and/or PSM for impact analyses of change/policy is rare in economic analyses of natural resources, primarily due to unavailability of spatially explicit datasets. On a plant-by-plant basis, we find that treatment effects vary across plants and are different from a single point estimate for all ethanol plants in the region. The state-level ethanol plant impact is found to be negative, insignificant and is not consistent with the differentiated plant-level impacts.

Further, the standard parallel paths assumption of the DID fails to hold in this study. We adapt the standard DID model to a more general framework that incorporates flexible trends differentiated across groups. The updated DID model requires multiple pre-treatment periods and so we restrict our analysis to the North Dakota plants. We estimate the new treatment effects by comparing *growth* of corn acres due to the presence of ethanol plants, rather than comparing *absolute* corn acres as in case of the standard DID. The updated framework finds both positive and negative ethanol plant impacts that may be insignificant. Negative treatment effects are surprising, and difficult to reconcile with the higher incentives to grow corn in treated parcels. A spatial placebo analysis indicates that the treatment effects are identified for only two out of four ethanol plants in North Dakota.

We conclude that, although our research framework allows for a local level analysis, identifying the localized impacts is challenging. Even though we do not find definitive ethanol plant impacts, strong incremental trends in corn acres are evident across all land parcels after the 2006–08 period. Therefore, failure to detect a local effect is not inconsistent with the existence of a national-level effect of ethanol policies resulting from higher national commodity prices.

Our novel research design incorporates remotely sensed data into an applied economic analysis with quasi-experimental setting. We point towards the shortcomings of our approach. First, the Euclidean distances may not be a good representation of the 'actual' distances of land parcels from ethanol plants. Future analyses may consider a '*Nearest Facility Analysis*'- GIS tool to utilize an actual road network. Second, we use ad-hoc treatment and control groups with an imperfect matching strategy. In some cases the average pre-treatment trends in corn acres were weaker for the treated parcels for than the controls, which further raises concerns on our understanding of the ethanol plants' location decisions. Access to public infrastructure, grain elevators and/or other market terminals may better explain the plants' location choice. We lack such data but these factors may impact the land use decisions along with the plant locations. Overall, our results warrant further investigation into the location decisions of ethanol plants and other potential drivers of land use.

TABLES

Table 1. List of Ethanol Plants in North Dakota and South Dakota for our Analysis.

S. No.	Ethanol Plant	Year Established	Capacity (Million gallons per year)	Location
North Dakota				
1	Red Trail Energy	2007	50	Richardton, Stark County
2	Blue Flint Ethanol	2007	65	Underwood, McLean County
3	Tharaldson Ethanol LLC	2006	153	Casselton, Cass County
4	Hankinson Renewable Energy	2008	145	Hankinson, Richland County
South Dakota				
1	POET Bio refinery (POET)	2008	110	Chancellor, Turner County
2	NuGen Energy (NuGen)	2008	100	Marion, Turner County
3	Advanced Bio Energy (ABE)	2008	53	Aberdeen, Brown County
4	Glacial Lakes Energy (GLE)	2008	100	Mina, Edmunds County

Table 2. Schematics of the Treatment and Control Groups of Ethanol Plants Analyzed in this study**.**

Ethanol Plant	**T1**	**T2**	**C1**	**C2**
RTE	5km-30km South	15km-40km South	50km-74km South	76km-100km South
BF	5km-30km South	15km-40km South	50km-74km South	76km-100km South
TE	5km-30km West	15km-40km West	50km-74km West	76km-100km West
HRE	5km-30km West	15km-40km West	50km-74km West	76km-100km West
POET & NuGen	5km-30km West of POET*	30km-55km West of POET*	70km-94km West of POET*	96km-120km West of POET*
ABE & GLE	5km-30km West of ABE*	30km-55km West of ABE*	70km-94km West of ABE*	96km-120km West of ABE*
Spatial Placebo	5km-30km South	15km-40km South	50km-74km South	76km-100km South

* GLE lies ~30 km west of ABE – the location of T & C groups can be visualized accordingly.

Notes on Planar Dimensions of our Treatment and Control Rectangles (Part of Table 2):

- Red Trail Energy & Blue Flint Ethanol: **25 km N-S X 50 km E-W**.
- Tharaldson Ethanol: **25 km E-W X 50 km N-S**.
- Hankinson Renewable Energy: **25 km E-W X 40 km N-S**. The North Dakota State boundary is located 15 km south of this plant and the N-S dimensions accommodate this.
- Cluster (POET and NuGen): **25 km E-W X 40 km N-S**. The rectangles excluded a circle of radius 2.5 km from NuGen, i.e. permanent development (township).
- Cluster (ABE and GLE): **25 km E-W X 50 km N-S**. The rectangles exclude a circle of radius 7 km from GLE to avoid a large water pond in land use characterization.
- Spatial Placebo: **25 km N-S X 30 km E-W**

Table 3. Propensity Score Estimation using Logit regressions. Dependent Variable: $P(d_i = 1)$.

Variable	RTE	BF	TE	HRE	ABGL	PBNE	S.P.
Intercept	24.42** (3.52)	1.60** (0.48)	14.48 (9.64)	9.99** (1.70)	-59.32** (5.41)	11.66** (1.09)	56.41*** (10.51)
$WLCC$	-40.18** (3.10)	0.63* (0.35)	-12.25 (7.76)	-2.61** (1.05)	11.65** (1.70)	-5.33** (0.98)	-44.23*** (8.44)
$WLCC^2$	7.53** (0.61)	-0.11** (0.04)	2.38 (1.60)	0.33* (0.18)	-2.01** (0.31)	0.79** (0.23)	-8.60*** (1.70)
$WSLP$	6.52** (0.48)	-0.31** (0.10)	6.20** (2.39)	-2.77** (0.31)	30.71** (4.23)	-2.63** (0.44)	2.26 (3.00)
$WSLP^2$	-0.40** (0.03)	0.01** (0.005)	-1.95** (0.43)	2.88** (0.38)	-5.29** (0.76)	0.33** (0.05)	-1.50* (0.80)
AIC	946	1222	709	1211	991	977	582
SC	972	1246	734	1235	1016	1002	605
-2 Log L	936	1212	699	1201	981	967	572

** means significant at 95% C.I. * means significant at 90% C.I. Standard error in parentheses.

Table 4. Matching Performance.

H_o^1: Means of variable X_i^a are statistically equal across groups (t-test).

H_o^2: Variances of variable X_i^a are statistically equal across groups (F-test).

Ethanol Plant	Sample Size		Caliper	X_i^a	Mean		H_o^1 p-value	Variance		H_o^2 p-value
	Pre-Match	Post-Match			T	C		T	C	
RTE	1224	130	0.0004	$WLCC$	2.36	2.30	0.42	0.15	0.14	0.66
				$WSLP$	7.92	7.46	0.11	2.72	2.62	0.87
BF	1012	548	0.01	$WLCC$	3.77	3.68	0.57	2.82	3.20	0.28
				$WSLP$	9.77	9.73	0.93	16.97	18.84	0.42
TE	1155	240	0.01	$WLCC$	2.09	2.07	0.48	0.05	0.04	0.21
				$WSLP$	2.83	2.83	0.98	0.02	0.03	0.06
HRE	980	322	0.005	$WLCC$	2.97	2.88	0.34	0.69	0.72	0.77
				$WSLP$	3.03	3.14	0.39	1.21	1.32	0.54
ABGL	1118	200	0.0005	$WLCC$	2.04	2.06	0.57	0.12	0.08	0.09
				$WSLP$	3.17	3.24	0.20	0.18	0.14	0.28
PBNE	971	314	0.005	$WLCC$	2.04	2.06	0.57	0.12	0.08	0.10
				$WSLP$	3.17	3.24	0.20	0.18	0.14	0.27
Spatial Placebo	735	180	0.01	$WLCC$	2.22	2.23	0.85	0.14	0.13	0.81
				$WSLP$	1.92	1.89	0.62	0.13	0.15	0.60

Table 5. Placebo Estimates with 'Logarithm of CS' as dependent variable

	Red Trail Energy	Blue Flint Ethanol	Tharaldson Ethanol	Hankinson Renewable Energy
F.T. – 1 (2000)	*-1.63***	*1.09****	*-1.27****	*-0.29****
ACTUAL TREATMENT	***-0.28***	***-0.50*****	***-0.54******	***0.09***
F.T. – 2 (2011)	*0.21*	*0.32*	*-0.14****	*-0.46***

Table 6. Estimates of the fully-flexible DID model. Dependent Variable: $C_{i,t}$

Variable	RTE	BF	TE	HRE	POOLED
Intercept	8.62 (3.18)***	33.05 (5.20)***	-24.60 (5.86)***	77.38 (10.48)***	61.60 (5.33)***
$W_{i,t-1}$	0.003 (0.01)	-0.003 (0.02)	-0.02 (0.02)	-0.36 (0.04)***	-0.20 (0.02)***
$S_{i,t-1}$	0.41 (0.26)	0.09 (0.06)	0.17 (0.02)***	0.25 (0.04)***	0.17 (0.02)***
$G_{i,t-1}$	-0.02 (0.01)***	-0.07 (0.01)***	-0.09 (0.02)***	-0.27 (0.03)***	-0.19 (0.01)***
d_i	-0.20 (1.98)	-7.14 (1.56)***	11.84 (4.42)***	-28.52 (8.76)***	-9.45 (3.17)***
$I_{[t=1998]} \times d_i$	-0.07 (1.96)	12.75 (2.46)***	-9.48 (5.72)	10.50 (10.57)	17.54 (4.16)***
$I_{[t=1999]} \times d_i$	1.65 (2.15)	12.77 (2.32)***	-7.76 (6.18)	44.58 (9.91)***	21.61 (3.57)***
$I_{[t=2000]} \times d_i$	1.36 (2.17)	-0.88 (1.70)	-33.15 (5.84)***	-26.55 (9.63)***	-12.19 (3.39)***
$I_{[t=2001]} \times d_i$	-2.42 (1.90)	12.40 (2.21)***	-34.66 (7.07)***	6.32 (10.59)	4.95 (3.67)
$I_{[t=2002]} \times d_i$	-4.32 (2.01)***	3.13 (2.05)	-33.29 (7.86)***	10.78 (9.71)	4.50 (3.49)
$I_{[t=2003]} \times d_i$	-0.58 (1.97)	8.67 (1.80)***	-33.10 (6.38)***	-29.81 (11.72)***	-5.05 (3.83)
$I_{[t=2004]} \times d_i$	-5.38 (3.86)	4.23 (1.70)***	38.58 (8.60)***	30.58 (11.21)***	18.39 (3.92)***
$I_{[t=2005]} \times d_i$	-0.19 (1.90)	6.90 (2.04)***	1.23 (8.56)	68.96 (9.35)***	22.19 (3.44)***
$I_{[t=2006]} \times d_i$	0.66 (2.50)	12.89 (2.59)***	--	2.41 (9.70)	--
$I_{[t=2007]} \times d_i$	--	--	24.26 (11.18)**	23.60 (9.80)**	--
$I_{[t=2008]} \times d_i$	-2.21 (2.19)	2.53 (2.63)	-1.42 (11.95)	--	--
$I_{[t=2009]} \times d_i$	0.54 (4.29)	3.78 (2.64)	29.33 (10.22)***	41.69 (9.93)***	19.29 (3.82)***
$I_{[t=2010]} \times d_i$	3.64 (4.18)	1.71 (2.72)	22.71 (12.06)*	26.83 (10.22)***	14.60 (4.15)***
$I_{[t=2011]} \times d_i$	8.93 (4.62)*	-1.81 (3.40)	20.85 (11.85)*	14.32 (10.53)	9.90 (4.24)**
$I_{[t=2012]} \times d_i$	14.01 (12.26)	-1.80 (4.55)	46.06 (14.65)***	22.11 (11.06)**	17.87 (5.36)***
$I_{[t=2013]} \times d_i$	29.87 (8.35)***	-5.93 (4.57)	56.18 (12.84)***	27.10 (11.52)***	19.09 (5.29)***
$I_{[t=1998]}$	-4.28 (1.80)**	-12.78 (1.57)***	42.06 (4.58)***	90.67 (8.04)***	20.09 (2.93)***

Table 6 continued

$I_{[t=1999]}$	-3.03 (1.22)***	-10.55 (1.54)***	37.40 (4.44)***	37.48 (7.30)***	10.76 (2.43)***
$I_{[t=2000]}$	0.80 (1.17)	-3.23 (1.38)**	49.31 (5.21)***	81.09 (7.65)***	27.77 (2.63)***
$I_{[t=2001]}$	-1.82 (1.19)	-11.34 (1.44)***	51.44 (5.10)***	43.44 (8.36)***	15.12 (2.72)***
$I_{[t=2002]}$	-0.47 (1.41)	-3.70 (1.49)***	44.04 (5.25)***	24.51 (7.04)***	11.27 (2.46)***
$I_{[t=2003]}$	-4.53 (1.41)***	-18.59 (2.09)***	40.26 (4.38)***	53.81 (9.40)***	6.76 (3.10)**
$I_{[t=2004]}$	5.72 (2.82)**	-1.03 (1.25)	38.03 (5.08)***	60.47 (7.95)***	25.75 (2.55)***
$I_{[t=2005]}$	-2.86 (1.15)***	-4.23 (1.38)***	34.12 (5.54)***	1.76 (7.43)	4.13 (2.34)*
$I_{[t=2006]}$	3.33 (1.62)	-3.19 (1.40)**	--	51.65 (7.59)***	--
$I_{[t=2007]}$	--	--	84.25 (7.51)***	80.39 (7.54)***	--
$I_{[t=2008]}$	3.05 (1.48)**	8.45 (2.01)***	98.26 (7.88)***	--	--
$I_{[t=2009]}$	6.45 (2.81)**	8.95 (2.05)***	62.18 (6.70)***	44.99 (7.34)***	31.40 (2.56)***
$I_{[t=2010]}$	2.30 (1.92)	6.99 (1.87)***	68.43 (7.71)***	29.51 (7.49)***	23.49 (2.78)***
$I_{[t=2011]}$	3.43 (1.55)**	16.93 (2.35)***	55.92 (6.91)***	84.62 (8.33)***	41.53 (2.83)***
$I_{[t=2012]}$	20.43 (6.28)***	27.17 (2.87)	113.28 (8.93)***	80.72 (8.20)***	56.33 (3.38)***
$I_{[t=2013]}$	6.11 (3.49)*	31.02 (3.08)	111.97 (8.48)***	89.84 (8.16)***	58.94 (3.39)***
R^2	0.16	0.20	0.41	0.32	0.38

* p<0.1; ** p<0.05; *** p<0.01; -- signifies advent of the ethanol plants. S.E.s in parentheses.

Table 7. $ATT(s,2|Z_i)$ for the Four ND Ethanol Plants.

Ethanol Plant (Year Established)	Red Trail E. (2007)	Blue Flint (2007)	Tharaldson E. (2006)	Hankinson E. (2008)	POOLED (2006-'08)
2007	-	-	60.38***	-	-
2008	-3.73	-16.35***	11.67	-	-
2009	1.91	-4.74	68.10***	-3.09	-6.70
2010	2.25	-8.06***	30.73*	-36.05***	-8.50
2011	4.44	-9.51***	35.50*	-33.70***	-8.50
2012	4.23	-5.97	62.56**	-13.39	4.17
2013	15.01	-10.12**	47.46**	-16.19	-2.58

* p<0.1; ** p<0.05; *** p<0.01

Table 8. Estimation of the Fully-flexible DID Model for our Spatial Placebo. Dependent Var. $C_{i,t}$

Variable	TE *'2006'*	RTE/BF *'2007'*	HRE *'2008'*	POOLED *'2006-'08'*
Intercept	10.57 (4.50)**	11.69 (4.26)**	10.33 (4.33)**	11.17 (4.27)***
$W_{i,t-1}$	-0.05 (0.02)**	-0.05 (0.02)***	-0.04 (0.02)**	-0.04 (0.02)***
$S_{i,t-1}$	0.11 (0.03)***	0.09 (0.03)***	0.10 (0.03)***	0.09 (0.03)***
$G_{i,t-1}$	-0.10 (0.02)***	-0.09 (0.02)***	-0.09 (0.02)***	-0.08 (0.02)***
d_i	-2.70 (3.38)	-3.07 (3.30)	-3.13 (3.26)	-3.47 (3.19)
$I_{[t=1998]} \times d_i$	7.88 (5.70)	7.35 (5.64)	7.72 (5.71)	7.41 (5.68)
$I_{[t=1999]} \times d_i$	1.40 (5.07)	0.07 (4.88)	0.81 (4.85)	-0.04 (4.76)
$I_{[t=2000]} \times d_i$	-1.10 (4.23)	-1.21 (4.13)	-1.17 (4.19)	-1.26 (4.11)
$I_{[t=2001]} \times d_i$	21.31 (5.51)***	18.50 (5.21)***	19.83 (5.26)***	17.92 (5.05)***
$I_{[t=2002]} \times d_i$	11.10 (4.10)**	10.56 (4.01)**	10.77 (4.04)***	10.43 (3.97)***
$I_{[t=2003]} \times d_i$	-9.03 (5.28)*	-9.34 (5.02)*	-8.41 (5.07)*	-8.70 (5.01)*
$I_{[t=2004]} \times d_i$	-46.05 (8.10)***	-44.85 (7.98)***	-44.05 (7.88)***	-43.25 (7.67)***
$I_{[t=2005]} \times d_i$	23.47 (6.54)***	22.43 (6.35)***	23.32 (6.41)***	22.52 (6.27)***
$I_{[t=2006]} \times d_i$	--	-0.39 (6.57)	0.23 (6.62)	--
$I_{[t=2007]} \times d_i$	-48.70 (10.59)***	--	-48.58 (10.55)***	--
$I_{[t=2008]} \times d_i$	-36.38 (10.69)***	-36.51 (10.68)***	--	--
$I_{[t=2009]} \times d_i$	-46.32 (9.71)***	-46.40 (9.69)***	-46.27 (9.73)***	-46.26 (9.73)***
$I_{[t=2010]} \times d_i$	-59.14 (9.74)***	-59.50 (9.74)***	-59.45 (9.76)***	-59.63 (9.76)***
$I_{[t=2011]} \times d_i$	-42.83 (10.09)***	-43.20 (10.06)***	-43.11 (10.10)***	-43.38 (10.07)***
$I_{[t=2012]} \times d_i$	-81.92 (12.37)***	-82.24 (12.43)***	-81.78 (12.35)***	-81.99 (12.35)***

Table 8 continued

$I_{[t=2013]} \times d_i$	-52.30 (10.62)***	-52.52 (10.53)***	-52.27 (10.58)***	-52.46 (10.53)***
$I_{[t=1998]}$	20.53 (4.61)***	19.89 (4.55)***	19.54 (4.61)***	19.02 (4.49)***
$I_{[t=1999]}$	11.12 (4.87)**	10.32 (4.67)**	9.87 (4.56)**	9.27 (4.50)**
$I_{[t=2000]}$	13.91 (4.58)***	12.25 (4.44)**	12.22 (4.31)***	11.03 (4.17)***
$I_{[t=2001]}$	-4.54 (5.16)	-4.22 (4.81)	-5.31 (4.91)	-5.11 (4.71)
$I_{[t=2002]}$	5.18 (4.07)	4.43 (3.97)	4.21 (3.84)	3.59 (3.75)
$I_{[t=2003]}$	10.87 (5.14)**	10.36 (4.92)**	9.55 (4.88)*	9.16 (4.81)*
$I_{[t=2004]}$	37.67 (7.33)***	37.05 (7.20)***	36.09 (7.24)***	35.76 (7.04)***
$I_{[t=2005]}$	6.78 (4.77)	7.46 (4.44)*	6.32 (4.57)	6.88 (4.41)
$I_{[t=2006]}$	--	24.91 (5.28)***	24.15 (5.30)***	--
$I_{[t=2007]}$	86.02 (10.69)***	--	84.73 (10.46)***	--
$I_{[t=2008]}$	79.38 (9.56)***	78.43 (9.52)***	--	--
$I_{[t=2009]}$	84.32 (8.43)***	83.63 (8.39)***	83.46 (8.42)***	82.95 (8.42)***
$I_{[t=2010]}$	76.53 (9.32)***	76.28 (9.32)***	76.13 (9.29)***	75.92 (9.27)***
$I_{[t=2011]}$	65.38 (9.41)***	64.74 (9.39)***	64.45 (9.37)***	64.03 (9.44)***
$I_{[t=2012]}$	104.64 (11.45)***	105.19 (11.50)***	104.45 (11.39)***	104.83 (11.40)***
$I_{[t=2013]}$	64.21 (10.01)***	64.51 (9.92)***	64.14 (9.97)***	64.38 (9.93)***
R^2	0.32	0.31	0.32	0.33

* p<0.1; ** p<0.05; *** p<0.01; -- signifies advent of the ethanol plants. S.E.s in parentheses.

Table 9. Estimate of $ATT(s,2|Z_i)$ for our Spatial Placebo.

Ethanol Plant (Year Established)	TE *'2006'*	RTE/BF *'2007'*	HRE *'2008'*	POOLED *'2006-'08'*
2007	-141.69***	-	-	-
2008	-57.21***	-13.31	-	-
2009	-79.46***	12.93	51.12***	-134.54***
2010	-82.35***	9.72	35.63**	-79.14***
2011	-53.21***	39.11***	65.16***	-49.51***
2012	-108.62***	-16.22	10.14	-104.39***
2013	-39.90***	52.54***	78.32***	-36.22***

* p<0.1; ** p<0.05; *** p<0.01

Table 10. T-statistic: Testing the Equivalence of n^{th}-order and $(n-1)^{th}$-order assumptions .

n	H_0	Red Trail E. (2007)	Blue Flint (2007)	Tharaldson E. (2006)	Hankinson E. (2008)
3	$\Delta^2\beta^d_{t^*}=0$	-4.35	3.32	-109.03***	87.74***
4	$\Delta^3\beta^d_{t^*}=0$	-14	-3.79	-180.51***	192.68***
5	$\Delta^4\beta^d_{t^*}=0$			-253.168***	275.61***

* p<0.1; ** p<0.05; *** p<0.01

Table 11. Estimate of $ATT(s,3|Z_i)$ where Equivalence Assumptions Failed (Table 10).

Ethanol Plant (Year Established)	Tharaldson E. (2006)	Hankinson E. (2008)
2007	169.40***	-
2008	60.32***	-
2009	165.46***	-90.83***
2010	71.65***	-120.70***
2011	113.80***	-85.39***
2012	136.09***	-67.43***
2013	93.93***	-90.54***

* p<0.1; ** p<0.05; *** p<0.01

Table 12. Estimation of the Fully-flexible DID Model for **Eastern Treatment & Control Groups** of the BF. Dependent Variable $C_{i,t}$.**T1: 15km-40km East & C2: 85km-110km East.**

Variable	BF (2007)
Intercept	1.82 (2.95)
$W_{i,t-1}$	0.04 (0.01)***
$S_{i,t-1}$	0.12 (0.03)***
$G_{i,t-1}$	-0.03 (0.01)***
d_i	1.00 (1.60)
$I_{[t=1998]} \times d_i$	2.62 (2.00)
$I_{[t=1999]} \times d_i$	-0.32 (2.06)
$I_{[t=2000]} \times d_i$	-2.63 (1.72)
$I_{[t=2001]} \times d_i$	-2.66 (2.48)
$I_{[t=2002]} \times d_i$	-3.49 (2.32)
$I_{[t=2003]} \times d_i$	-4.04 (1.93)**
$I_{[t=2004]} \times d_i$	4.10 (2.35)*
$I_{[t=2005]} \times d_i$	-6.73 (3.61)*
$I_{[t=2006]} \times d_i$	-0.17 (2.79)
$I_{[t=2007]} \times d_i$	--
$I_{[t=2008]} \times d_i$	-8.97 (4.69)*
$I_{[t=2009]} \times d_i$	-11.92 (4.64)***
$I_{[t=2010]} \times d_i$	-2.69 (4.44)
$I_{[t=2011]} \times d_i$	-3.85 (4.87)
$I_{[t=2012]} \times d_i$	-30.47 (7.84)***
$I_{[t=2013]} \times d_i$	-9.99 (7.34)

Table 12 continued

$I_{[t=1998]}$	-0.96 (1.69)
$I_{[t=1999]}$	3.05 (1.79)*
$I_{[t=2000]}$	4.23 (1.72)**
$I_{[t=2001]}$	4.45 (2.40)*
$I_{[t=2002]}$	4.65 (2.05)**
$I_{[t=2003]}$	1.81 (1.96)
$I_{[t=2004]}$	1.76 (1.75)
$I_{[t=2005]}$	9.07 (3.62)**
$I_{[t=2006]}$	4.48 (2.38)*
$I_{[t=2007]}$	--
$I_{[t=2008]}$	18.75 (4.31)***
$I_{[t=2009]}$	18.91 (4.56)***
$I_{[t=2010]}$	9.22 (3.78)**
$I_{[t=2011]}$	12.89 (4.48)***
$I_{[t=2012]}$	43.01 (7.42)***
$I_{[t=2013]}$	32.19 (5.94)***
R^2	0.20

* p<0.1; ** p<0.05; *** p<0.01; -- signifies advent of the ethanol plant. S.E.s in parentheses.

Table 13. Treatment Estimates for the **Eastern Treatment & Control Groups** of the BF.

Ethanol Plant (Year Established)	$ATT'(s,2\mid Z_i)$	$ATT'(s,3\mid Z_i)$
2008	-15.35***	-32.73***
2009	-9.51	-11.54
2010	2.68	-5.20
2011	-7.72	-27.78*
2012	-33.17***	-42.83***
2013	13.92	29.71

* p<0.1; ** p<0.05; *** p<0.01

FIGURES

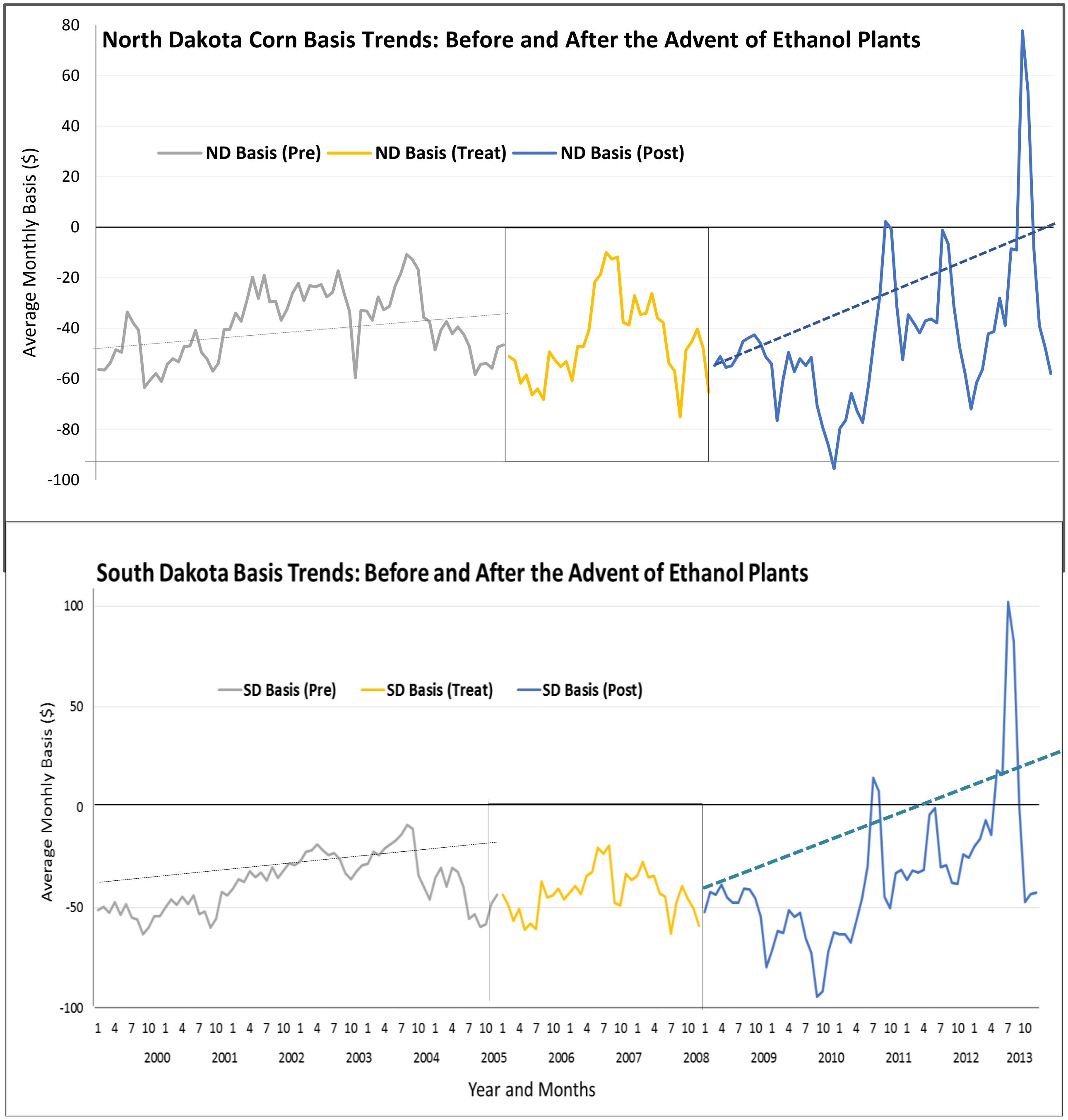


Figure 1. Comparative corn basis trends for counties that house Dakota ethanol plants that started operations in the 2006–2008 period**.**

Notes: The acronym 'treat' denotes the period when these ethanol plants started operations, 'pre' ('post') means years prior to (after) the 2006–2008 period.

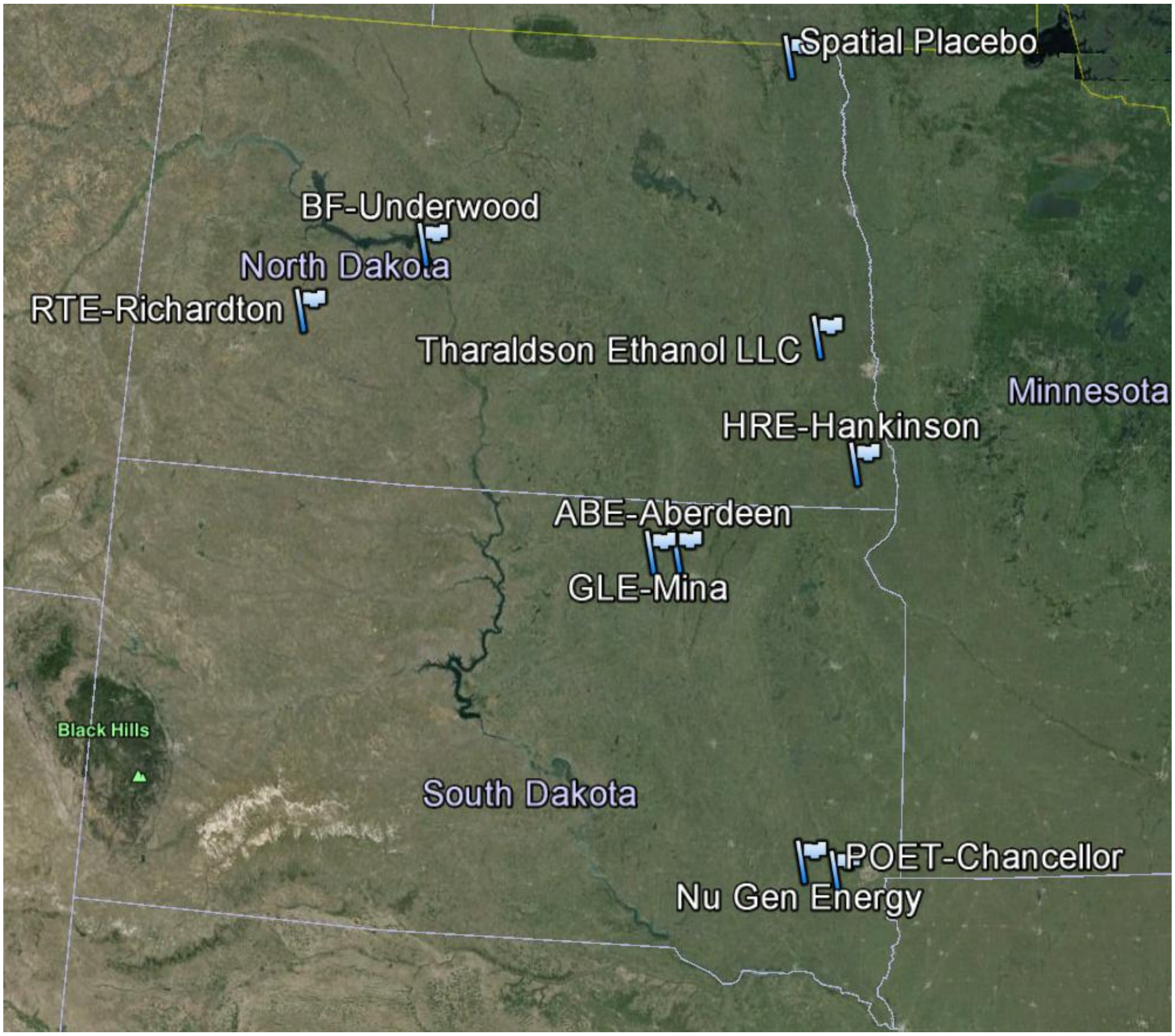
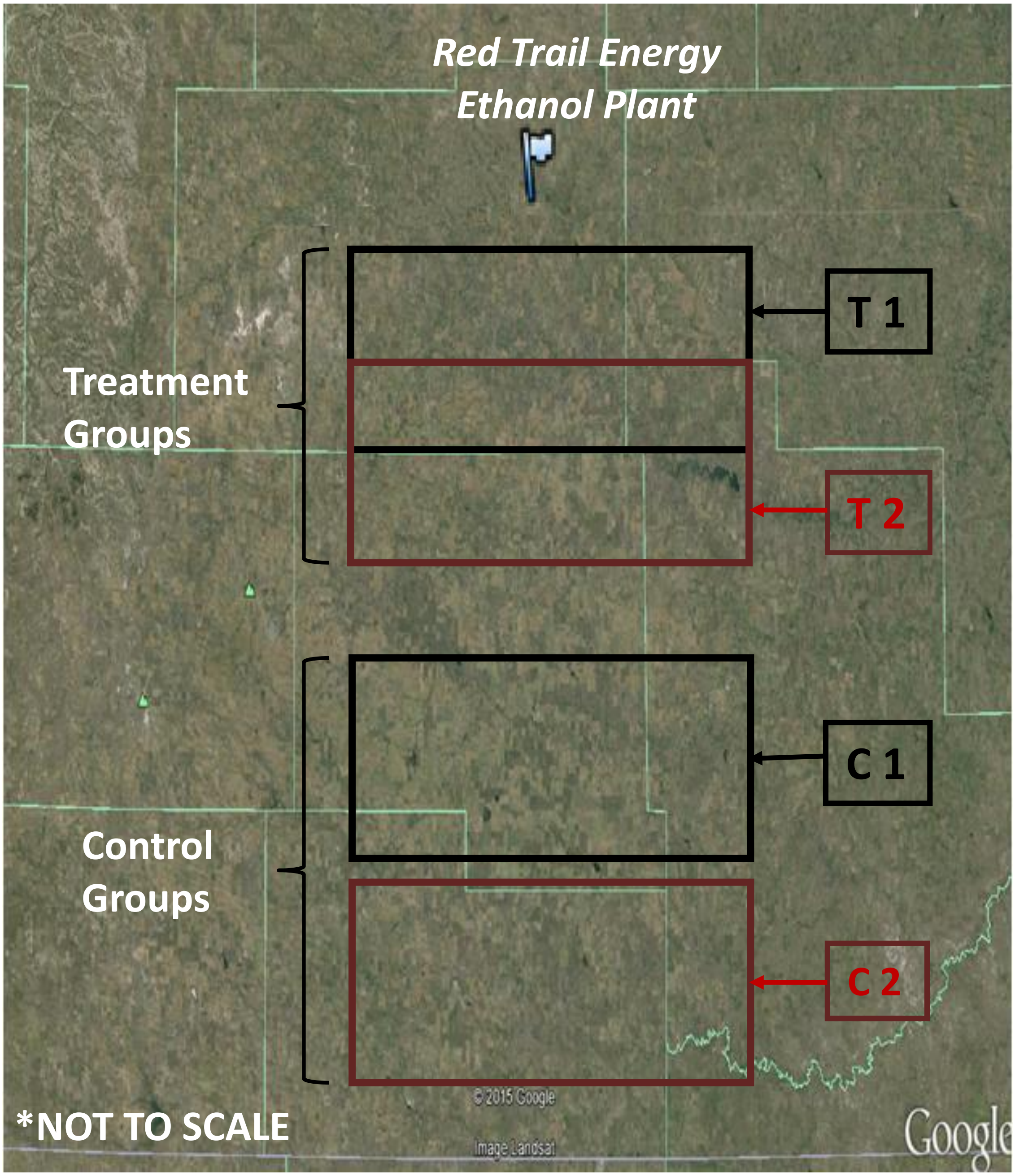
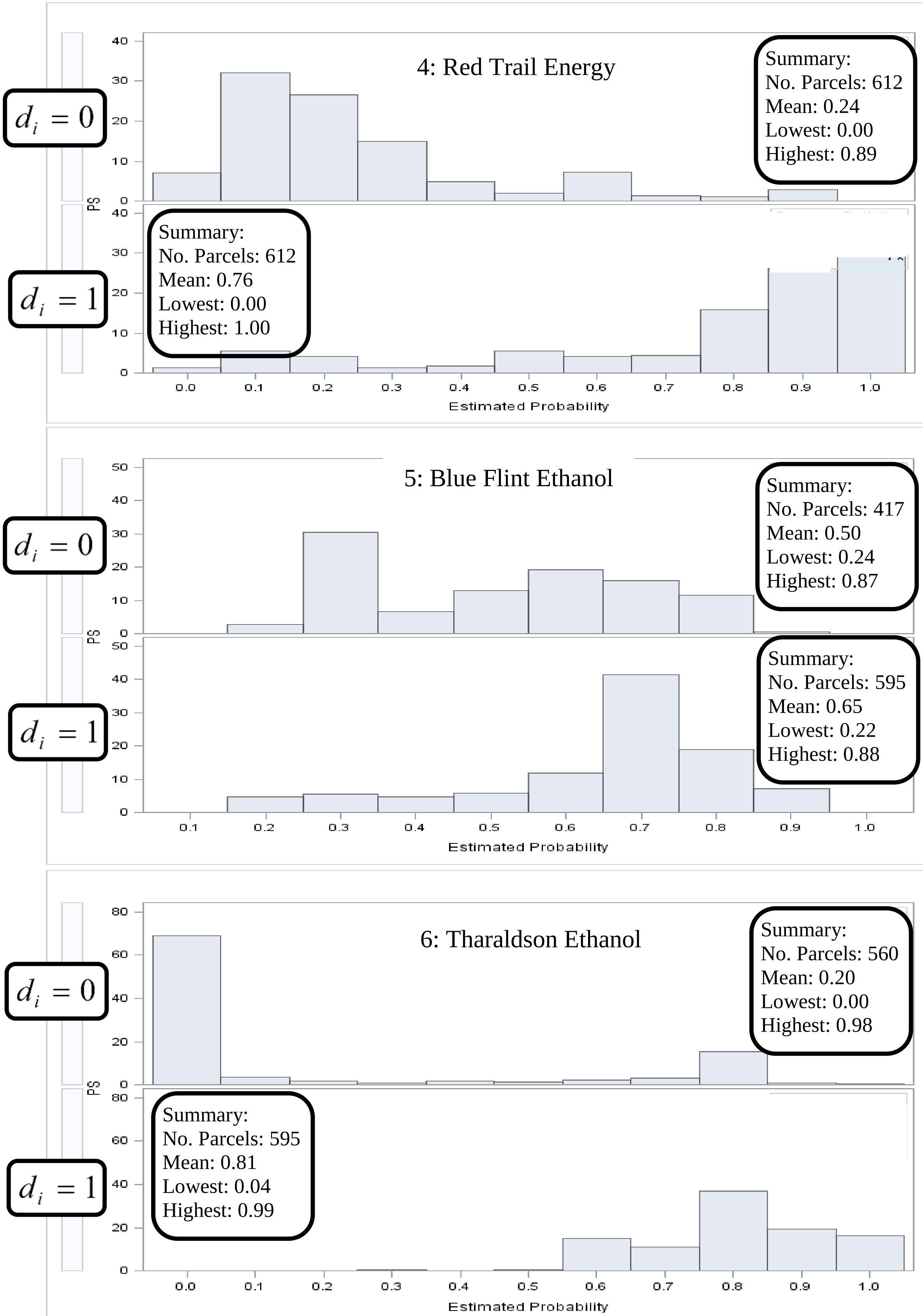


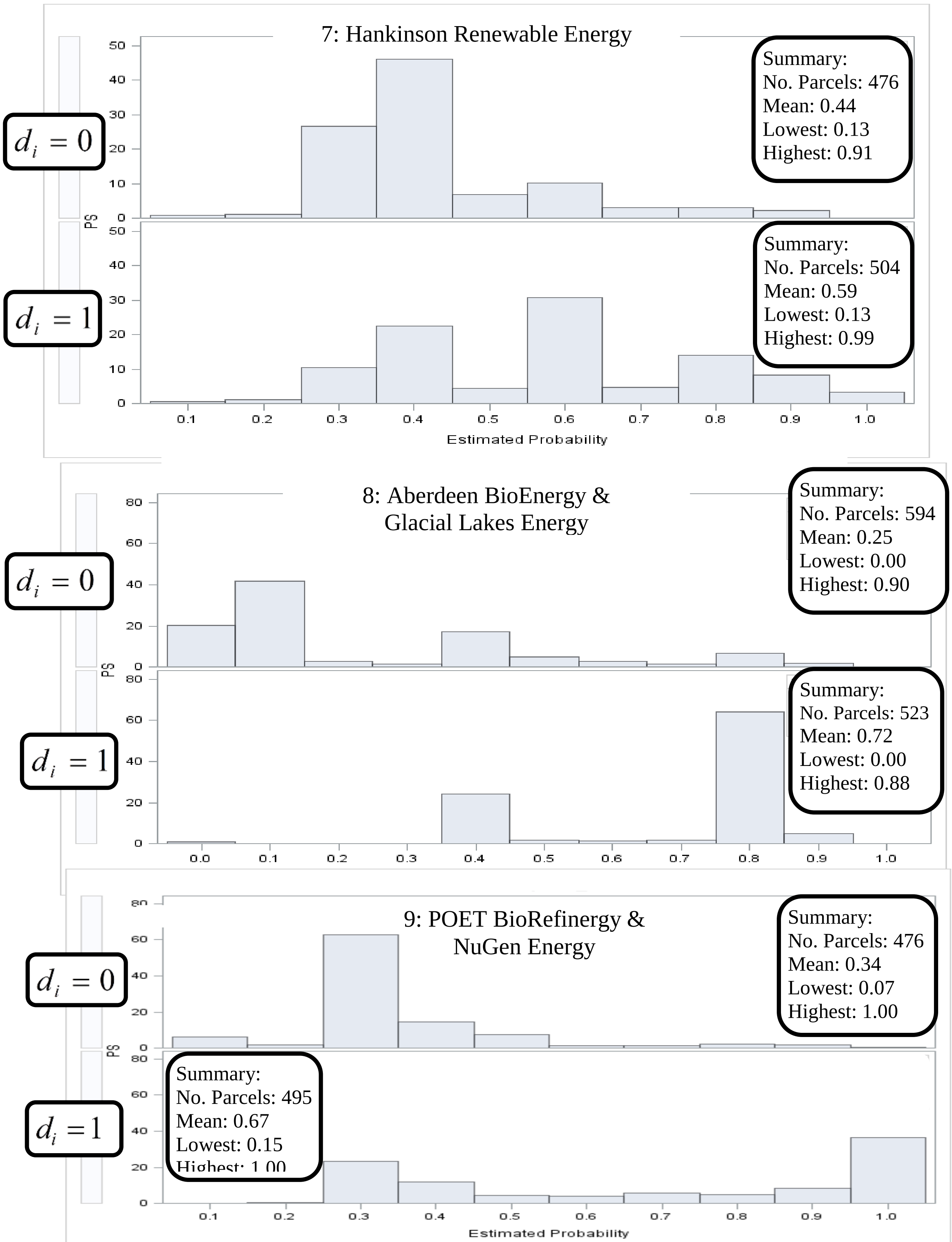
Figure 2. Spatial locations of the 8 ethanol plants included in this analysis.
Image
Source: Google Earth: “North and South Dakota.” 5122554.70 m N and 393724.99 m E. **Google Earth.** April 9, 2013. August 8, 2015.



Source: “North Dakota” 33704.21m E, 5249274.59m N. Google Earth. April 9, 2014. October 20, 2014.

Figure 3. Schematics of treatment and control group: an example.


4: Red Trail Energy
$d_i = 0$
Summary:
No. Parcels: 612
Mean: 0.24
Lowest: 0.00
Highest: 0.89
$d_i = 1$
Summary:
No. Parcels: 612
Mean: 0.76
Lowest: 0.00
Highest: 1.00
PS
Estimated Probability
5: Blue Flint Ethanol
$d_i = 0$
Summary:
No. Parcels: 417
Mean: 0.50
Lowest: 0.24
Highest: 0.87
$d_i = 1$
Summary:
No. Parcels: 595
Mean: 0.65
Lowest: 0.22
Highest: 0.88
PS
Estimated Probability
6: Tharaldson Ethanol
$d_i = 0$
Summary:
No. Parcels: 560
Mean: 0.20
Lowest: 0.00
Highest: 0.98
$d_i = 1$
Summary:
No. Parcels: 595
Mean: 0.81
Lowest: 0.04
Highest: 0.99
PS
Estimated Probability



Figures 4-9. Distribution of Treatment Probability across treatment and control groups.

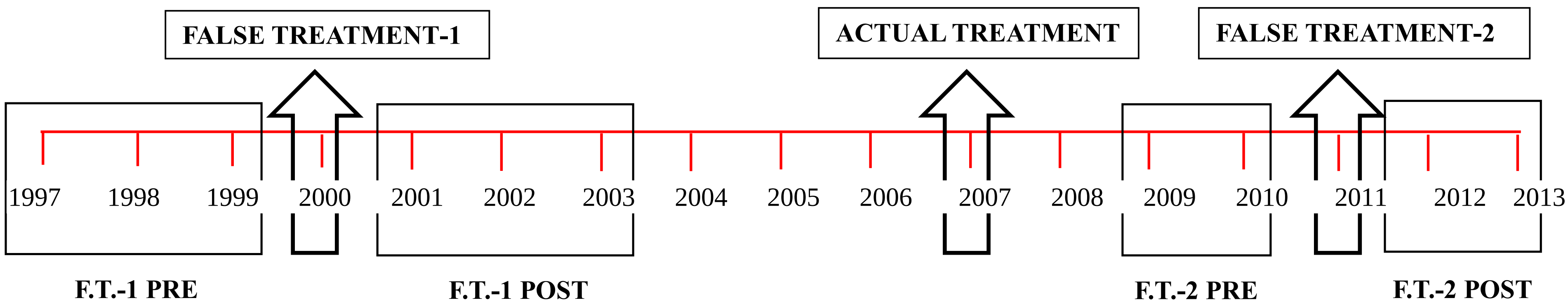


Figure 10. Temporal placebo schematics: validating the estimates from the standard DID model.
Moving Away from the Parallel Paths Assumption

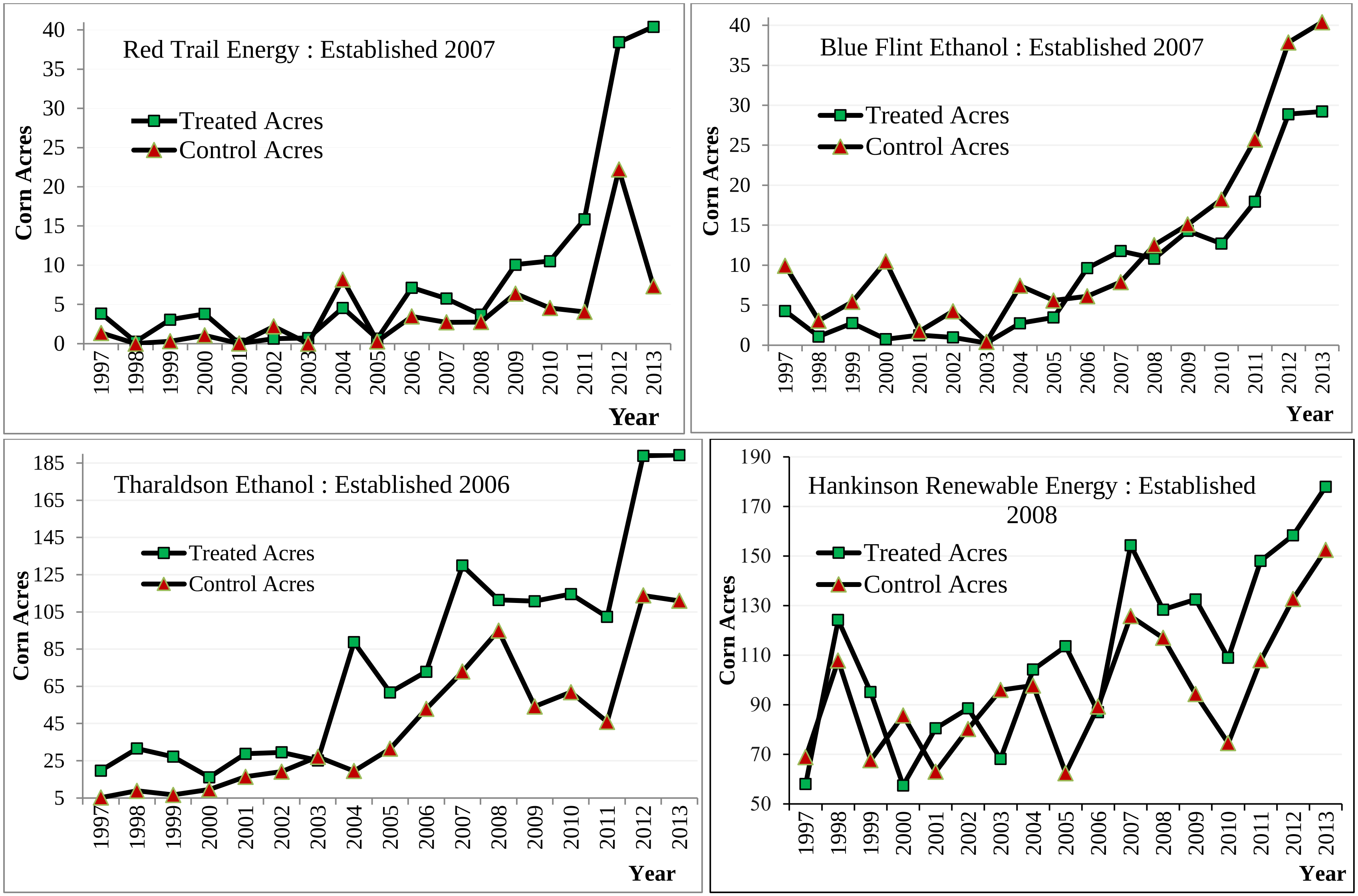


Figure 11. Average corn acre-trends for treated & control groups of the North Dakota ethanol plants. *Focus*: Pre-treatment trends.

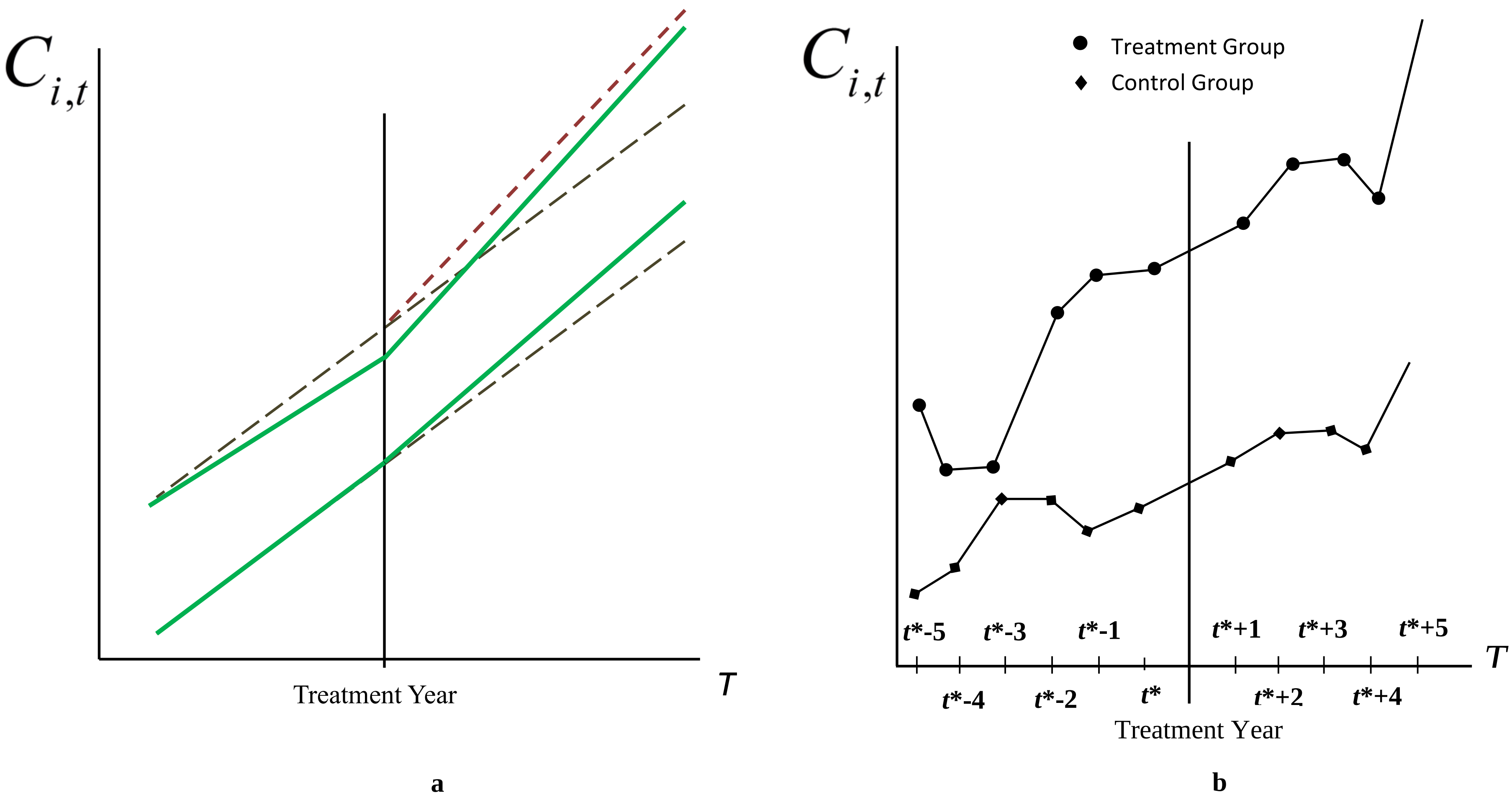


Figure 12 (a, b). The issue of non-parallel trends among treatment and control groups.

REFERENCES

Abadie, A. 2005. “Semiparametric Difference-in-Difference Estimators,” *Review of Economic Studies* 72(1):1-19. (Cited in the *Supplementary Information*)

Bertrand. M., Duflo, E., Mullainathan, S. 2004. “How Much Should We Trust Difference-In-Difference Estimates,” *Quarterly Journal of Economics* 119(1):249-275.

Brown, J.C., Hanley, E., Bergtold, J.S., Caldas, M., Barve, V., Peterson, D.,L. 2014. “Ethanol plant location and intensification vs. extensification of corn cropping in Kansas,” *Applied Geography* 52:141-148.

Caliendo, M., Kopeinig, S. 2008. “Some practical guidance for the implementation of propensity score matching,” *Journal of Economic Surveys* 22(1): 31-72.

Claassen, R., Cooper, J.C., Carriazo, F. 2011. “Crop Insurance, Disaster Payments, and Land Use Change: The Effect of Sodsaver on Incentives for Grassland Conversion,” *Journal of Agricultural and Applied Economics* 43(2): 195–211.

Dehejia, R.H., Wahba, S. 1999. “Causal Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs,” *Journal of American Statistical Association* 94(448):1053-1062.

Du, X., Hennessy, D.A., Edwards, W.M. 2007. “Determinants of Iowa Cropland Cash Rental Rates: Testing Ricardian Rent Theory,” *Working Paper 07-WP 454, Center for Agricultural and Rural Development, Iowa State University.*

Fraeman, K.H. 2010. “An Introduction to Implementing Propensity Score Matching With SAS®,” *Northeast SAS Users Group Conference Proceedings, Baltimore, M.D.*

Heckman, J.J., Ichimura, H., Todd, P.E. 1997. “Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme,” *The Review of Economic Studies* 64(4): 605-654.

Henderson, J., Gloy, B.A. 2009. “The Impact of Ethanol Plants on Cropland Values in the Great Plains,” *Agricultural Finance Review* 69(1): 36–48.

Johnston, C.A. 2014. “Agricultural Expansion: Land Use Shell Game in the U.S. Northern Plains,” *Landscape Ecology* 29(1):81-95.

Katchova, A.L. 2009. "The Spatial Effect of Ethanol Biorefinery Locations on Local Corn Prices," Selected paper, *2009 AAEA Annual Meeting, Milwaukee, WI.*

Lark, T.J., Salmon, J.M., Gibbs, H.K. 2015. "Cropland Expansion Outpaces Agricultural and Biofuel Policies in the United States," *Environmental Research Letters* 10(4):044003.

Lewis, K.E. 2010. "The Impact of Ethanol on Corn Market Relationships and Corn Price Basis Levels," *M.S. Thesis, Dept. of Ag., Food, and Res. Economics, Michigan State University.*

List, J.A., Millimet, D.L., Fredriksson, PG., McHone, W.W. 2003 "Effects of Environmental Regulations on Manufacturing Plant Births: Evidence from a Propensity Score Estimator," *The Review of Economics and Statistics* 85(4): 944-952.

McNew, K., Griffith, D. 2005. "Measuring the Impact of Ethanol Plants on Local Grain Prices," *Review of Agricultural Economics* 27(2): 164–180.

Meyer, B.D. 1995. "Natural and Quasi-Experiments in Economics," *Journal of Business and Economic Statistics* 13(2): 151-161. (Cited in the *Supplementary Information*)

Miao, R. 2013. "Impact of Ethanol Plants on Local Land Use Change," *Agricultural and Resource Economics Review 42(2):291-309.*

Mora, R., Reggio I. 2012. "Treatment Effect Identification Using Alternative Parallel Assumptions," *UC3M Working Paper 12-33, Economic Series (48).*

Motamed, M.J., McPhail, L.L. 2011. "Spatial Dimensions of US Crop Selection: Recent Responses to Markets and Policy," Selected Paper, *2011 AAEA & NAREA Joint Annual Meeting*, Pittsburgh, PA.

Motamed, M.J., McPhail, L.L., Williams, R. 2016. "Corn Area Response to Local Ethanol Markets in the United State: A Grid Cell Level Analysis," *American Journal of Agricultural Economics* Advance Access: 1–18; doi: 10.1093/ajae/aav095.

Mueller, S., Copenhaver, K. 2009. "Determining the Land Use Impact of Two Midwestern Corn Ethanol Plants," *Energy Resources Center, University of Illinois at Chicago*. Retrieved from: http://www.erc.uic.edu/assets/pdf/twoplantlucstudyEPASubmissionv3.pdf

O'Brien, D. 2009. "The Effects of the Micro-Market Structure for Kansas Grain Elevators on Spatial Grain Price Differentials," *NCCC-134 Applied Commodity Price Analysis, Forecasting and Market Risk Management Conference, St. Louis, Missouri*.

Reber, S.J. 2005. "Court-Ordered Desegregation Success and Failures Integrating American Schools since Brown versus Board of Education," *Journal of Human Resources 40(3): 559-590.*

Rosenbaum, P., Rubin, D. 1985. "Constructing a Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score," *The American Statistician* 39:33-38.

Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture. Web Soil Survey. Available online at http://websoilsurvey.nrcs.usda.gov/. Accessed 01/15/2015.

Stephens, S.E., Rotella, J.J., Lindberg, S., Taper, M.L., Ringelman, J.K. 2005. "Duck Nest Survival in the Missouri Coteau of North Dakota: Landscape effects at multiple spatial scales," *Ecological Applications* 15: 2137-2149.

Stephens, S.E., Walker, J.A., Blunck, D.R., Jayaraman, A., Naugle, D.E., Ringelman, J.K., Smith, A.J. 2008. "Predicting Risk of Habitat Conversion in Native Temperate Grasslands," *Conservation Biology* 22(5):1320-1330.

Stevens, A. 2015. "Fuelling Local Water Pollution: Ethanol Refineries, Land Use, and Nitrate Runoff," Selected paper, *2015 AAEA &WAEA Joint Annual Meeting*, San Francisco, CA.

Turnquist, A., Fortenbery, R.T., Foltz, J. 2008. "Progress or Devastation? The Effects of Ethanol Plant Location on Local Land Use," Selected paper, *2008 AAEA Annual Meeting, Orlando, FL*.

USDA National Agricultural Statistics Service Cropland Data Layer. 1997-2013. Published crop-specific data layer [Online]. Available at http://nassgeodata.gmu.edu/CropScape/ (accessed 01/15/2015; verified 01/15/2015). USDA-NASS, Washington, DC

USDA National Agricultural Statistics Service Economics, Statistics and Market Information System. 2006-2010. "Agricultural Land Values". (http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1446).

USDA National Agricultural Statistics Service Quick Stats. 2012. http://quickstats.nass.usda.gov/.

United States Department of Agriculture – Natural Resources Conservation Service, "Soil Data Viewer 6.0 User Guide", Document Version: 2, 2011.

Wright, C.K., Wimberly, M.C. 2013. “Recent land use change in the Western Corn Belt threatens grasslands and wetlands,” *Proceedings of the National Academy of Sciences USA,* 110:4134-4139.

Zhang, W., Irwin, E.G., Nickerson, C. 2012. “The Expanding Ethanol Market and Farmland Values: Identifying the changing influence of proximity to agricultural delivery points,” Selected Paper*, 2012 AAEA Annual Meeting, Seattle, WA.*

APPENDIX [SUPPLEMENTARY INFORMATION]

Modelling Differentiated Trends into Our DID Framework

In this section we develop the DID framework to incorporate differentiated trends among treatment and control groups as well as between pre- and post-treatment periods. In this process, we will exploit the variations in corn acres in multiple periods before and after the advent of an ethanol plant. Capturing differentiated trends across groups alters the interpretation of regression coefficients that estimate treatment effects along with the identification strategies (Mora and Reggio, 2012). We will first explain the implications of a failed PPA for pre-treatment years (Figure 11) and then layout a 'fully-flexible' model, originally developed by Mora and Reggio, to capture trends that could vary between different years and among groups. We also discuss a family of identifying assumptions tied to estimating treatment effects under a fully-flexible model. As stated, this section is meant to enable a smooth transition from the standard DID to the fully-flexible DID model for our readers.

<u>The standard DID framework and the role of Parallel Paths assumption</u>

Reconsider our equation(1), that is $C_{i,t} = \beta_0 + \beta_1\delta_t + \beta_2 d_i + \beta_3 d_i\delta_t + \beta_{4,t}Z_i + \varepsilon_{i,t}$, where the definitions of these variables and parameters are same as in the 'Methodology' section above. Equation (2) implies that $ATT = E[C_{i,t^+} - C_{i,t^-} \mid Z_i, d_i = 1] - E[C_{i,t^+} - C_{i,t^-} \mid Z_i, d_i = 0]$ and so mechanics of computing the treatment effects using regression equation (1) are as under:

$d_i = 1;\ \delta_t = 1 \rightarrow E[C_{i,t^+} \mid Z_i] = \beta_0 + \beta_1 + \beta_2 + \beta_3 + \beta_{4,t}\overline{Z_{i|d_i=1}}$,

$d_i = 1;\ \delta_t = 0 \rightarrow E[C_{i,t^-} \mid Z_i] = \beta_0 + \beta_2 + \beta_{4,t}\overline{Z_{i|d_i=1}}$,

$d_i = 0;\ \delta_t = 1 \rightarrow E[C_{i,t^+} \mid Z_i] = \beta_0 + \beta_1 + \beta_{4,t}\overline{Z_{i|d_i=0}}$,

$d_i = 0;\ \delta_t = 0 \rightarrow E[C_{i,t^-} \mid Z_i] = \beta_0 + \beta_{4,t}\overline{Z_{i|d_i=0}}$. Note that $\overline{Z_{i|d_i}}$ is an unconditional mean.

Hence, $ATT = \beta_3$

It is, however, critical to note that by definition the ATT equals $E[C^{T}_{i,t^{+}} - C^{U}_{i,t^{+}} \,|\, d_i = 1]$ (where superscripts T (U) represent corn acres in the presence (absence) of ethanol plant in $t \in t^{+}$) and the parallel paths assumption must hold for β_3 to represent the impact of ethanol plants on corn acres. Figure 12 provides a visualization of the underlying implications when the parallel paths assumption fails. Basically, this assumption ensures that the treatment and control groups evolve in a parallel fashion (grey-dashed lines) and any difference in their post-treatment trends (orange- *vs.* grey-dashed lines) is purely due to the advent of the ethanol plant (or the treatment). This difference is β_3. However, the process depicted by green-solid lines in Figure 12 seems more realistic in the event that the parallel paths assumptions fails to hold. That is, we are potentially dealing with the group-specific pre- and post-treatment trends. We incorporate such differentiated trends into the standard DID model below.

The DID framework with differentiated trends

We motivate the implications of incorporating differentiated trends into the standard DID model through a specialized example here. We will discuss the mechanics involved in estimating the treatment effects within a new framework, including the underlying identifying assumptions, and show how these are different from the standard case. We will then move towards a generalized model proposed by Mora and Reggio's (2012) and its applicability for our analysis.

To incorporate the group-specific trends, consider the following econometric model.

(A.1) $$C_{i,t} = \beta_0 + \beta_0' t + \beta_1\delta_t + \beta_1' t\delta_t + \beta_2 d_i + \beta_2' t d_i + \beta_3 d_i\delta_t + \beta_3' t d_i \delta_t + \beta_{4,t} Z_i + \varepsilon_{i,t},$$

Where variable t represents trends such that $t = 1$ for year =1997 (2006) for North (South) Dakota ethanol plants, which increases by one for each subsequent year. While the standard DID model in equation (1) allows distinct intercepts for treatment/control groups and pre-/post-treatment periods, the updated model in equation (A.1) allows for distinct linear trends (slopes), as well as intercepts, for these groups and periods. Repeating our earlier exercise to compute treatment effects from equation (A.1), we get

$d_i = 1;\ \delta_t = 1 \rightarrow E[C_{i,t^+} \mid Z_i] = \beta_0 + \beta_0' t + \beta_1 + \beta_1' t + \beta_2 + \beta_2' t + \beta_3 + \beta_3' t + \beta_{4,t} \overline{Z_{i|d_i=1}}$,
$d_i = 1;\ \delta_t = 0 \rightarrow E[C_{i,t^-} \mid Z_i] = \beta_0 + \beta_0' t + \beta_2 + \beta_2' t + \beta_{4,t} \overline{Z_{i|d_i=1}}$,
$d_i = 0;\ \delta_t = 1 \rightarrow E[C_{i,t^+} \mid Z_i] = \beta_0 + \beta_0' t + \beta_1 + \beta_1' t + \beta_{4,t} \overline{Z_{i|d_i=0}}$,
$d_i = 0;\ \delta_t = 0 \rightarrow E[C_{i,t^-} \mid Z_i] = \beta_0 + \beta_0' t + \beta_{4,t} \overline{Z_{i|d_i=0}}$. And again, $\overline{Z_{i|d_i}}$ is an unconditional mean.
So, $E[C_{i,t^+} - C_{i,t^-} \mid Z_i, d_i = 1] - E[C_{i,t^+} - C_{i,t^-} \mid Z_i, d_i = 0] = \beta_3 + \beta_3' t$, which notably changes with t.

However, we already know that the ATT (= $\beta_3 + \beta_3' t$, here) remains unidentified. Now, subtracting equation (A.1) from its one-period lagged counterpart, we have

(A.2) $$\Delta C_{i,t} = \beta_0' + \beta_1' \delta_t + \beta_2' d_i + \beta_3' d_i \delta_t + \Delta\beta_{4,t} Z_i + \Delta\varepsilon_{i,t},$$

where $\Delta C_{i,t} = C_{i,t} - C_{i,t-1}$, $\Delta\beta_{4,t} = \beta_{4,t} - \beta_{4,t-1}$ and $\Delta\varepsilon_{i,t} = \varepsilon_{i,t} - \varepsilon_{i,t-1}$.

Evidently, the mechanics of computing the treatment effects for regression equation (A.2) are similar to those of equation (1), with pertinent differences in notations of the outcome variable and the parameters. So, our ‘new’ average treatment effect for the treated (ATT') is given as:

(A.3)

$$ATT' = E[\Delta C_{i,t} - \Delta C_{i,t'} \mid Z_i, d_i = 1] - E[\Delta C_{i,t} - \Delta C_{i,t'} \mid Z_i, d_i = 0] = \beta_3' \ \forall\ t \in t^+,\ t' \in t^- \ \&\, t > t'.$$

Here, it is important to realize that the interpretation of ATT' is not the same as our standard ATT . Expanding the mathematical expression of ATT' from equation (A.3) gives

(A.4)
$$ATT' = \{E[C_{i,t} - C_{i,t'} \mid Z_i, d_i = 1] - E[C_{i,t} - C_{i,t'} \mid Z_i, d_i = 0]\} - \{E[C_{i,t-1} - C_{i,t'-1} \mid Z_i, d_i = 1] - E[C_{i,t-1} - C_{i,t'-1} \mid Z_i, d_i = 0]\} \ \forall\ t \in t^+,\ t' \in t^- \ \&\ t > t'$$

We can re-write our 'new' average treatment effect for the treated as a function of ATT, $ATT'(t,t' \mid Z) = ATT(t,t' \mid Z) - ATT(t-1,t'-1 \mid Z) \triangleq \Delta ATT(t,t' \mid Z)\ \forall\ t \in t^+,\ t' \in t^- \ \&\ t > t'$, which in turn suggests that ATT' measures the impact of treatment as a change in the standard treatment effects (ATT) between a specific post-treatment period and a specific pre-treatment period. In the context of ethanol plants, ATT' would measure a one-period change in corn acres from a post-treatment year relative to a one-period counterpart from a pre-treatment year.

The identification of ATT' is consistent with that of the standard DID. That is, by definition, ATT' equals $E[\Delta C^T_{i,t} - \Delta C^U_{i,t} \mid d_i = 1, Z_i]$, where superscripts *T* (*U*) represent corn acres in presence (absence) of ethanol plant in $t \in t^+$. As with the standard DID, since $\Delta C^U_{i,t}$ is not observed for the post-treatment years, we would need an identification assumption to be able to compute ATT' as β'_3 in equation (A.2). Hence, the identification assumption for ATT' is

(A.5)
$$E[\Delta C^U_{i,t} - \Delta C^U_{i,t'} \mid Z_i, d_i = 1] = E[\Delta C^U_{i,t} - \Delta C^U_{i,t'} \mid Z_i, d_i = 0]\ \forall\ t \in t^+ \ \&\ t' \in t^-.$$

Note that the new identifying assumption compares first-differences in outcome levels among treatment and control groups, as opposed to the outcome levels as in the identifying assumption for the standard ATT (see equation (1)). The new estimator is termed as as a difference-in-first-difference estimator (following Mora and Reggio, 2012).

An aspect of the updated model and its identifying assumption is that it allows estimating a (change in) treatment effects for each of the multiple post-treatment periods (i.e., for every $t \in t^-$). Alongside, it also allows using multiple pre-treatment years (i.e., each $t' \in t^-$). However, it would suffice to estimate the impact of treatment from the last pre-treatment period, say t^*. To see this, consider $ATT'(s \mid Z_i)$ defined s periods ahead of t^* such that that $t = t' + s$ and $t' = t^*$.

Hence, the identifying assumption and $ATT'(s \mid Z_i)$ are given by equations (A.6) and (A.7) respectively.

(A.6) $$E[\Delta C^U_{i,t^*+s} - \Delta C^U_{i,t^*} \mid Z_i, d_i = 1] = E[\Delta C^U_{i,t^*+s} - \Delta C^U_{i,t^*} \mid Z_i, d_i = 0].$$

(A.7) $$ATT'(s \mid Z_i) = E[\Delta C_{i,t^*+s} - \Delta C_{i,t^*} \mid Z_i, d_i = 1] - E[\Delta C_{i,t^*+s} - \Delta C_{i,t^*} \mid Z_i, d_i = 0]$$

We can write $ATT'(s \mid Z_i)$ as a function of the original ATT:

(A.8) $$\begin{aligned} ATT'(s \mid Z_i) &= \{E[C_{i,t^*+s} - C_{i,t^*} \mid Z_i, d_i = 1] - E[C_{i,t^*+s} - C_{i,t^*} \mid Z_i, d_i = 0]\} - \\ &\quad \{E[C_{i,t^*+s-1} - C_{i,t^*-1} \mid Z_i, d_i = 1] - E[C_{i,t^*+s-1} - C_{i,t^*-1} \mid Z_i, d_i = 0]\} \\ \therefore\ ATT'(s \mid Z_i) &= ATT(s \mid Z_i) - ATT(s-1 \mid Z_i) \end{aligned}$$

Now, to evaluate the impact of ethanol plants our primary interest still lies in estimating ATT from the standard model. Since $ATT'(s \mid Z_i) = \beta_3'$, independent of s, the ATT can be recursively calculated for each post-treatment year as s increases by 1. That is, $ATT(s+1 \mid Z_i) = ATT(s \mid Z_i) + \beta_3'$ for $s \geq 2$. For $s = 1$, first see that $ATT(0 \mid Z_i) = 0$ because $E[C^T_{i,t^*} - C^U_{i,t^*} \mid d_i = 1, Z_i] = 0$[13], which in turn yields that $ATT'(1 \mid Z_i) = ATT(1 \mid Z_i)$. Since $ATT'(1 \mid Z_i)$ is identified by (12) and $ATT(1 \mid Z_i)$ is not, we compute $ATT'(1 \mid Z_i)$ below.

---

[13] $E[\Delta C^T_{i,t'} - \Delta C^U_{i,t'} \mid d_i = 1, Z_i] = E[C^T_{i,t'} - C^U_{i,t'} \mid d_i = 1, Z_i] = 0\ \forall\ t' \leq t^*$. This is one of the reasons why it would suffice to consider only the last pre-treatment period to evaluate the treatment effects.

We know that,

$$ATT'(1|Z_i) = \{E[C_{i,t^*+1} - C_{i,t^*} | Z_i, d_i = 1] - E[C_{i,t^*+1} - C_{i,t^*} | Z_i, d_i = 0]\} -$$
$$\{E[C_{i,t^*} - C_{i,t^*-1} | Z_i, d_i = 1] - E[C_{i,t^*} - C_{i,t^*-1} | Z_i, d_i = 0]\}$$

We explicitly write-out the expressions for C_{i,t^*+1}, C_{i,t^*} and C_{i,t^*-1} below because

$d_t = 1$ only for t^*+1.

$$C_{i,t^*+1} = \beta_0 + \beta_0'(t^*+1) + \beta_1 + \beta_1'(t^*+1) + \beta_2 d_i + \beta_2'(t^*+1).d_i + \beta_3 d_i + \beta_3'(t^*+1).d_i + \beta_{4,t^*+1} Z_i + \varepsilon_{i,t^*+1}$$
$$C_{i,t^*} = \beta_0 + \beta_0'(t^*) + \beta_2 d_i + \beta_2'(t^*).d_i + \beta_{4,t^*} Z_i + \varepsilon_{i,t^*}$$
$$C_{i,t^*-1} = \beta_0 + \beta_0'(t^*-1) + \beta_2 d_i + \beta_2'(t^*-1).d_i + \beta_{4,t^*-1} Z_i + \varepsilon_{i,t^*-1}$$

It can now easily be shown that $ATT(1|Z_i) = ATT'(1|Z_i) = \beta_3 + \beta_3'(t^*+1)$. The way $ATT(1|Z_i)$ depends on t^* also justifies the use of last pre-treatment period as sufficient to compute $ATTs$ for all post-treatment periods. If we were to use the penultimate pre-treatments period instead of the last pre-treatment period, only (t^*+1) would be replaced by (t^*+2) in the expression for $ATT(1|Z_i)$ as the base period has changed. However, doing this would require at least three pre-treatment years which may not be practically available (as is the case of South Dakota for this article).

Hence, the recursive solution to estimate treatment effects, using a DID framework that incorporates differentiated trends, by estimating equation (A.2) is given as:

(A.9) $$ATT(s|Z_i) = \beta_3 + \beta_3'(t^*+s) \ \forall s \geq 1 \ .$$

Given a recursive formulation to compute ATT for each subsequent post-treatment period, the periods prior to t^* would not matter.

Now that we have motivated the idea of incorporating trends into the standard DID framework, we address two further issues addressed by Mora and Reggio (2012). First, that the parallel first-difference assumption that identifies our 'new' average treatment effects for the treated can be generalized into a family of parallel *n*-differences assumptions. The formulation and interpretation of the average treatment effects in those cases would, however, differ. Second, the authors provide a 'fully-flexible DID model' by incorporating trends through indicator variables for each time period. This model has two advantages, when compared to the linear-trends model: (a) it incorporates flexible trends visualized in Figure 12, and (b) it allows testing for equivalence between the parallel *n*-differences assumptions. The linear-trends DID model that we have developed in this sub-section is essentially a special case of the fully-flexible DID model' presented hereafter. An alternative way to incorporate flexible trends into the standard DID model would be to introduce non-linear functional forms for trends (e.g., quadratic trends). Since the fully-flexible version includes a dummy variable for each time-period, different functional forms for the non-linear trends are only special cases.

Before presenting the mechanics of a fully-flexible DID model we will motivate the specifics of the family of generalized parallel *n*-differences assumption using our updated DID model in equation (A.1). The parallel first-difference assumption of (A.6) that identifies $ATT'(s|Z_i)$ is re-written as follows:

(A.10) $$E[\Delta_s \Delta C^U_{i,t^*+s} \mid Z_i, d_i = 1] = E[\Delta_s \Delta C^U_{i,t^*+s} \mid Z_i, d_i = 0] \ ,$$

Where, U represents the case of no treatment (or no ethanol plant) and $\Delta_s \triangleq (1 - L^s)$ so that we compute the treatment effect s periods ahead of t^* relative to the first difference in outcome levels at t^*. A generalized parallel n-differences assumption including higher-order differences of outcome levels to identify ATT' for all post-treatment periods similar to that in equation (A.10). A parallel n-differences assumption, notated as parallel (n-s) assumption by Mora and Reggio (2012) is given as:

(A.11) $$E[\Delta_s \Delta^{n-1} C^U_{i,t^*+s} \mid Z_i, d_i = 1] = E[\Delta_s \Delta^{n-1} C^U_{i,t^*+s} \mid Z_i, d_i = 0]$$

See that for $n = 1$ equation (A.11) reduces to a parallel paths assumption and for $n = 2$ it is the parallel first-difference assumption. For $n > 2$, however, we move towards higher order differences. For example, $n = 3$ implies a $\Delta^2 [= (1 - \mathrm{L}) - (\mathrm{L} - \mathrm{L}^2)]$ operator on the s period ahead outcome variable. We will require at least three pre-treatment years in our dataset to exploit such an operator due to the parallel double-differences assumption. Thus, the generalizations introduced by $n > 2$ cases are only applicable to the cases of North Dakota ethanol plants. The generalized average treatment effects from parallel n-differences assumption is given as[14]

(A.12)

$$ATT'(s, n \mid Z_i) = \Delta^{n-1} ATT(s \mid Z_i) = E[\Delta_s \Delta^{n-1} C^U_{i,t^*+s} \mid Z_i, d_i = 1] - E[\Delta_s \Delta^{n-1} C^U_{i,t^*+s} \mid Z_i, d_i = 0]$$

For the $n = 3$ case of our linear-trends model,

$ATT'(s, 3 \mid Z_i) = \Delta^2 ATT(s \mid Z_i) = ATT(s \mid Z_i) - 2ATT(s-1 \mid Z_i) + ATT(s-2 \mid Z_i)$, which will recursively identify $ATT(s \mid Z_i) = ATT'(s, 3 \mid Z_i) + 2ATT(s-1 \mid Z_i) - ATT(s-2 \mid Z_i)$. Similar to the $n = 2$ case, for $s = 1,\ 2$ we will have $ATT(s \mid Z_i) = ATT'(s, 3 \mid Z_i)$. It is quite evident here that the treatment effects estimated under parallel double-differences assumption will not equal those under parallel first-difference or parallel paths assumptions. It is, however, interesting to note

[14] See Theorem 1 in Mora and Reggio (2012).

that the treatment effects estimated using an exactly same model in equation (A.5) can be very different in magnitude, as well as interpretation, depending on the identifying assumption used.

Note that these updated assumptions for incorporating trends into DID cannot be validated since they are defined as nth-order difference in outcome variable including the post-treatment periods. However, these assumptions can be tested for equivalence using the fully-flexible model discussed next. A parallel n-differences assumption is equivalent to a parallel (n-1)-differences assumption (OR $ATT'(s,n|Z_i)=ATT'(s,n-1|Z_i)\ \forall\ s$) if and only if $E[\Delta^{n-1}C^{U}_{i,t*}|Z_i,d_i=1]-E[\Delta^{n-1}C^{U}_{i,t*}|Z_i,d_i=0]$ [15].

Supplementary Information

Data notes - soil quality

USDA-NRCS's soil surveys are conducted at pre-designated spatial units, known as map units (MUs), which represent common management requirements towards various land uses (Soil Data Viewer 6.0 User Guide, 2011 pp. 11). Although MUs are the finest spatial resolution in the soil surveys, they are composed of multiple map unit components that are horizontal strips of similar soil characteristics. The MUs may vary in size (2 acres to 2,000 acres) depending upon the variability among their respective map unit components. We aggregate LCC and slope up to the MUs using a 'Soil Data Viewer' application. The aggregation criteria are differ as LCC is a categorical variable and slope is a continuous variable.

Representative slope was aggregated as a weighted-average of representative slope for all map unit components within each MU, where weights are the respective area-shares. Variable

[15] See Theorem 2 in Mora and Reggio (2012).

LCC was aggregated by a ‘dominant condition’ criterion that assigned the LCC value of the map unit component that was designated the highest area-share among other components. Note that the ‘dominant condition’ aggregation criterion may assign the LCC value that represents as little as 25% area-share. Higher LCC value was assigned when different LCCs had equal area-shares. Although the tie-breaker was applicable to only 4 out of 156 MUs in North Dakota (0.7% of the state’s area), and only 2 out of 260 MUs in South Dakota (0.6% of the state’s area).

The DID model in conjugation with PSM

This section discusses the working of a standard Difference-in-Difference model (DID) in conjunction with Propensity Score Matching (PSM). We follow the DID model framework of Abadie (2005). Consider a representative land parcel i with $C_{i,t}$ and $CS_{i,t}$ as its corn acreage and combined corn and soy acreage respectively at time period t. We introduce binary variables d_i and δ_t to designate treatment/control groups and pre-/post-treatment periods respectively. So, $d_i = 1$ for treated parcels and 0 otherwise, and $\delta_t = 1$ for the years after an ethanol plant was established and 0 otherwise. Further, denote $t^+(t^-)$ as the set of post-treatment (pre-treatment) time periods with t_0 as the treatment year.[16] Intuitively, to evaluate a treatment effect for treated parcel i we would compare its corn acreage with and without the ethanol plant in the post-

[16] For example, the Red Trail Energy ethanol plant that came up in 2007, $t^+ = \{1997, 1998, ..., 2006\}$ and $t^- = \{2008, 2009, ..., 2013\}$.

treatment era (i.e., $C_{i,i}$ [17] with $t \in t^{+}$). Consequently, an average treatment effect for the treated (*ATT*) equals $E[C^{T}_{i,t^{+}} - C^{U}_{i,t^{+}} \mid d_i = 1]$, where *T*(*U*) denote presence (absence) of the plant.

However, we do not observe the post-treatment outcome levels without the treatment. DID tackles this by assuming that treated and control parcels follow parallel land use changes if the ethanol plant had not emerged at (Abadie, 2005). This assumption is key to identify the estimates of treatment effects because in the event that this assumption fails our estimates could not be trusted. Also, observing individual land parcels allows controlling for soil quality and land use shares at time $t_0 - 1$ as covariates. That is, we estimate the *ATT* conditional on covariates other than the treatment dummy. The parallel land use changes assumption among both groups can be expressed as

(SI.1) $$E[C^{u}_{i,t^{+}} - C^{u}_{i,t^{-}} \mid Z, d_i = 1] = E[C^{u}_{i,t^{+}} - C^{u}_{i,t^{-}} \mid Z, d_i = 0],$$

In equation (SI.1) the superscript u signifies that both groups stay untreated and Z is the set of covariates. If (1) holds true then the *ATT* is calculated as

(SI.2) $$ATT = E[C_{i,t^{+}} - C_{i,t^{-}} \mid Z_i, d_i = 1] - E[C_{i,t^{+}} - C_{i,t^{-}} \mid Z_i, d_i = 0]$$

ATT, in equation (SI.2) can be estimated as β_3 from the regression framework in equation (SI.3) below.

(SI.3) $$C_{i,t} = \beta_0 + \beta_1\delta_t + \beta_2 d_i + \beta_3 d_i\delta_t + \beta_4 Z_i + \beta_5\delta_t Z_i + \varepsilon_{i,t}$$

[17] We present the model for corn acreage. An extension for combined corn and soy acreage follows by changing the notation from $C_{i,t}$ to $CS_{i,t}$.

In equation (SI.3) $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$ and β_5 are regression coefficients. Note that β_4 and β_5 allow capturing mean difference in the effect of time-invariant covariates (Z_i) on corn acres across pre- and post-treatment years (Abadie, 2005).

To illustrate the extension of a standard DID model that incorporates PSM, consider the decomposition of the set of covariates $Z_i = \{X_i^a, X_i^b\}$. Here, the set X_i^a contains the soil quality variables LCC and slope and set X_i^b represents the initial land use conditions for parcel i. We match the parcels based on their soil quality parameters. The justification for matching on soil quality is that we seek to ensure random placement of land parcels in their respective groups relative to the location of the ethanol plant. An ethanol plant's location decision must be based on the potential for corn production based on land quality. But to say that the plant chooses to locate only by the land use status in the year before it was established is logistically infeasible. Miao (2013) acknowledges that the ethanol plant goes on-line as early as 3-years prior to starting operations. We use a logistic model with d_i as dependent variable and X_i^a as the set of regressors to estimate a propensity score (denoted by $P(X_i^a)$) for each parcel in the treatment and control groups. Specifically, we use the weighted LCC index for land quality (denoted, *WLCC*) and weighted slope (denoted by *WSLP*) as regressors in the logit regression. The weights used are area of soil map units, contained in each land parcel, represented by their land quality attributes, LCC and slope. We match the parcels using a nearest-neighbor matching algorithm by Fraeman (2010). By matching, we seek to ensure that parcels' propensity to be treated is alike across groups, conditional of the time-invariant intrinsic property of land – soil quality. Post-matching, we use the DID regression framework as in equation (SI.3) with covariates reduced to

X_i^b. A conceptual expression for the ATT from our extended model, denote as ATT^m, can be written as

(SI.4) $$ATT^m = E[C_{i,t^+} - C_{i,t^-} \mid P(X_i^a), X_i^b, d_i = 1] - E[C_{i,t^+} - C_{i,t^-} \mid P(X_i^a), X_i^b, d_i = 0]$$

The estimation of ATT^m follows from equation (SI.3) with Z_i replaced by X_i^b and the sample data used for this post-matching estimation will be a subset of its counterpart in (SI.3). Therefore, if β_3^m is the estimate of our new ATT, then it can be retrieved estimating the following regression equation

(SI.5) $$C_{i,t} = \beta_0^m + \beta_1^m \delta_t + \beta_2^m d_i + \beta_3^m d_i \delta_t + \beta_4^m X_i^b + \beta_5^m \delta_t X_i^b + \varepsilon_{i,t}.$$

Note that we designate the advent of an ethanol plants as treatment, which itself is a market outcome. The implication of this endogenous intervention is that we do not have exogenous control groups. Rather, our treatment and control groups follow the ‘rule of thumb’ that treated parcels are located nearer to the ethanol plant than their untreated counterparts. This allows innumerable possibilities of treatment and control groups near each ethanol plant’s location and practically inexhaustible combinations. In order to conduct robustness checks we designate two treatment groups and two control groups for each ethanol plant. The control groups are kept apart to ensure independence in robustness checks for each treatment group (see Figure 3 – Main Text). We conjecture that treatment effects using the nearest treatment and the farthest control groups will be larger and more significant than other combinations and present full regression results for this particular combination. We include the other combinations as robustness checks. Specifically, we run 24 regressions for each ethanol plant (Tables A14 and A15 summarize these results, discussed later). In cases where we have sufficient pre-treatment and post-treatment years we also estimate treatment effects for multiple combinations of pre-or post-treatment years (advocated by Meyer, 1995). Bertrand et al. (2004) found serial correlation in the treatment-effect indicator variable ($d_i \times \delta_t$) over-reject the null hypothesis of no treatment-effect. A remedy, as suggested by Bertrand et al. (2004) to overcome this issue is aggregating through pre- and post-treatment years by using mean outcome levels rather than for individual years' is implemented here.

The Placebo Treatment Effects

Further, in recognition of the non-exogenous treatment we utilize placebo tests or falsified treatments to validate the robustness of our results. We conduct temporal placebos, meaning that we assume the advent of an ethanol plant in a year that predates the actual treatment. These temporal placebos are conducted for North Dakota plants since a longer time-series data is available. We designate various falsified treatments and the pre- and post-treatment years for each of these (Figure 10 – Main Text). Placebo tests are important as they allow validating our identification strategy to estimate treatment effects.

The farthest treated and control parcels are located at a maximum distance of 100 km (62 miles) from each other in our empirical setup. We, therefore, anticipate that the physical characteristics of these parcels and their initial land use shares will play a major role in identifying treatment effects. Weather may be another variable of interest, which we assume to be uniform across our treated and control parcels. Since weather data points are collected at weather stations covering multiple counties and our analysis only spans 60 miles strips, we think that our assumption is reasonable. By definition, distance from ethanol plants are the sole differentiator of treated and untreated land parcels. However, these end up contained within multiple boundaries. Although the markets and incentive structure may vary substantially across counties, we do not expect these to affect how much corn farmers grow due to advent of an ethanol plant in their vicinity. Even if we were to consider county-fixed effects for each of the parcels, they would cancel out due to the first difference operator inherent to the DID estimator, on pre- and post-treatment outcome levels of each parcel. Despite the fact that we have been careful in choosing the covariates for the above regression framework, there might still be factors that we fail to control. An example would be matching the parcels based on soil moisture, not done here due to incomplete data. However, a good or bad rainfall year could influence the impact the advent of an ethanol plant in our treatment and control groups even if we assume uniform rainfall measured across all parcels. The right amount of precipitation leading to higher soil moisture on a LCC II, flat sloped land could influence farmers' decision to grow water-thirsty corn, with or without an ethanol plant in the vicinity. To address our inability to capture such effects that may confound the estimated treatment effects, we include temporal placebos. If we successfully control for all relevant covariates and our matching strategy is perfect, we should get a zero or statistically insignificant placebo treatment effect. However, a significant (positive or negative) placebo treatment effect would point towards ambiguity in our identification strategy and allow statistical correction of our estimates of the actual treatment.

Estimation results

As mentioned earlier, there are 19 ethanol plants in North and South Dakota. We include all four North Dakota ethanol plants, but restrict our analysis for South Dakota to four out of 15 ethanol plants that ensure at least two pre-treatment years. The CDL data for South Dakota only goes back until 2006.The four South Dakota ethanol plants, included here (see Table 1 in main text), started operations in 2008. This allows implementing the DID estimation strategy through pre- and post-treatment years. We analyze the effects of POET and NuGen ethanol plants together as cluster 1 and ABE and GLE as cluster 2 due to their spatial proximity. A vector description (dimensions and directions) for the treatment and control groups of each of these ethanol plants is provided in Table 2 (main text). These rectangular-shaped groups can be visualized in Figure 3, as an example. Another factor that determined which land parcels entered treatment and control rectangles was the existence of 'other' ethanol plants nearby. We follow the linear city model and consider all ethanol plants as market terminals with designated capacity. So, while deciding which land parcels enter our rectangles we ensure that linear distance of a parcel is minimum to the ethanol plant under study. The linear distances are normalized by ethanol plants' capacities. For instance, if two ethanol plants with annual capacities of 20 and 80 million gallons are 100 km apart, then market designated for the larger (smaller) ethanol plant is 80 (20) km from its location. Such details for ethanol plants considered for our analysis are added in Table 2 (see the 'Remarks' column, main text).

Treatment effects' estimates

To estimate the treatment effects, we modify our regression framework (equation (SI.5)) to include the first differences of pre- and post-treatment outcomes as dependent variables. Our regression estimates, therefore, are to be viewed as regression coefficients of equation (SI.6) below.

(SI.6) $$C_{i,t^+} - C_{i,t^-} = \beta_1^m + \beta_3^m d_i + \beta_5^m X_i^b + (\varepsilon_{i,t^+} - \varepsilon_{i,t^-})$$ [18]

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[7] Equation (SI.6) is retrieved by taking a difference on the pre- and post-treatment versions of equation (SI.5). That is $\{C_{i,t^+} = \beta_0^m + \beta_1^m + \beta_2^m d_i + \beta_3^m d_i + \beta_4^m X_i^b + \beta_5^m X_i^b + \varepsilon_{i,t^+}\}$ −

Where, C_{i,t^+} is the average of corn acres in post-treatment years and C_{i,t^-} is the average if corn acres in pre-treatment years. In addition, β_1^m captures the trend-effects of moving between pre- and post-treatment periods, β_3^m is the estimate of ATT^m (defined earlier), and β_5^m is the differentiated role of the set of controls X_i^b on change in corn acreage through pre- and post-treatment periods. We now present our estimation results for each ethanol plant included in Table 1 (main text). Our regression analysis also includes $\ln(C_{i,t^+}) - \ln(C_{i,t^-})$ as a dependent variable to compare rate of change in outcomes pre- and post-treatment. This is especially useful when, in the pre-treatment period, outcome levels (corn acres in this case) between treatment and control groups differ significantly. Illustratively, say the conditional mean of corn acreage for control groups is *a* acres while it is *2a* acres for the treatment group. If there were no treatment effect and both groups would grow by a factor of 2, then post-treatment corn acres for control and treatment groups will be *2a* and *4a* respectively. Our definition of ATT will yield a positive treatment effect, even though it was zero. Using log-linear regressions will compare the rate of change and would help avoid such confounding results.

<u>Red Trail Energy</u>

For the Red Trail Energy ethanol plant (RTE) that started operations in year 2007, we have $t^- = \{1997,...,2006\}$ and $t^+ = \{2008,...,2013\}$. Consequently, $X_i^b = \{W_{i,2006}, G_{i,2006}\}$, where $W_{i,2006}$

$\{C_{i,t^-} = \beta_0^m + \beta_2^m d_i + \beta_4^m X_i^b + \varepsilon_{i,t^-}\}$. Again, similar results follow for the combined corn and soybeans case by changing the notation $C_{i,t}$ to $CS_{i,t}$.

is the 2006 wheat acreage on a representative parcel i and $G_{i,2006}$ is the 2006 grass cover on i. For RTE, the pre- and post-treatment summary statistics for both treatment and control groups are included in Table A2 and the corresponding estimation results are included in Table A3.

Table A2 reveals that the unconditional change of mean corn acres is higher for the treatment group. However, the treatment effect estimate for RTE is negative and highly significant. This result is irreconcilable with the economic incentives, the aforementioned increase in corn basis and lower transportation costs, arising from this ethanol plant. The regression estimates for pre-treatment wheat and grass acres are negative, revealing that growing corn on wheat/grass acres is costly. However, switching from wheat to corn is relatively less expensive than converting from grass to corn, as the coefficient for pre-treatment wheat acres is less negative than the coefficient for pre-treatment grass. This is reasonable due to the land preparation costs towards converting grass for agricultural use, which can be avoided when switching wheat acres to corn. It is noteworthy that pre-treatment grass acres in control group are higher (while wheat acres are lower) as compared to the treatment group. A higher impediment for conversion in the form of relatively more grass (and less wheat) in control group seems to have neutralized the higher increase in unconditional change in corn acres for treatment group. The conditional rate of change of corn (and soy) are also negatively affected due to the ethanol plant, though the change is insignificantly different from zero at 95% level of confidence. It should be noted that the intercept, in absolute value, is larger than treatment effects' estimate and other controls. Since the intercept captures trend-effects (discussed earlier), large intercepts relative to treatment effects suggest that ethanol plants are only responsible for a small fraction of overall difference in land use change among the groups.

Blue Flint

For the Blue Flint ethanol plant (BF) that started operations in year 2007, we have $t^{-}=\{1997,...,2006\}$ and $t^{+}=\{2008,...,2013\}$. Consequently, $X_i^b=\{W_{i,2006},G_{i,2006}\}$, where $W_{i,2006}$ is the 2006 wheat acreage on a representative parcel i and $G_{i,2006}$ is the 2006 grass cover on i. For BF, the pre- and post-treatment summary statistics for both treatment and control groups are included in Table A4 and corresponding estimation results are included in Table A5.

Due to the ethanol plant, unconditional mean of corn acres grew almost equivalently for each of the two groups while the combined corn and soy acreage grew more for the treated. Again, grass acres are a significant impeding factor for conversion due a negative coefficient for their pre-treatment levels. Pre-treatment grass acres are also higher for the control group's parcels, potentially neutralizing higher increase in unconditional corn acres in treated parcels as compared to the controls. However, while comparing the rate of change among parcels treatment effect is positive for corn acres and negative for combined corn and soy, although insignificant. A positive growth rate of corn acres and negative rate for corn and soy combined may have implications for crop rotation, suggests intensified corn cropping while declining combined corn and soy acreage. Also, for the log linear regressions coefficients on initial wheat acres (in 2006) are positive and significant revealing opportunity to switch to corn. At the same time, negative (insignificant) coefficients on initial wheat acres in the linear regressions suggest costs of switching to corn production that are lower than conversion costs from grass acres. Again, large intercepts relative to the treatment effects suggest that ethanol plants are not a major determinant of overall land use change for the groups.

Tharaldson Energy

For the Tharaldson Energy ethanol plant (TE) that started operations in year 2006, we have $t^{-}=\{1997,...,2005\}$ and $t^{+}=\{2007,...,2013\}$. Consequently, $X_i^b=\{W_{i,2005},G_{i,2005}\}$, where $W_{i,2005}$ is the 2005 wheat acreage on a representative parcel i and $G_{i,2005}$ is the 2005 grass cover on i. For TE, the pre- and post-treatment summary statistics for both treatment and control groups are included in Table A6 and corresponding estimation results are included in Table A7.

A feature that distinctly distinguishes TE from RTE and BF is the higher pre-treatment acres of corn and soybeans for both treated and untreated groups. Also, with treated groups having more than twice as many corn acres and, also that many combined corn and soy acres comparing rates of change is more reasonable than the absolute changes. Specifically, log-linear regressions will provide more reasonable inferences as compared to their linear counterparts. The treatment effect here is found to be negative, although more negative for combined acres of corn and soy. This suggests intensifying corn cropping and forgone corn-soy rotations in the process. Trend-effects again dominate the treatment effects in this case. However, grass acres may serve as an opportunity to grow corn, despite higher conversion costs, due to lower grass cover prior to the ethanol plant.

Hankinson Renewable Energy

For the Hankinson Renewable Energy ethanol plant (HRE) that started operations in year 2008, we have $t^{-}=\{1997,...,2007\}$ and $t^{+}=\{2009,...,2013\}$. Consequently, $X_i^b=\{W_{i,2007},G_{i,2007}\}$, where $W_{i,2007}$ is the 2007 wheat acreage on a representative parcel i and $G_{i,2007}$ is the 2007 grass cover on i. Since there are too many pre-treatment years compared to post-treatment years, we introduce $t_1^- = \{2003,...,2007\}$ as an alternative pre-treatment years to seek any difference in treatment estimates. For HRE, the pre- and post-treatment summary statistics for both treatment and control groups are included in Table A8 and corresponding estimation results are included in Table A9.

The regression results for HRE suggest that this ethanol plant has had a positive impact on corn acres, and on the corn and soy acres combined. However, it is clear that impact on corn acreage has been greater than that on the combined corn and soy acreage. This may have implications for corn and soy rotation. Similar to our inferences above, corn acres seem to intensify, leading to lesser corn-soy rotations due to the advent of the ethanol plant. This inference on rotations is especially quite strong if we compare the historical pre-treatment years (starting 1997), rather than the recent ones (starting 2003). Once again, higher wheat acres in the year before the ethanol plant lead to positive significant increase in corn acres (and combined corn/soy acres as well). Also, unlike the previous three ethanol plants trend-effects are dominated by HRE's treatment effect for log-linear regressions while trend-effects dominate in the linear regressions case. This may be a result of model specification.

Cluster 1: POET Bio refinery and NuGen Energy

Cluster 1, which is a conglomerate of POET Bio refinery and NuGen Energy, (PBNE) started operations in 2008. So, we have $t^- = \{2006, 2007\}$, $t^+ = \{2009,...,2013\}$ and $X_i^b = \{W_{i,2007}, G_{i,2007}\}$, where $W_{i,2007}$ is the 2007 wheat acreage on a representative parcel i and $G_{i,2007}$ is the 2007 grass cover on i. We also include $t_1^+ = \{2009, 2010\}$ as an alternative post-treatment years' set to seek any difference in treatment estimates. For PBNE, the pre- and post-treatment summary statistics for both treatment and control groups are included in Table A10 and corresponding estimation results are included in Table A11.

The corn acres seem to be positively impacted by emergence of PBNE in later years (2011–2013), as the treatment effect is insignificant for the post-treatment years t_1^+. The rate of growth in corn acres, however, was not significant due the plants. Given that initial corn acreage between treated and control parcels is significantly different, the inference on rate of growth is more reliable than absolute acres. But, the effect of these ethanol plants on the combined acreage of corn and soybeans is uniformly positive and significant. This implies that, unlike in North Dakota, these South Dakota ethanol plants have de-intensified corn cropping and encouraged corn-soy rotations. Another finding that differs here from the analysis of North Dakota plants is negative trend effects. It seems as if the higher corn acres are driven due to the advent of these ethanol plants, since treatment effects and intercept are comparable in size. Further, higher initial (2007) wheat and grass acres have positive and significant impact on both, corn acreage and combined acreage of corn and soy.

Cluster 2: Aberdeen Bio energy and Glacial Lakes Energy

Cluster 2, which is a conglomerate of Aberdeen Bio energy and Glacial Lakes Energy, (ABGL) started operations in 2008. So, we have $t^- = \{2006, 2007\}$, $t^+ = \{2009, ..., 2013\}$ and $X_i^b = \{W_{i,2007}, G_{i,2007}\}$, where $W_{i,2007}$ is the 2007 wheat acreage on a representative parcel i and $G_{i,2007}$ is the 2007 grass cover on i. We also include $t_1^+ = \{2009, 2010\}$ as an alternative post-treatment years' set to seek any difference in treatment estimates. For ABGL, the pre- and post-treatment summary statistics for both treatment and control groups are included in Table A12 and corresponding estimation results are included in Table A13.

The initial average corn (combined corn and soy) acreage for the treatment group is almost twice (thrice) when compared to the control group. Hence, we draw our inferences for this ethanol plant from rate of change equations. We find negative impacts of these ethanol plants on treated corn acreage, which is driven by the decreasing corn and combined corn and soy acreage for treatment groups coupled with corresponding increase for control group. A more negative treatment effect for combined corn and soy acreage points out to intensified corn cropping relative to corn-soy rotations. Also, as in the other cluster in South Dakota, trend-effects are negative and are dominated by the treatment effects here. Initial wheat and grass acres have positive significant effects on corn and soy production.

Summarizing the Estimation Results

The treatment effects are found to vary in size, sign, and significance by individual ethanol plants. This finding disagrees with the single point estimates for ethanol plants' impacts reported for all of Iowa or, even, the U.S. Midwest by prior studies. However, the negative significant treatment effects are both surprising and irreconcilable due to earlier argued higher relative incentives near the ethanol plants. This was because transportation costs (that are monotonic in distance) are quite significant compared to cropland rentals values in the Dakotas. To understand and validate these negative treatment effects, we examine impact of ethanol plants on county-level corn basis and evaluate placebo treatment effects. The placebos and robustness checks from multiple treatment and control groups are discussed in the next section.

We also find that intensity and type of impact of ethanol plants on local land use depends on its spatial location, rather than only its capacity as controlled for in previous literature.

Specifically, for ethanol plants that lie on the Corn Belt (HRE, PBNE and ABGL) we find treatment effects to dominate or be at least comparable to the trend-effects. Whereas, for RTE, BF (located west of the edge of the Corn Belt) and TE (located north of the Corn Belt) the treatment effects are dominated by the trend-effects. So, ethanol plants could be a major factor in determining the overall evolution of corn and soybean acres in their proximity when they operate among areas densely planted in corn/soy. We also find that the advent of ethanol plants could impact corn-soy rotations in an area. In 5 out of 6 cases considered in this analysis, we find corn intensification relative to combined corn and soy acreage. We also find initial wheat and grass acres to significantly affect the evolution of corn and soybean acres in post ethanol plants years. Controlling for these variables reveals that more wheat encourages corn relative to more grass, potentially due to higher conversion costs (of sod-busting) than switching costs among crops.

Corn-Basis Analysis

We had conjectured earlier that proximity to ethanol plants could offer strong incentives to grow more corn production. This conjecture was primarily based on our back of the envelope calculations and also, partially, on the existing literature. Our findings, in contrast to the conjecture, of insignificant or negative treatment effects are indeed surprising. To better understand and reconcile these findings we analyze the effects of ethanol plants on corn basis. If the advent of an ethanol plant were to incentivize corn production in its proximity, these incentives should be observable in a market setting as an increase in corn basis. So, the treated parcels should have a higher increase in basis post-treatment as compared to the untreated ones. This would ultimately feed into land use decisions and lead to higher corn acres in close vicinity of the ethanol plant. Our back of the envelope calculations focused on the maximum willingness to pay for an ethanol plant to incentivize corn production for a supplier unit closer to its location.

As opposed to the maximum willingness to pay calculated earlier, an increase in basis would provide increase in payments by ethanol plants as observed in their proximity. In case that the actual willingness to pay for the ethanol plants does not increase as expected, we can, at least, justify the insignificant treatment effects estimates found earlier.

We retrieved a county-level dataset providing monthly corn basis from 2000 to 2013, for North and South Dakota[19]. We present comparative basis trend-plots from 2000 to 2013 for the counties that contained the treatment and control groups for 4 out of six ethanol plants (or clusters) included here (Figures 4–7). In Figures 4-7, the county that contains the ethanol plant (its home-county) is plotted as a solid series while others are plotted as hashed series. If the ethanol plant were to significantly increase the compensation to farmers for supplying corn in its close vicinity, we should be able to visualize it through its home-county's basis time-series plot. In an event of significant impact of the advent of an ethanol plant, we expect the basis series for it home-county to deviate upwards from its counterparts. Further, the home-counties for RTE and BF and their respective neighbors suffer with missing values and are inappropriate to deduce any impacts of these plants.

Figures 4–7 show increased relative basis for Richland county (home to HRE) and Turner county (home to Cluster 1). This justifies the positive significant treatment effects for these two cases. However, corn basis for Cass county (home to TE) seems to have stagnated in the post-treatment years. Also for cluster 2, stationed in two counties, corn basis for Brown had fallen relative to its neighbors, while there was a temporary rise in corn basis for Edmunds which was not sustained in later years. These observations provide some understanding of why the ethanol

[19] Dataset Source: *Geo Grain*.

plants yielded non-positive treatment effects for TE and Cluster 2. Note that our claims are not founded here on robust statistical tools (like regressions), but only on some summary statistics. Our purpose here is to only garner some understanding and support the quasi-experimental design of this study.

Discussion

Our robustness checks using multiple treatment and control groups reveal that the treatment estimates are generally stable across these combinations. The size and sign of these are especially similar by control group. That is, combinations 'T1 and C2' and 'T2 and C2' will generally yield similar estimates. However, we find significant placebo treatment effects pointing out to the fact that either our matching strategy is not perfect or we are not able to control for all the factors that affect growth of corn acres in equation (6). To reconcile the failed placebo tests, we first consider the pre-treatment trends for treatment and control groups for the North Dakota ethanol plants to validate the Parallel Paths assumption of DID estimation strategy (see equation SI.1). Figure 11 (in the Main Text) shows that the Parallel Paths assumption does not hold and thus the estimates of the standard DID model are not identified. Therefore, we incorporate differentiated trends between pre- and post-treatment periods and between treatment and control groups. We follow Mora and Reggio (2012) to incorporate flexible trends into the DID model. The model is developed and estimated in the main text of this text.

TABLES (APPENDIX)

Table A1. *Actual "**Google Map**" Distances of the Nearest Treatment Groups and the Farthest Control Groups from respective ethanol plants.*

Ethanol Plant	Nearest Treated - T1 (km)	Farthest Control – C2 (km)	Difference (km)
RTE (South)	18.8	91.4	72.6
BF (South)	33.2	124.2	91.0
BF (East)	53.3	129.9	76.6
TE (West)	23.5	94.8	71.3
HRE (West)	18.3	97.7	79.4
POET (West)	17.2	111.2	94.0
ABE (West)	17.7	111.7	94.0

Notes: See Table 2 in the main text for schematics of the treatment and control groups.

Table A2. Summary Statistics for Red Trail Energy, C2 and T1 combination. Caliper = 0.0004.

	Control			Treatment		
	Mean	Std. dev.	N	mean	Std. dev.	N
C_{i,t^-}	1.69	2.65	65	2.46	3.30	65
C_{i,t^+}	7.88	15.44	65	19.83	26.16	65
CS_{i,t^-}	1.84	2.75	65	2.75	3.41	65
CS_{i,t^+}	7.98	15.72	65	19.83	26.16	65
$W_{i,2006}$	106.53	101.12	65	221.52	116.91	65
$G_{i,2006}$	347.85	115.62	65	207.73	115.35	65

Table A3. Treatment Effects' Estimates with Heteroskedasticity corrected t-stats in parentheses

	$C_{i,t^+} - C_{i,t^-}$	$CS_{i,t^+} - CS_{i,t^-}$	$\ln(C_{i,t^+}) - \ln(C_{i,t^-})$	$\ln(CS_{i,t^+}) - \ln(CS_{i,t^-})$
Treatment	2.58 (-0.63)	2.38 (0.58)	-0.24 (-0.36)	-0.28 (-0.43)
$W_{i,2006}$	-0.09 (-1.76)*	-0.09 (-1.71)*	-0.007 (-1.33)	-0.006 (-1.25)
$G_{i,2006}$	-0.14 (-2.69)***	-0.14 (-2.63)***	-0.02 (-3.34)***	-0.02 (-3.34)***
Constant	63.82 (2.69)***	63.68 (2.63)***	5.65 (2.64)***	5.40 (2.55)***
R^2	0.20	0.19	0.14	0.15

* p<0.1; ** p<0.05; *** p<0.01

Table A4. Summary statistics for Blue Flint Ethanol: C2 and T1 combination. Caliper = 0.01

	Control			Treatment		
	mean	Std. dev.	N	mean	Std. dev.	N
C_{i,t^-}	5.44	5.73	274	2.72	7.89	274
C_{i,t^+}	24.97	26.23	274	18.98	31.52	274
CS_{i,t^-}	6.40	6.43	274	4.99	9.73	274
CS_{i,t^+}	26.28	27.38	274	23.04	36.47	274
$W_{i,2006}$	149.91	92.08	274	101.00	74.40	274
$G_{i,2006}$	288.13	103.59	274	277.64	100.59	274

Table A5. Treatment Effects' Estimates with Heteroskedasticity corrected t-stats in parentheses

	$C_{i,t^+} - C_{i,t^-}$	$CS_{i,t^+} - CS_{i,t^-}$	$\ln(C_{i,t^+}) - \ln(C_{i,t^-})$	$\ln(CS_{i,t^+}) - \ln(CS_{i,t^-})$
Treatment	-9.02	-7.59	0.01	-0.50
	(-3.97)***	(-3.12)***	(0.04)	(-2.00)**
$W_{i,2006}$	-0.08	-0.08	0.0005	0.0007
	(-2.76)***	(-2.39)***	(0.29)	(0.44)
$G_{i,2006}$	-0.16	-0.18	-0.006	-0.007
	(-6.32)***	(-6.01)***	(-4.14)***	(-4.71)***
Constant	80.53	83.53	2.71	2.63
	(6.59)***	(6.13)***	(3.93)***	(4.25)***
R^2	0.27	0.28	0.06	0.09

* p<0.1; ** p<0.05; *** p<0.01

Table A6. Summary statistics for Tharaldson Ethanol: C2 and T1 combination. Caliper = 0.01

	Control			Treatment		
	mean	Std. dev.	N	mean	Std. dev.	N
C_{i,t^-}	15.97	14.32	120	36.49	25.69	120
C_{i,t^+}	79.21	49.61	120	135.31	54.38	120
CS_{i,t^-}	93.57	40.67	120	223.52	58.19	120
CS_{i,t^+}	249.35	98.38	120	361.36	75.88	120
$W_{i,2005}$	115.47	100.74	120	120.74	98.62	120
$G_{i,2005}$	92.61	65.10	120	42.92	50.03	120

Table A7. Treatment Effects' Estimates with Heteroskedasticity corrected t-stats in parentheses

	$C_{i,t^+} - C_{i,t^-}$	$CS_{i,t^+} - CS_{i,t^-}$	$\ln(C_{i,t^+}) - \ln(C_{i,t^-})$	$\ln(CS_{i,t^+}) - \ln(CS_{i,t^-})$
Treatment	18.86 (3.19)***	-44.70 (-5.51)***	-0.31 (-2.55)***	-0.54 (-13.43)***
$W_{i,2005}$	-0.04 (-1.45)	0.06 (1.66)*	0.002 (3.34)***	0.0004 (1.95)*
$G_{i,2005}$	-0.34 (-7.76)***	-0.53 (-7.75)***	-0.002 (-2.25)**	-0.001 (-2.37)**
Constant	99.54 (13.00)***	197.85 (17.08)***	1.73 (10.87)***	1.04 (16.45)***
R^2	0.28	0.28	0.08	0.40

* p<0.1; ** p<0.05; *** p<0.01

Table A8. Summary statistics for Hankinson Renewable Energy: C2 and T1 combination. Caliper = 0.005.

	Control			Treatment		
	mean	Std. dev.	N	mean	Std. dev.	N
C_{i,t^-}	85.87	63.41	161	93.76	64.53	161
C_{i,t_1^-}	94.25	65.83	161	105.49	69.01	161
C_{i,t^+}	112.40	76.24	161	145.20	79.58	161
CS_{i,t^-}	155.78	94.86	161	228.39	106.76	161
CS_{i,t_1^-}	184.07	107.01	161	241.79	115.77	161
CS_{i,t^+}	199.37	125.33	161	287.69	131.18	161
$W_{i,2007}$	13.40	36.21	161	25.62	43.51	161
$G_{i,2007}$	121.98	118.01	161	73.88	96.59	161

Table A9. Treatment Effects' Estimates with Heteroskedasticity corrected t-stats in parentheses

	$C_{i,t^+}-C_{i,t^-}$	$C_{i,t^+}-C_{i,t_1^-}$	$\ln(C_{i,t^+})-\ln(C_{i,t^-})$	$\ln(C_{i,t^+})-\ln(C_{i,t_1^-})$
Treatment	19.47	17.46	0.28	0.24
	(4.36)***	(3.84)***	(3.69)***	(2.85)***
$W_{i,2007}$	0.18	0.19	0.004	0.004
	(3.03)***	(3.22)***	(4.64)***	(4.28)***
$G_{i,2007}$	-0.07	-0.04	-0.001	-0.0001
	(-3.73)***	(-1.93)*	(-1.04)	(-0.65)
Constant	32.16	20.07	0.21	0.08
	(7.70)***	(4.39)***	(2.33)**	(0.83)
R^2	0.17	0.12	0.11	0.06
	$CS_{i,t^+}-CS_{i,t_1^-}$	$CS_{i,t^+}-CS_{i,t_1^-}$	$\ln(CS_{i,t^+})-\ln(CS_{i,t^-})$	$\ln(CS_{i,t^+})-\ln(CS_{i,t_1^-})$
Treatment	7.10	24.98	0.09	0.24
	(1.33)	(4.86)***	(1.28)	(3.20)***
$W_{i,2007}$	0.29	0.36	0.001	0.001
	(4.42)***	(5.50)***	(1.76)*	(2.34)**
$G_{i,2007}$	-0.11	-0.03	-0.002	-0.002
	(-4.61)***	(-1.05)	(-2.03)**	(-1.79)*
Constant	52.73	13.44	0.25	0.04
	(10.13)***	(2.61)***	(2.79)***	(0.43)
R^2	0.15	0.19	0.09	0.10

* p<0.1; ** p<0.05; *** p<0.01

Table A10. Summary statistics for PBNE, C2 and T1 combination. Caliper = 0.01

	Control			Treatment		
	mean	Std. dev.	N	mean	Std. dev.	N
C_{i,t^-}	118.09	49.32	157	189.13	76.98	157
C_{i,t_1^+}	120.76	50.59	157	197.52	76.25	157
C_{i,t^+}	137.90	48.78	157	209.55	73.75	157
CS_{i,t^-}	220.15	88.38	157	304.78	97.33	157
CS_{i,t_1^+}	249.53	88.27	157	331.62	92.58	157
CS_{i,t^+}	273.46	87.18	157	346.95	89.41	157
$W_{i,2007}$	50.11	60.68	157	21.96	31.15	157
$G_{i,2007}$	158.55	92.52	157	108.42	78.68	157

Table A11. Treatment Effects' Estimates with Heteroskedasticity corrected t-stats in parentheses

	$C_{i,t_1^+} - C_{i,t^-}$	$C_{i,t^+} - C_{i,t^-}$	$\ln(C_{i,t_1^+}) - \ln(C_{i,t^-})$	$\ln(C_{i,t^+}) - \ln(C_{i,t^-})$
Treatment	15.89	11.87	0.16	0.08
	(2.92)***	(2.40)**	(3.23)***	(2.00)**
$W_{i,2007}$	0.26	0.33	0.003	0.003
	(5.04)***	(7.79)***	(5.29)***	(8.31)***
$G_{i,2007}$	0.05	0.04	0.001	0.001
	(1.98)**	(1.54)	(2.07)**	(3.15)***
Constant	-19.21	-3.03	-0.23	-0.12
	(-2.79)***	(-0.48)	(-3.45)***	(-2.09)* *
R^2	0.08	0.13	0.10	0.20

	$CS_{i,t_1^+} - CS_{i,t^-}$	$CS_{i,t^+} - CS_{i,t^-}$	$\ln(CS_{i,t_1^+}) - \ln(CS_{i,t^-})$	$\ln(CS_{i,t^+}) - \ln(CS_{i,t^-})$
Treatment	15.20	6.37	0.05	0.02
	(2.66)***	(1.18)	(1.97)**	(0.72)
$W_{i,2007}$	0.44	0.46	0.002	0.002
	(7.17)***	(7.37)***	(7.05)***	(7.22)***
$G_{i,2007}$	0.10	0.09	0.001	0.001
	(3.46)***	(3.41)***	(5.05)***	(7.54)***
Constant	-9.44	15.71	-0.10	-0.04
	(-1.24)	(2.23)***	(-2.94)***	(-1.42)
R^2	0.20	0.23	0.24	0.35

* p<0.1; ** p<0.05; *** p<0.01

Table A12. Summary statistics for ABGL, C2 and T1 combination. Caliper = 0.01.

	Control			Treatment		
	mean	Std. dev.	N	mean	Std. dev.	N
C_{i,t^-}	41.28	39.96	100	135.03	79.73	100
C_{i,t_1^+}	38.22	41.17	100	71.11	50.36	100
C_{i,t^+}	50.29	45.17	100	115.41	57.23	100
CS_{i,t^-}	66.33	61.75	100	231.55	115.23	100
CS_{i,t_1^+}	71.70	68.38	100	146.84	88.64	100
CS_{i,t^+}	88.48	74.49	100	225.20	100.27	100
$W_{i,2007}$	49.06	59.91	100	29.47	44.03	100
$G_{i,2007}$	357.29	107.09	100	171.85	118.09	100

Table A13. Treatment Effects' Estimates with Heteroskedasticity corrected t-stats in parentheses

	$C_{i,t_1^+} - C_{i,t^-}$	$C_{i,t^+} - C_{i,t^-}$	$\ln(C_{i,t_1^+}) - \ln(C_{i,t^-})$	$\ln(C_{i,t^+}) - \ln(C_{i,t^-})$
Treatment	-21.01	-1.36	-0.23	0.08
	(-2.44)**	(-0.18)	(-2.73)***	(0.42)
$W_{i,2007}$	0.27	0.25	0.001	0.002
	(3.57)***	(4.57)***	(0.63)	(1.51)
$G_{i,2007}$	0.19	0.12	0.003	0.004
	(5.15)***	(3.99)***	(3.00)***	(4.62)***
Constant	-82.85	-46.40	-0.98	-0.82
	(-5.01)***	(-3.47)***	(-2.73)***	(-3.12)***
R^2	0.40	0.23	0.14	0.16
	$CS_{i,t_1^+} - CS_{i,t^-}$	$CS_{i,t^+} - CS_{i,t^-}$	$\ln(CS_{i,t_1^+}) - \ln(CS_{i,t^-})$	$\ln(CS_{i,t^+}) - \ln(CS_{i,t^-})$
Treatment	-38.58	1.02	-0.40	-0.06
	(-3.28)***	(0.10)	(-2.26)**	(-0.37)
$W_{i,2007}$	0.38	0.34	0.002	0.0001
	(4.14)***	(5.45)***	(1.69)*	(0.09)
$G_{i,2007}$	0.24	0.12	0.001	0.003
	(5.09)***	(3.48)***	(1.99)**	(4.04)***
Constant	-98.11	-38.56	-0.39	-0.45
	(-4.55)***	(-2.45)**	(-1.51)	(-2.15)**
R^2	0.50	0.23	0.17	0.15

* p<0.1; ** p<0.05; *** p<0.01

Table A14. Robustness Checks for treatment effects on Corn Acres. All combinations of multiple treatment and control groups.

Ethanol Plant	Combinations	$\ln(C_{i,t^+}) - \ln(C_{i,t^-})$	$\ln(C_{i,t^+}) - \ln(C_{i,t_1^-})$	$\ln(C_{i,t_1^+}) - \ln(C_{i,t^-})$
Red Trail Energy	T1 and C2	**-0.64***	n/a	n/a
	T2 and C2	**-0.87*****	n/a	n/a
	T1 and C1	**-0.80*****	n/a	n/a
	T2 and C1	**-1.11*****	n/a	n/a
Blue Flint	T1 and C2	**0.50**	n/a	n/a
	T2 and C2	**0.05**	n/a	n/a
	T1 and C1	**0.47****	n/a	n/a
	T2 and C1	**0.33**	n/a	n/a
Tharaldson Ethanol	T1 and C2	**-0.21****	n/a	n/a
	T2 and C2	**-0.18*****	n/a	n/a
	T1 and C1	**-0.18*****	n/a	n/a
	T2 and C1	**-0.12****	n/a	n/a
Hankinson Renewable Energy	T1 and C2	**0.28****	**0.22****	n/a
	T2 and C2	**0.34*****	**0.30*****	n/a
	T1 and C1	**0.17*****	**0.12*****	n/a
	T2 and C1	**0.18*****	**0.15*****	n/a
Cluster 1: POET Bio Refinery and NuGen Energy	T1 and C2	**0.09****	n/a	**0.12****
	T2 and C2	**0.09*****	n/a	**0.12*****
	T1 and C1	**0.02**	n/a	**0.02**
	T2 and C1	**0.03***	n/a	**0.03**
Cluster 2: Advanced Bio Energy and Glacial Lakes Energy	T1 and C2	**0.37****	n/a	**-0.58****
	T2 and C2	**-0.25***	n/a	**-0.74*****
	T1 and C1	**0.42****	n/a	**-0.38*****
	T2 and C1	**-0.07**	n/a	**-0.64*****

* $p<0.1$; ** $p<0.05$; *** $p<0.01$; **N/A** means 'not applicable' for the case.

Table A15. Robustness Checks for treatment effects on Corn&Soy Acres. All combinations of multiple treatment and control groups.

Ethanol Plant	Combinations	$\ln(CS_{i,t^+})-\ln(CS_{i,t^-})$	$\ln(CS_{i,t^+})-\ln(CS_{i,t_1^-})$	$\ln(CS_{i,t_1^+})-\ln(CS_{i,t^-})$
Red Trail Energy	T1 and C2	**-0.61***	n/a	n/a
	T2 and C2	**-0.88*****	n/a	n/a
	T1 and C1	**-0.83*****	n/a	n/a
	T2 and C1	**-1.11*****	n/a	n/a
Blue Flint	T1 and C2	**-0.22**	n/a	n/a
	T2 and C2	**-0.65****	n/a	n/a
	T1 and C1	**-0.12**	n/a	n/a
	T2 and C1	**-0.22**	n/a	n/a
Tharaldson Ethanol	T1 and C2	**-0.44*****	n/a	n/a
	T2 and C2	**-0.43*****	n/a	n/a
	T1 and C1	**-0.28*****	n/a	n/a
	T2 and C1	**-0.26*****	n/a	n/a
Hankinson Renewable Energy	T1 and C2	**0.06***	**0.19*****	n/a
	T2 and C2	**0.04**	**0.16*****	n/a
	T1 and C1	**0.02**	**0.09*****	n/a
	T2 and C1	**0.01**	**0.09*****	n/a
Cluster 1: POET Bio Refinery and NuGen Energy	T1 and C2	**0.04*****	n/a	**0.05*****
	T2 and C2	**0.04*****	n/a	**0.07*****
	T1 and C1	**0.04*****	n/a	**0.05*****
	T2 and C1	**0.04*****	n/a	**0.06*****
Cluster 2: Advanced Bio Energy and Glacial Lakes Energy	T1 and C2	**-0.005**	n/a	**-0.72*****
	T2 and C2	**-0.31*****	n/a	**-0.69*****
	T1 and C1	**0.08**	n/a	**-0.46*****
	T2 and C1	**-0.25*****	n/a	**-0.63*****

* p<0.1; ** p<0.05; *** p<0.01; N/A means such case is ‘not available’ here.

CHAPTER 3

ASSESSING THE REGIONAL IMPACTS OF CLIMATE CHANGE ON AGRICULTURAL PRODUCTIVITY AND LAND USE ALLOCATION DECISIONS

(PAPER II)

by

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ABSTRACT

Land use changes are tied to the socio-economic well-being of agricultural production systems. Weather variations are central to agricultural productivity of croplands. Amidst evolving weather patterns, land use change is one way for private landowners to adapt to sustain or enhance farm profits. Many studies have analyzed the national or global scale impacts of climate change on agricultural profits, farmland values and crop yields. We present a new integrated framework to analyze climate change impacts on regional agricultural productivity and private land use decisions. We implement our framework to demonstrate the agricultural impacts of climate change on recent land use transitions in the Northern Great Plains. We first estimate a yield-weather relationship for all of a region's major crops and incorporate several extensions that are novel to a commonly implemented yield-weather model. We incorporate trend-weather and soil-weather interaction terms, and differentiate between the detrimental impacts of isolated and consecutive heat events on yields. We further estimate yield-weather elasticities to evaluate asymmetric productivity impacts of weather across crop types. We then utilize a non-linear system of logistic models to identify the role of weather-driven crop yields on observed land use shares, including grassland shares among the crop types. We find evidence that weather-driven returns determine regional land use allocations. We finally evaluate the medium-term land use implications of the A1B climate change scenario by 2031-'60, relative to 1981-2010.

Introduction

Agricultural land use transitions are central to the economic and ecological output of agroecosystems. Private landowners derive marketable agricultural produce and ecosystem services from their lands. The ecological components provide habitat for diverse species, and help reduce the soil's nutrient run-off thereby sustaining regional agricultural productivity. Private land use allocations are driven by multiple factors like market prices of production inputs and outputs, local infrastructure, technology, seeds, fertilizers, soil quality, climate, and agri-environmental policy. Among these, soil quality and climate are natural endowments that determine the land's productivity towards cropping, grazing, or other uses. Unlike soils, weather varies from year-to-year, and is ex-ante unknown to the private landowners when deciding upon their land use allocations. Economists have utilized the exogenous spatial and annual variability in weather to identify the climate change impacts on agriculture.

Growing season weather interacts with the region's soils to support crop growth. The length and timing of a region's growing seasons differ across crops due to their distinct phenology. Similar heat and moisture levels in a growing season may have different developmental implications for different crops. For example, favorable weather conditions would enhance the overall agricultural yields but this effect may be stronger for some crops. Such asymmetric yield impacts of weather fluctuation can encourage private landowners to allocate higher acreage to more productive crops to enhance their profitability. Therefore, weather-driven productivity impacts not only drive a region's economic returns from agricultural land use but could also alter its land use profile overtime affecting the social, ecological and environmental well-being of the region. Such implications are especially relevant when arable land is limited and so, the annual variations in weather may lead to intensive and extensive land use transitions among crops, pasturelands, grasslands and/or forestlands. An understanding of the past impacts of weather on yields and land use changes can also shed light on the climate change implications on the future agricultural productivity, land use and overall welfare for agroecosystems.

Economic analyses have largely analyzed the national and global-level climate change impacts on farmland values, agricultural profits and crop yields. Early studies implemented the Ricardian framework to evaluate U.S. farmland values as a function of growing-season temperature and precipitation (Mendelsohn et al. 1994; Schlenker et al 2005; Schlenker et al. 2006). Deschenes and Greenstone (2007) found this approach to be sensitive to model specifications that provided a wide range of negative and positive climate change impacts. The authors suggested modelling per-acre farm profits instead to derive stable estimates of climate change impacts. Although land values are closely related to farm productivity and crop prices, they may be impacted by macroeconomic factors like inflation and interest rates as well. Infact apart from the fundamental economic forces, idiosyncratic factors like fads and overreactions too play an important role in determining the short-run farmland values (Falk and Lee, 1998) found that,). Crop yields, on the other hand, are directly related to the plant's biological growth cycle that interacts with weather that leads to agricultural productivity. Recent economics literature has shifted focus on estimating the impact of warming on agricultural yields.

Schlenker and Roberts (2009) identified a non-linear yield-temperature relationship for county-level corn, soybeans and cotton yields in the U.S. during 1950-2005. Their modeling strategy was similar to that of Thompson (1975) where marginally higher temperatures enhanced yields up to a threshold, and beyond that higher temperatures were detrimental to crop yields. This literature has since advanced to account for spatial adaptation to warming (Butler and Huybers 2012), the benefits of adopting genetically-engineered seeds (Xu et al. 2013), and studying the impacts of extreme weather events such as heat waves, hail and tornadoes (Massetti and Mandelson 2016). Corn has attracted most attention among researchers who have studied the economic impacts of climate change on U.S. agriculture. Understanding the productivity dynamics of corn due to changed weather conditions is critical to U.S. agricultural exports, food and biofuel production. Recently, Tack et al. (2015) analyzed field-trials of 264 seed varieties to estimate the effects of warming on the U.S. wheat yields. They found that extreme spring-time temperatures reduced wheat yields and that newer wheat varieties are relatively less heat-resistant than their older counterparts.

Here we study how weather fluctuations affect agricultural land allocations for a region where fixed or limited land area is available for several viable land use options. The underlying conceptual framework is presented in figure 1. We first estimate a yield-weather relationship for all of a region's major crops and incorporate several extensions that are novel to the commonly implemented yield-weather model. We analyze the impact of severe dry and wet conditions by using a Palmer's Z index that measures moisture deficiency by controlling for evapotranspiration and soil run-off (Karl 1986). Flexible trends are included as a proxy for technological innovations and land management practices. We introduce soil-weather interactions to differentiate yield-weather outcomes by soil quality, and we include trend-weather interactions to evaluate how the detrimental impacts of weather stressor evolved in the past. We also differentiate yield impacts due to isolated, single-day heat event from those due to consecutive two-or-more-day events. To our knowledge, this is the first study to analyze all of a region's major crops, besides incorporating the trend-weather and soil-weather interaction terms, and identifying the differentiated impacts of isolated and consecutive heat events.

We then estimate yield-weather elasticities to infer relative competitiveness among the region's commodities due to the crop productivity impacts of past weather realizations. We extend the idea of crop competitiveness and estimate a formal land use shares model where we identify how relative profitability of several crops attributable to short-term weather variability impacted the region's observed land use allocations. Our model for regional land use transitions as a function of weather outcomes is also new to the literature. We implement this integrated framework to study the role of weather on recent land use transitions in North Dakota and South Dakota. The Dakotas are part of the Northern Great Plains with substantial regional variability in soils and climate, away from any mountain or coastal effects. Wang et al. (2016) argued that this region's privately owned grasslands are at economic margin and land conversions to agricultural production are subject to various market forces and physical factors such as soils and climate.

We finally evaluate the medium-term climate change implications for regional agricultural productivity and land use changes. We use seven climate models to account for the underlying variability in future climate projections, where Burke et al. (2015) found that climate model selection can have large implications on climate-related policy recommendations.

This paper is subdivided into several sections. We first discuss our methodology including various data sources and variable specification. The methodology section presents our yields model with various considerations. We then describe crop competitiveness due to yield-soil-weather interactions and present a framework that models land use switching by using the yield estimates. We then briefly discuss our results and close with remarks on possible future steps.

Methodology

Study area

We analyze the land use impacts of climate change for two rain-fed states of the U.S. Northern Great Plains: North Dakota and South Dakota. The Dakotas are an appropriate region for this study by virtue of their location and the observed land use transitions. The eastern Dakotas are part of the Prairie Pothole Region, which includes a grassland-cropland frontier along the western edge of the Corn Belt. This region added most corn/soy acreage in the Northern Great Plains during 1995-2015 (figure 2). The increased corn/soy acreage displaced regional grasslands (Wright and Wimberley 2013), and traditionally grown crops like wheat and small grains (Johnston 2014). Grasslands are a natural resource that support Dakotas' biodiversity and sustain its semi-arid soils that are vulnerable to erosion, and thus are central to the region's socio-economic welfare. However, the grasslands are largely under private ownership and the observed land use switching is driven by economic, agronomic, and climate-related factors.

Weather is a determinant of a region's agricultural productivity. To see the correlation in weather and regional yields, see figure 3, where in the past the most prominent dips across all of the Dakotas' major commodities were either due to drought (1977, 1988, 2002, and 2012) or floods (1979, 1993, and 2006). The National Climate Assessment of 2014 predicted longer growing seasons by 2050 for the Northern Great Plains, relative to 1971-2000, as well as more frequent droughts and floods (Shafer et al. 2014). Therefore, the medium-term climate change impacts on this region's agricultural production are relevant.

Estimating crop-specific yields-weather relationship

Data and explanatory variables

We estimate a non-linear yield-weather relationship using annual county-level yields of all major crops in the 119 counties of North and South Dakota during 1950 to 2013.[20] The weather data, available from the Global Historical Climatological Network, are recorded daily across 306 weather stations in North Dakota and 397 stations in South Dakota. County-level weather variables, i.e. minimum/maximum temperature and precipitation, are constructed as an average of the values for stations located within county boundaries. Figure 4 shows the county-level weather station frequency in the Dakotas. Monthly Palmer Z (denoted *Z* hereafter) data for the Dakotas' 18 climate divisions, each containing multiple counties, are obtained from the National Oceanic and Atmospheric Administration. We calculate area-weighted *Z* values for all counties for every month during 1950-2013.

County-level time-invariant soil quality data are constructed from a survey-based point-level longitudinal National Resource Inventory (NRI) database. We utilize the Land Capability subclasses categorize soils based on their deficiencies, namely 'dry and shallow' soils, 'poor drainage/wet' soils, 'erosive' soils, and soil types that have 'climatic limitations'. These subclasses are appended to the commonly used Land Capability classes that classify soils in categories I-VIII based on their incremental constraints towards cropping. Category I are the best soils that do not suffer from any deficiency, whereas categories II-VIII may have multiple deficiencies. A detailed discussion of the NRI's nomenclature of these subclasses is provided in

[20] Survey based expected crop yields data are downloaded from National Agricultural Statistical Service's (NASS) QuickStats 2.0 portal. Expected yields are the weighted ratio of total production divided by total planted acreage in each county, and the weights represent respondent density in an agricultural statistical district (Statistical Methods Branch, USDA-NASS, 2012).

the Supplementary Material (SM). We constrain our analysis to categories II-IV since they provide for 85-90% of the Dakotas' crop acreage. Category V-VIII soils are considered inappropriate for cropping.

Table 1 describes the explanatory variables used to estimate our yield-weather model. Here, we provide the mathematical representation of these variables and the related specifics on their interpretation. We aggregate the daily temperature levels into threshold-based seasonal heat exposure variables called degree-days. The beneficial temperature levels are aggregated into growing degree days or *GD*s, and harmful temperature levels into stress degree-days or *SD*s. Following Xu et al. (2013), the mathematical representation of *GD*s and *SD*s for county *i* in month *m* of year *t* is provided in equation (1 a-b).

$$\begin{aligned} &\text{a) } GD_{i,m,t} = \sum\nolimits_{d \in m,t} 0.5\left(min\left(max\left(T_{i,d}{}^{max}, T^{l}\right), T^{h}\right) + min\left(max\left(T_{i,d}{}^{\min}, T^{l}\right), T^{h}\right)\right) - T^{l} \\ &\text{b) } SD_{i,m,t} = \sum\nolimits_{d \in m,t} 0.5\left(max\left(T_{i,d}{}^{max}, T^{k}\right) + max\left(T_{i,d}{}^{\min}, T^{k}\right)\right) - T^{k} \end{aligned} \qquad (1)$$

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

We prefer *Z* to precipitation to account for the actual moisture available for plant growth. *Z* measures short-term soil moisture deficiency and accounts for precipitation, evapotranspiration and soil's water storage capacity. Evapotranspiration is a function of monthly and annual average temperature, and so Z may be correlated with *GD*/*SD*.[21] Table 2 summarizes various categories of *Z*. A representative month where $Z < -1.24$ is designated droughty and when $Z > 1$ the month is designated as wetter than normal. We transform this index to capture a non-linear yield response to the degree of moisture-stress from severe-to-extreme dryness/wetness. We define our regressors in equation (2 a-b).

$$\begin{aligned} &\text{a) } DRYZ_{i,m,t} = -\min(Z_{i,m,t} + 1.99, 0) \\ &\text{b) } WETZ_{i,m,t} = \max(Z_{i,m,t} - 2.49, 0) \end{aligned} \qquad (2)$$

Here, $DRYZ_{i,m,t}$ and $WETZ_{i,m,t}$ are defined as a function of $Z_{i,m,t}$ such that higher *DRYZ* (*WETZ*) means higher degree of dryness (wetness) in county *i* for month *m* of year *t*. This specification will allow us to test whether droughts are the most harmful weather stressor towards crop yields as asserted by Massetti and Mandelsohn (2016). We also include an interaction term of *WETZ* with the *SD*s to evaluate the impact of humidity on agricultural yields.

To evaluate the role of soils on how weather stressors impact crop yields, we construct county-level time-invariant soil deficiency measures Q_i^{dry} and Q_i^{wet} from the land capability subclasses. Q_i^{dry} (Q_i^{wet}) is defined as the percentage acreage in county *i* with 'dry and shallow' ('poor drainage/wet') soils. Including only Q_i^{dry} and Q_i^{wet} in our regressions means that their coefficients capture a relative impact from excluded soils with other deficiencies.

[21] Palmer Drought Severity Index (*PDSI*) is an alternative index that is often used to account for moisture deficiency (e.g. Massetti and Mandelsohn, 2016). We rely on Karl's (1986) recommendation that *Z* is a more stable measure of short-term moisture deficiencies than *PDSI*.

The yield-weather model

We implement a two-step strategy for identifying crop-specific *GD* and *SD* thresholds. We first estimate a step-function by regressing crop yields onto each 1-degree Celsius bins having controlled for quadratic trends and precipitation. The estimated step-functions, presented in figures S1-S4 in the SM, provide an initial guide to the thresholds. We then refine the preliminary thresholds by implementing regression loops with the objective to maximizing our 'full' yield-weather model's fit (equation (3) below). Table 3 presents the crop-specific *GD & SD* thresholds along with the designated growing seasons. The decadal variable summaries are provided in table 4.

$$\begin{aligned} Y_{i,t} = \beta_0 + \sum\nolimits_n \beta_1^n D_n(t-n) + \beta_W W_{i,t} + \beta_{WETSD} WETZ_{i,t} \times SD_{i,t} + \beta_{DRYSD} DRYZ_{i,t} \times SD_{i,t} \\ + \beta_{Qd} Q_i^{dry} W_{i,t} + \beta_{Qw} Q_i^{wet} W_{i,t} + \beta_{tW} t W_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

Here, $Y_{i,t}$ represents crop-specific yields in county *i* for year *t*. Variable $D_n = 1 \; if \;\; t \geq n$ and 0 otherwise interacted with *t* specifies a continuous, linear spline with knots, n, at 1965, 1980 and 1995 to capture differentiated trend impacts every fifteen years. Weather outcomes vector, $W'_{i,t} = [GD_{i,t}, SD_{i,t}, DRYZ_{i,t}, WETZ_{i,t}]$ captures the concave yield response to heat and moisture deficiency. Variables Q_i^{dry} and Q_i^{wet} that represent percent dry/shallow and poorly drained soils in a county respectively are interacted with $W_{i,t}$ to infer whether soil deficiencies aggravate the yield impacts of weather stressors.[22] Our spline specification is intended to control for evolving

[22] County-level Q_i^{dry} and Q_i^{wet} do not vary by the crops grown on these soil types. So, we will be able to provide only a general inference on the impact of soil quality on agricultural yields when the coefficient estimates to each soil variable are of same sign across the region's *major* crops.

technology and land management practices that may enhance yields, and to capture potential shifts in yield trends from exogenous policy changes, e.g. 1996 Freedom-to-Farm Act, or lower commodity prices in mid-80s.[23] Thompson (1969) utilized a similar specification to capture shift in yield trends after 1960 from higher fertilizer adoption in the Corn Belt.

We also include trend-weather interactions to control how yield responses to weather stressors have evolved through time. The standalone trends are a surrogate for temporal adaptations as they likely reflect the impact of new technology or management practices on crop yields. Therefore, the trend-weather interactions may provide useful insights on how such innovations may have modified the impacts of weather on crop yields in the past. Finally, we include $WETZ \times SD$ to estimate the impact of humidity on agricultural yields. We include multiple interaction terms in model (3) and adopt a centered regression approach to ensure proper interpretation of the coefficients to these interacted variables.

We extend model (3) to understand differentiated yield impacts by the intensity of heat stress. In particular, we disaggregate total growing season *SD*s into isolated or single-day event (SD^{1}), two-to-three-consecutive-day (SD^{23}) and four-or-more-consecutive days (SD^{4+}). We divide these regressors, SD^{1}, SD^{23}, and SD^{4+}, by a normalizing factor such that the coefficient estimates across these variables are comparable. The details on the normalization procedure and why it is important are provided in the SM.

[23] We ruled out decadal knots because an F-test revealed that the degrees of freedom adjusted goodness-of-fit is higher for fifteen-year knots.

Weather may not have a uniform impact on crop's growth through the growing season. In order to control for any seasonally differentiated effects of weather, we also include weather variables from 1st and 2nd halves of the growing season separately in equation (3).

Weather realizations, crop competitiveness and land use change

A profit maximizing land use allocation is achieved when an extra unit of land generates equal marginal returns from all competing land use types. Marginal returns from cropping depend upon exogenous inputs like weather and soils, endogenous inputs like seeds and fertilizers, and the input & output prices. Given market prices, good (bad) weather will increase (decrease) a crop's yields, thereby making it more (less) profitable. If such weather impacts are heterogeneous across a region's commodities, landowners may allocate higher acreage towards more profitable crop(s). To infer upon crop competitiveness in a region, we calculate yield elasticities to weather. The yield-weather elasticity is defined as the percent change in yields due to a one percent change in each weather variable, measuring yields' sensitivity to change in that variable. Since elasticity is a unit-less measure, it is comparable across crops.

We extend the crop competitiveness idea to analyze acreage allocation among the Dakotas' five major land use types: corn (*c*), soy (*s*), spring wheat (*w*), alfalfa (*a*) and grass (*g*) during 1996-2013.[24, 25] The share of land allocated to use *u* in county *i* in year *t*, $s^u_{i,t}$, is defined as the ratio of its acreage to the total county acreage, and we find $s^u_{i,t} \in (0,1)\ \forall i,t$ in the Dakotas. Similar to Wu and Segerson (1995) and Miller and Plantinga (1999), we posit individual land use shares to be related to the per-acre returns from the competing land use types in set $U \equiv \{c, s, w, a, g\}$. That is, $s^u_{i,t} = f(X_{i,t}; \beta^u)$ with $X_{i,t} = \{(\pi^u_{i,t})_{u\in U}, (G^u_{i,t})_{u\in U}\}$. $\pi^u_{i,t}$ denotes per-acre profits generated, and $G^u_{i,t}$ denotes government payments received from land use *u* in county *i* in year *t*. We express each land use category's allocated shares as a multinomial logistic function such that the shares sum to one for every county in each year, and the estimate of each share lies between zero and one. That is, we need to estimate the following system of crop-share equations

$$s^u_{i,t}(X_{i,t}; \beta^u) = \frac{\exp[\beta^u X_{i,t} + \varepsilon^u_{i,t}]}{\sum_{v\in U} \exp\left[\beta^v X_{i,t} + \varepsilon^v_{i,t}\right]};\ u \in U \tag{4}$$

The system of equation in (4) is then transformed into a log-linear form by dividing grass-acreage shares from the remaining four land use share equations and taking a log on both sides of each equation in the resulting system. So, we estimate the following system of four equations.

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[24] Land allocated among these five land use categories was more than 90% (80%) of the total county acreage for 92 (111) out of 119 counties during 1996-2013.

[25] Each year's county-level grass acres are calculated as total county acreage minus the area under developed land, water, and cropland, including corn, soybeans, spring wheat, alfalfa, winter wheat, barley, dry beans, canola, oats, peas, rye, sorghum, sugarbeets and sunflower.

$$\log(s_{i,t}^{u} / s_{i,t}^{g}) = (\beta^{u} - \beta^{g}) X_{i,t} + \varepsilon_{i,t}^{u} - \varepsilon_{i,t}^{g}; \;\; u \in U \setminus g \equiv \{c, s, w, a\}$$

(5)

Our objective is to calculate the marginal effects of land use shares with respect to each exogenous variable $x_{i,t} \in X_{i,t}$, i.e., $\partial s_{i,t}^{u}(X_{i,t}; \beta^{u}) / \partial x_{i,t}$. To derive these marginal effects we first denote $\beta^{u} - \beta^{g} = \bar{\beta}^{u}$, $\varepsilon_{i,t}^{u} - \varepsilon_{i,t}^{g} = \bar{\varepsilon}_{i,t}^{u}$, and $U \setminus g \equiv \bar{U}$ and re-write the system of equations (4) as follows

$$s_{i,t}^{u} = \frac{\exp[\bar{\beta}^{u} X_{i,t} + \bar{\varepsilon}_{i,t}^{u}]}{1 + \sum_{v \in \bar{U}} \exp\left[\bar{\beta}^{v} X_{i,t} + \bar{\varepsilon}_{i,t}^{v}\right]}; \;\; u \in \bar{U}$$

and

$$s_{i,t}^{g} = \frac{1}{1 + \sum_{v \in \bar{U}} \exp\left[\bar{\beta}^{v} X_{i,t} + \bar{\varepsilon}_{i,t}^{v}\right]}$$

(6)

In order to calculate the marginal effects we differentiate the equations in (6) by exogenous variables $x_{i,t}$ (see SM for details). That is,

$$\begin{aligned} &\text{(i)} \;\; M(s_{i,t}^{u}, x_{i,t}) = \partial s_{i,t}^{u} / \partial x_{i,t} = s_{i,t}^{u}\left[\bar{\beta}_{x}^{u} - \sum_{v \in \bar{U}} \bar{\beta}_{x}^{v} s_{i,t}^{v}\right]; \;\; u \in \bar{U} \\ &\text{(ii)} \; M(s_{i,t}^{g}, x_{i,t}) = \partial s_{i,t}^{g} / \partial x_{i,t} = -s_{i,t}^{g} \sum_{v \in \bar{U}} \bar{\beta}_{x}^{v} s_{i,t}^{v} \end{aligned} \qquad (7)$$

Equation (7) represents the land allocation solution for a profit-maximizing agent upon a unit increase in exogenous variable $x_{i,t}$. To visualize the economic interpretation of (7), consider the case when $u = c$ and substitute $1 - s_{i,t}^{c} = s_{i,t}^{c} + s_{i,t}^{w} + s_{i,t}^{a} + s_{i,t}^{g}$. So, we have $(s_{i,t}^{c})^{-1} \partial s_{i,t}^{c} / \partial x_{i,t} = \sum_{v \in U \setminus c} (\beta^{c} - \beta^{v}) s_{i,t}^{v}$ where $U \setminus c \in \{s, w, a, g\}$. Hence, a unit increase in $x_{i,t}$ leads to a percent change in corn's acreage share that is equal to the increase in net per-acre returns associated with

$x_{i,t}$ upon allocating the land under other competing land use types to corn. We now discuss our strategy to isolate the impact of annual weather fluctuations on land use allocation decisions and the relevant estimation considerations for our land use shares model.

Linking the annual weather fluctuations to land use allocations

To identify the impact of weather variability on regional land use, we first define each crop's per-acre profit as a function of its yields and then utilize our yield-weather model in equation (3) to decompose total profits into trend-driven and weather-soil driven profit components. Specifically, we re-write the expression $\beta_\pi^u \pi_{i,t}^u$ for all $u \in U$ in equation (4) as follows:

$$\begin{aligned} \beta_\pi^u \pi_{i,t}^u &= \beta_\pi^u (P_t^u Y_{i,t}^u - C_t^u) \\ &= \beta_\pi^u \eta^u \pi_{i,t|t}^u + \beta_\pi^u \alpha^u \pi_{i,t|W,Q}^u \\ &= \beta_\pi^u \eta^u \left(P_t^u Y_{i,t|t}^u - C_t^u \right) + \beta_\pi^u \alpha^u \left(P_t^u Y_{i,t|W,Q}^u - C_t^u \right) \\ s.t. \quad & \eta^u + \alpha^u = 1,\ (\eta^u, \alpha^u) \in [0,1]^2;\ u \in U \end{aligned} \tag{8}$$

Equation (8) formally presents the decomposition of total profits, $\pi_{i,t}^u$, as the sum of a trends-driven component, $\pi_{i,t|t}^u = P_t^u Y_{i,t|t}^u - C_t^u$, and a weather-soil driven component, $\pi_{i,t|W,Q}^u = P_t^u Y_{i,t|W,Q}^u - C_t^u$, where $Y_{i,t|t} = \beta_0 + \sum_n \beta_1^n D_n(t-n)$ and $Y_{i,t|W,Q} = Y_{i,t}^u - Y_{i,t|t}^u$ from equation (3).[26] Here, P_t^u and C_t^u represent the per-bushel price and per-acre cost of production for land use *u*, discussed later. We introduce parameters η^u and α^u as weights attached to each profit

[26] We assume the $\beta_{tW} = 0$ to allow for yields decomposition, potentially biasing other estimates. We re-estimate equation (3) with $\beta_{tW} = 0$ in this section and find other coefficients to be largely similar, see table S10 in the SM.

component to test whether the impacts of trend-driven and weather-driven profits respectively are significantly different from the corresponding impact of total crop profits on land use changes. We constrain $\eta^u + \alpha^u = 1$ to ensure $\pi^u_{i,t} = \pi^u_{i,t|t} + \pi^u_{i,t|W,Q}$, and we require $(\eta^u, \alpha^u) \in [0,1]^2$ to ensure that the absolute value of the impact of each profit component is restricted to be only as large as, and of same sign as, that of total profits.

Notice that at the time farmers make land allocation decisions (generating the left-hand-side of equation (4)), growing-season weather and post-harvest-time market prices are not yet realized. Thus, we incorporate landowner expectations of post-harvest prices by using pre-planting settlement in February of each years for December Futures contracts of corn (Chicago Board of Traders or CBOT) and spring wheat (Minneapolis Grain Exchange), and November contracts of soybeans (CBOT).[27] We acquire the per-acre cost of production for corn, soybeans and spring wheat from the 'Commodity Costs and Returns 2016' dataset made available by the USDA Economic Research Service. Since alfalfa futures are not traded, we utilize alfalfa prices and costs for the Dakotas made available by the FINBIN database hosted by the University of Minnesota (https://finbin.umn.edu).[28] To account for the net returns from grass-based production we include price and cost information for the Dakotas CRP lands, fallow lands and cattle production from FINBIN database. Government payments data are acquired from the Environmental Working Group's Farm Subsidy Database.

[27] Futures prices for agricultural commodities were downloaded from Quandl.com.

[28] We find regional-level prices to be highly correlated with the pre-planting Futures prices in this region, see figure S5 in the SM.

We further incorporate landowner expectation for each year's growing-season weather based on the *predicted* weather, $W^{u}_{i,t}$, from an AR(4) process described in equation (9).

$$W^{u}_{i,t} = \phi^{u}_{o}\mathbf{1} + \phi^{u}_{t}t\mathbf{1} + \left[\sum_{l=1}^{4}\phi^{u}_{W,l}W^{u}_{i,t-l}\right]\mathbf{1} \tag{9}$$

where, $\phi^{u}_{W,l} = \left[\phi^{u}_{GD,l}, \phi^{u}_{SD,l}, \phi^{u}_{DRYZ,l}, \phi^{u}_{WETZ,l}\right]$, $\mathbf{1'} = [1,1,1,1]$ and $W_{i,t}$ is as defined earlier.[29]

To control for government payments we include insurance subsidies for corn, soy and wheat; disaster payments and other farming subsidies to account for government payments.[30] Insurance subsidies are important for land use allocations as they mitigate crop failure risks (Claassen et al. 2011b, Miao et al. 2014), which is relevant for the Dakotas' marginal soils and weather. Land use allocations are endogenous to insurance subsidies and other forms of government payments. This is because the decision to buy insurance is likely to be simultaneous to the farmer's land use allocation decision prior to the growing season. In this sense, cropping would be incentivized against staying out of cultivation (or staying in grass) when the government subsidizes insurance premiums.

We therefore implement an IV estimation approach and instrument government payments as a function of expected prices and weather, as demonstrated in equation (10) below. As for the choice of instruments, we needed variables that are correlated with landowners' land use share

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[29] Non-stationarity tests for each weather variable are presented in tables S10-S15 in the SM.

[30] 'Other farming subsidy' payments 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 program, agricultural trade adjustment assistance program, hard winter wheat incentive program, and miscellaneous subsidies.

allocation decisions and uncorrelated with the residuals in (6). We use the futures prices of crops to instrument government payments because these would determine farmer's expectation of post-harvest market-driven profitability of crops (which is also why we used futures prices to calculate per-acre profits above). We also use landowners' expectation of weather from equation (9) to control for the farmers' expectation of crop's post-harvest weather-driven profitability, which we also utilize to define weather-driven profits earlier.

$$G_{i,t}^{u} = \lambda_0^{u} + \lambda_P^{u} P_t^{u} + \lambda_W^{u} W_{i,t}^{u}, \tag{10}$$

where $\lambda_W^u = [\lambda_{GD}^u, \lambda_{SD}^u, \lambda_{DRYZ}^u, \lambda_{WETZ}^u]$. Our proposed instruments are the pre-planting landowner expectations and are assumed to be uncorrelated with the error from estimating equation (10). Finally, in order for the constraint that $\eta^u + \alpha^u = 1$ in equation (5) to be satisfied we set $\eta^u + \alpha^u = 1 \; \forall u$ and to ensure that $\alpha^u \in [0,1]$ we set $\alpha^u = \exp(a^u)/(1+\exp(a^u)) \; \forall u$ where a^u is unrestricted.

Hence, the non-linear system of equations to be estimated that corresponds to (6) and identifies the impact of short-run weather fluctuations on Dakotas' observed land use shares during 1996-2013 is given as

$$\begin{aligned} &\log(s_{i,t}^{u} / s_{i,t}^{g}) = \sum\nolimits_{v \in \bar{U}} \left\{ \bar{\beta}_{\pi}^{v} (1-\alpha^{v}) \pi_{i,t|t}^{v} + \bar{\beta}_{\pi}^{v} \alpha^{v} \pi_{i,t|W,Q}^{v} + \bar{\beta}_{G}^{v} G_{i,t}^{v} \right\} + \bar{\varepsilon}_{i,t}^{u}; \; u \in \bar{U} \\ &s.t. \quad \alpha^{v} = \exp(a^{v}) / (1+\exp(a^{v})); \; u, v \in \bar{U} \end{aligned} \tag{11}$$

We utilize the non-linear seemingly-unrelated regressions framework to estimate (11) as common regressors may lead to contemporaneous correlation among residuals, $\bar{\varepsilon}_{i,t}^{u}$, across crops-share equations, which is the second-step after the IV regressions for government payments in

(10). We also present the elasticity of land use shares to weather-driven own- and cross-profits, which is calculated below using the marginal effects formula in (7).

Land use share elasticity with respect to the total and weather-driven profits is given as

$$\mathrm{E}(s_{i,t}^{u},\pi_{i,t}^{v}) = \frac{\pi_{i,t}^{v}}{s_{i,t}^{u}}\frac{\partial s_{i,t}^{u}}{\partial \pi_{i,t}^{v}} = \pi_{i,t}^{v}\left[\bar{\beta}_{\pi}^{u} - \sum\nolimits_{v\in\bar{U}}\bar{\beta}_{\pi}^{v}s_{i,t}^{v}\right]$$

$$\mathrm{E}(s_{i,t}^{g},\pi_{i,t}^{v}) = \frac{\pi_{i,t}^{v}}{s_{i,t}^{g}}\frac{\partial s_{i,t}^{g}}{\partial \pi_{i,t}^{v}} = -\pi_{i,t}^{v}\sum\nolimits_{v\in\bar{U}}\bar{\beta}_{\pi}^{v}s_{i,t}^{v},$$

and with respect to weather-driven profits as

$$\mathrm{E}(s_{i,t}^{u},\pi_{i,t|W,Q}^{v}) = \pi_{i,t|W,Q}^{v}\left[\bar{\beta}_{\pi}^{u}\alpha^{u} - \sum\nolimits_{v\in\bar{U}}\bar{\beta}_{\pi}^{v}\alpha^{v}s_{i,t}^{v}\right]$$

$$\mathrm{E}(s_{i,t}^{g},\pi_{i,t}^{v}) = -\pi_{i,t|W,Q}^{v}\sum\nolimits_{v\in\bar{U}}\bar{\beta}_{\pi}^{v}\alpha^{v}s_{i,t}^{v};\ \ u,v\in\bar{U}$$

(12)

Land use elasticity in equation (12) represents the the % change in crop *u*’s share as a result of 1% change in *u*’s per-acre profit, which is proportional to net per-acre returns from allocating a unit acreage *u* from each of its competing land use types.

Although our modeling strategy would identify the role of annual weather fluctuations in regional land use switches, some caveats remain. First, each crop’s growing season and temperature thresholds for *GD*s/*SD*s overlap, see table 3, implying high multicollinearity among weather-driven profits. Second, crop yield-trends after 1996 are also highly correlated (figure 5) leading to multicollinearity among trend-driven profits as well. Therefore, weather effects may not be separable across crops. Third, crop rotations are not explicitly captured in our model but in the county-level context crop rotations may not be as relevant as with fine-scale data.

Regional climate change implications on yields and land use change

We consider the Intergovernmental Panel on Climate Change’s (IPCC) A1B emission scenario (IPCC, 2012, p.4) to study the implications of climate change for this study. The A1B scenario assumes rapid global economic growth until the end of this century with a balanced use of fossil and non-fossil energy sources. Under this scenario, global temperatures are expected to rise by [1.7ºC, 4.4ºC] in 2090-’99, relative to the 1980-’99 levels (Collins et al. 2013, figure 12.39). We utilize daily climate projections from seven distinct climate models: CNRM, PCM, ECHAM5, HadCM3, ECHO, CGCM3/T47, and CGCM3/T63 for the Dakotas’ 18 climate divisions. Multiple climate model outputs are included since a definitive model has not emerged from the climate science literature, and the variance among different model-based outputs can be significant (Burke et al. 2015).

To study regional-level change in weather and its implications, we construct future weather projections by superimposing a change-vector from daily climate projections onto the historical stations-level weather data, discussed hereafter. We do not use climate model-based projections directly for two reasons. First, the identification of weather variable coefficients in equation (3) relies on weather being a random phenomenon. The model-based climate projections are derived from simulated systems of interactions among the atmosphere, oceans, land surface, and ice, and are therefore not random. Further, the statistically downscaled climate projections under-represent heat-stress, see figures S5 a-c in the SM.

To construct weather projections, we impose a 50-year mean-shift from the climate projections data onto daily historical weather realizations to obtain weather projections for 2031-’60 period relative to 1981-2010. Let $F_{k,y,m,d}$ represent the historical realizations of temperature and precipitation in climate division *k* on day *d* of month *m* in year *t*, and $F_{k,y,m,d}$ represent climate model-based projections of weather. Define $\Delta F_{k,y',y,m,d} = F_{k,y',m,d} - F_{k,y,m,d}$ as the daily-shift in projected weather in *k* to the same date 50-years apart or $y' = y + 50$. A potential candidate for future weather variables is $F_{k,y',m,d} = F_{k,y,m,d} + \Delta F_{k,y',y,m,d}$. However, we find that such shifts lead to nonsensical $F_{k,t'}$ like negative precipitation. We further find *average* daily-shifts or mean-shifts to reduce such nonsensical projections, and so decide to use them.

For robustness, we calculate the average-shifts in three distinct forms: a) 31-day moving average (MA); b) monthly average; c) annual average over months within the growing season, i.e. April-August. We present the results based on the daily projections derived using the 31-day MA mean-shifts. The alternative shifts provide similar inference for climate change and are included in the SM. The mathematical representation of 31-day daily mean-shifts and projected weather are provided in equation 9 (a-b).

$$\text{a) } \Delta F^{MA(31)}_{k,y',y,m,d} = \frac{\sum_{\mu=-15}^{15} \Delta F_{k,y',y,m,d+\mu}}{31} \qquad (13)$$

$$\text{b) } F^{MA(31)}_{i,t'} = F_{i,t} + \Delta F^{MA(31)}_{i,y',y,m,d}$$

Recall that we utilize seven distinct sets of climate projections. Therefore, each equation in (13 a-b) is evaluated for all seven sets of climate model outputs. To draw a comparison between historical weather realizations (1981-2010) and the weather projections (2031-’60), we utilize median values from the output of seven climate models. Briefly, average temperature and total precipitation is projected increase for all months in the growing season. The highest increase in average temperature is projected in April (33%) and May (18%), and least increase in July (12%). August precipitation will increase the most (15%). Monthly *Z* will become more negative in future, primarily driven by higher future temperatures.[31] Detailed climate change implications for our weather regressors are discussed in the SM and presented in table S22.

We utilize the projected weather to predict individual crop yields during 2031-'60 relative to 1981-2010 conditional on regional soil quality and trends. To obtain future yield projections, we multiply the historical weather's coefficient estimates in equation (3) by weather projections. We use static trends at 2010 levels when comparing yields during 2031-'60 vs. 1981-2010.[32] Burke et al. (2015) identified two types of errors in yield forecasts: climate model uncertainty and regression uncertainty. Climate model uncertainty arises from yield predictions based on seven climate model outputs. The regression uncertainty is the out-of-sample forecast error when using the coefficient estimates of a historical regression. We compute bootstrapped errors in yield forecasts during 1950-2013. We randomly exclude 10% of the years, re-estimate equation (3), and evaluate the difference between observed and predicted yields for the excluded years as forecast errors.[33] We incorporate 500 iterations to deduce the distribution of forecast errors, and hence the variance for the yield forecasts. Finally, we feed our yield forecasts in equation (8) to infer upon the impact of climate change on future land use.

Estimation Results

Our yield-weather model reveals that the marginal yield trends were positive for all of the Dakotas' major crops, the strongest for corn and the weakest for alfalfa, during 1950-2013

[31] We model historical *Z* with monthly weather, prior to its projections. See SM for details.

[32] It is hard to predict any technological breakouts or how trends would evolve by 2060. Static trends (e.g. at 2010 level) allow temporal comparisons in yields in a consistent manner.

[33] Bootstrapping errors across years is appropriate as weather may be spatially correlated, hence non-random, across counties (Schlenker and Roberts, 2009).

(figure 5). Yield trends were positive for all crop types post-1995, and negative for all crops during 1980-'95. The post-1995 trends might be attributed to the 1996 Freedom-to-Farm Act. The Act gave farmers the flexibility to align their cropping choices with market valuations, which might have encouraged adoption of better farming practices potentially enhancing yields. It is interesting that spring wheat yields initially grew more rapidly, but were overtaken by the corn yields around 1970. Corn has sustained the strongest since then, which is correlated with the higher investment and adoption of corn's hybrid, genetically engineered seed varieties in the Dakotas since 1948 (Griliches 1960).

Our coefficient estimates for historical weather outcomes, i.e. *GD*, *SD*, *DRYZ* and *WETZ*, reveal a non-linear, concave yield-weather relationship (see table 5). The rate of decline in yields due to an extra unit of *SD* is found to be greater than the rate of increase in yields due to an extra unit of G*D*. This finding is consistent with Roberts and Schlenker (2009), and we extend it to two more commodities-spring wheat and alfalfa. Similarly, we find drought, as measured by *DRYZ*, to be the most harmful among weather stressors, consistent with Massetti and Mandelson (2016) and extended to spring wheat and alfalfa. Alfalfa is particularly interesting as it is a legume crop, often grown for forage or rotated with row crops for nitrogen-fixation in soils. We find severe wetness to be harmful towards wheat yields, beneficial towards soybean and alfalfa yields and insignificant towards corn yields. The non-decreasing impact of *WETZ* on corn and soybeans could be due to these crops' high water demand for growth. We find humidity ($WETZ \times SD$) to be beneficial towards crop yields. We cannot reconcile the positive and significant coefficient for $DRYZ \times SD$, which might be due to collinearity among its components. High values of *DRYZ* and *SD* both reflect high temperature levels.

The coefficient estimates on the trend-weather interaction terms are positive for *GD*, and negative for the weather stressors across crop-types, except for soybeans where the $t \times DRYZ$ coefficient is negative but insignificant.[34] So, the detrimental impact of *SD* and *DRYZ* has worsened over time. We find evidence above that positive trends for corn are correlated with technological advancements. Therefore, we expected the trend-weather interactions to exhibit higher yield tolerance to weather stressors over time. Our finding here is at variance with Yu and Babcock (2010) who found that corn beacme more drought tolerant in Indiana, Illinois and Iowa, and soybeans had constant drought-related through time. Lastly, our soil-weather interactions reveal that dry, shallow soils aggravate the negative impacts of *DRYZ*, and poorly drained, wet soils aggravate the impact of *WETZ*. As discussed earlier, we only provide a qualitative inference since soil quality varies at the county-level, and we do not information of soils by crop types.

Our disaggregation of total *SD*s reveals that the higher intensity of heat-stress due to its incidence in continuum causes more damage to crop yields than from isolated events, see table 6. In addition, the isolated heat events enhanced soybean and spring wheat yields, which is akin to the conept of '*hormesis*' in toxicology. Hormesis occurs when low-doses of an agent are stimulating while the higher-doses may be toxic or lethal. We also find seasonally differentiated impacts on crop yields, where early season *SD*s also enhance soybean and spring wheat yields

Differentiated weather impacts on crop yields

Table 7 reveals that during 1950-2013 an extra unit of *GD*s enhanced soybean yields the most (elasticity = 0.12), followed by alfalfa (0.06), spring wheat (0.06) and corn (0.04). On the

[34] This result could be due to positive trends in the weather variables. We do not find *GD*, *SD*, and *DRYZ* to exhibit such trends historically. See tables S14-S17 in the SM.

other hand, an extra unit of *SD*s was most harmful to spring wheat yields (-0.09), followed by alfalfa (-0.08), corn (-0.08) and soy (-0.04). An extra unit of *DRYZ* was most harmful to alfalfa (-0.06), followed by spring wheat (-0.05), corn (-0.04) and soybeans (-0.04). As presented earlier in table 4, the Dakotas have experienced increased incidence of *GD*s, *SD*s and *DRYZ* since the 1950s, although these trends were relatively moderate in the more recent decades. Our yield-weather elasticities suggest that amidst the observed trends in historical weather outcomes soybeans and corn have become more productive than spring wheat overtime. This productivity difference across the region's crops is consistent with the observed shift of production systems away from wheat, and towards corn and soybeans.

Land allocation among competing uses

Our land use shares estimation is a two-step process. First, the IV-regressions estimate government payments, which are endogenous to contemporary land use allocations, as a function of expected weather and regional prices (equation (7), table 8). We find that higher commodity prices lead to lower per-acre farm-level subsidies including direct and counter-cyclical payments, but higher insurance subsidies. High commodity prices could drive insurance premiums upward as the market value of the farm's output increases, which explains why higher prices predict higher insurance subsidies. The crop insurance subsidies and disaster payments have similar weather dependence as in our yield-weather models. That is, more *GD*s imply lower payments, whereas higher *SD*s, *DRYZ*s or *WETZ*s imply higher payments.

Most soybeans production occurred on east of the Missouri River, and so soybean yields data are only available for counties in the eastern Dakotas. We incorporate this inconsistency in data by estimating model (8) in two sets: (i) east of Missouri River including soy shares, and ii) west of the river excluding soy shares. Tables 9 (11) presents the estimation results for set (i) ((ii)) regressions and table 10 (12) present corresponding acreage share elasticities with respect to crop-specific total and weather-driven profits.[35]

Our modeling framework posited the five major land use types competing for fixed county acreage. We expected that an increase in profits of a particular crop would imply higher acreage allocation towards that crop and lower acreage allocation towards its substitutes. In eastern Dakotas, we find that higher corn profits to enhance its share allocation and reduce acreage allocated towards alfalfa and grass. However, higher corn profits favor the acreage shares of soybeans and wheat, even though higher wheat profits imply fewer corn acres. We attribute such spurious estimates to high multicollinearity across crops' profits, discussed earlier. Our estimation framework identifies the overall impact of weather-driven profits, but land allocation impacts from crop-specific profits remain undifferentiated. We also find that higher insurance subsidies enhance the crop's acreage allocation, while disaster payments and farm subsidies are associated with lower crop acreage except for spring wheat.

We estimate the elasticity of each crop's land use shares with respect to weather-driven profits. These elasticities are indicative of the impact of annual variability in weather on regional land use change. In the eastern Dakotas, higher weather-driven profits for spring wheat imply

[35] To formally test whether our profit-decompositions matter, we conduct an F-test to compare sum of standard errors (SSEs) from a full model (with decomposed profits) and a restricted model (with total profits) of land use shares. We find that SSEs were statistically smaller in case of the full model for all crops, except for alfalfa in the western counties where restricted model yielded a better fit (or lower SSE). Overall, we conclude that profit decomposition is important when data permits, to the extent that it likely generates a better fit for land use share models.

more wheat and soy acres and fewer acres for corn, alfalfa and grasses. An increase in the weather-driven alfalfa profits, however, enhances the acreage shares allocation for all crop types except for itself while implying fewer grass acres. In the western counties, similar results hold with the impact of weather-driven profits statistically significant in most cases. Overall, we find that weather-driven profits are an important determinant of acreage allocation among all land use types, but the shares' elasticity is at times negative with respect to the own-profits and positive with respect to the cross-profits.

Land use and Yield changes due to Climate Change

We find soybeans yield losses to be modest (11%) relative to the other crops, followed by corn (34%), spring wheat (51%) and alfalfa (65%) by 2031-'60, relative to the 1981-2010 levels, see figures 6-9. These individual crop yield losses translate into lowered weather-driven profits of the region's crops as a result of the projected weather during 2031-'60. These changes in weather-driven profits, at their means, are then fed into the estimated system of land share equations, holding other variables constant at their means, to evaluate regional implications of climate change on the land use allocations. We find that, in the eastern Dakotas' counties, the percent change in average shares of corn (-3.2%) and soybeans (-3.6%), whereas spring wheat shares will decline by 21.2% by 2-31-'60 relative to 1996-2013. Alfalfa and grass shares are projected to remain about the same. A significant decline in spring wheat shares can be explained by lowered weather-driven profits of wheat and alfalfa, due to large yield shocks for these crops, which have positive, significant marginal effects on spring wheat shares. On the other hand, in the western Dakotas' counties, percent change in average shares of corn, spring wheat and grass are projected to change modestly, whereas alfalfa share are projected to increase by 20.4% by 2031-'60 relative to 1996-2013 (see table 13 for details). The marginal effects of weather-driven profits of individual crop-types are largely insignificant in case of these western counties. Overall, a regional consequence of medium-term changes in climate is that the cropland acreage is likely to decline leading to higher allocation towards grass and alfalfa categories in the Dakotas. Our acreage share projections are driven solely by weather, not accounting for any potential technological/policy interventions, or any national or global-level adaptations in production systems in the future.

Discussion

Temperature and moisture are critical crop production inputs. Variations in weather influence agricultural yields, farm profits and farmland values. Many studies have analyzed the implications of climate change on agriculture, with an extensive focus on corn production in the U.S. This paper presents a new integrated framework to assess the regional impacts of climate change on agricultural productivity, and evaluates relevant implications for agricultural land use decisions. For this, we exploit the differentiated productivity impacts of weather fluctuations on a region's viable cropping choices that compete for acreage given limited availability of arable land. We first estimate each crop's yield-weather relationship, and then combine the model-based yield predictions with annual price information to calculate the crop-specific per-acre profits due to the weather-driven component of yields. These per-acre profits are then utilized as explanatory variables in a land use shares model to identify and estimate the role of weather fluctuations on a region's land use decisions.

We demonstrate our framework by analyzing the agroecosystem along the western fringes of the Corn Belt in North and South Dakota, where corn/soy cultivation has displaced native grasses and traditionally grown small grains in the past decade. Land use changes are central to the socio-economic welfare of this region. Given its marginal soils that are susceptible to erosion, the region has limited availability of good quality cropland that is allocated among several viable land uses, and agricultural yields rely upon annual weather conditions. Our analysis reveals a consistent yield-weather relationship for all of the region's major crops: corn, soy, wheat and alfalfa. Alfalfa is particularly interesting as it is primarily used for forage, and so are the region's grasslands.

We estimate yield-weather elasticities to compare the crop-specific weather impacts on yields. In our attempt to quantify crop competitiveness due to historical weather, we find soybeans to be the most responsive to benevolent heat and least responsive to harmful heat. Given past weather outcomes, this reveals favorable conditions towards soybeans yields relative to spring wheat and alfalfa. Such differentiated impacts are correlated with the region's land use dynamics, where in recent years less land is allocated to spring wheat and alfalfa and more towards soybean production. Our land use shares model formally analyzes the role of weather-driven crop returns towards the region's within-cropland dynamics and grass acreage. We find that weather-driven productivity impacts play a significant role in determining land use decisions across the region's croplands and grasslands. However, identifying crop-specific impacts is challenging due to high multicollinearity among the per-acre profits because there is substantial overlap in the crops' growing seasons and their beneficial and harmful temperature levels.

We apply our framework to evaluate the climate change implications for regional agricultural productivity and land use allocations during the 2031-'60 period, relative to 1981-2010. We find yield losses across crop types, with least losses for soybean and highest losses for spring wheat and alfalfa. The climate change impacts on crop yields will reduce the per-acre profitability of each crop, which in turn will lead to lower acres allocated to crops and higher allocation to grass on the east of the Missouri River. Alfalfa acreage, which is a grass substitute, is expected to be higher on the west of the Missouri River by 2060. These results indicate that weather projections due to the A1B scenario of IPCC support higher grass acres in the Dakotas. Notice, however, that the scope of our study's implications is restricted to this region. A projected decline in yields and acreages do not account for national or global level adaptations of crop growing regions, nor do we account for any future technological innovations that may mitigate the impacts of climate change. Furthermore, our findings do not account for corn rotations. As such our finding that corn acres will increase and soybeans will vanish on the east of the Missouri River is unrealistic as corn-soy rotations would mean that soybeans will still be cultivated as we project higher corn acreage in future.

Our findings have implications for crop-based and livestock-based agricultural systems. Addressing land use switches that involve regional grasses may garner interests among conservation enthusiasts and those interested in related ecosystem services from the Great Plains, as well among those interested in how climate change affects food production. Our framework can be further extended to analyze the climate change implications towards a region's total agricultural output and future nutrient supply.

TABLES

Table 3. List of explanatory variables for estimating the yield-weather model

Variable	Definition
$GD_{i,t}$	Growing degree days, a cumulative measure of the incidence of benevolent degrees in county *i* during year *t*'s growing season#.
$SD_{i,t}$	Stress degree days, a cumulative measure of the incidence of harmful degrees in county *i* during year *t*'s growing season#.
$SD_{i,t}^{1}$	Stress degree days that occur as a single-day event in county *i* during year *t*'s growing season#.
$SD_{i,t}^{23}$	Stress degree days that occur as two-to-three-consecutive-day event in county *i* during year *t*'s growing season#.
$SD_{i,t}^{4+}$	Stress degree days that occur as four-or-more-consecutive-day event in county *i* during year *t*'s growing season#.
$DRYZ_{i,t}$	Captures the total intensity of severe-to-extreme drought in county *i* during year *t*'s growing season#.
WETZ	Captures the total intensity of severe-to-extreme wetness in county *i* during year *t*'s growing season#.
Q_i^{dry}	% soils in county *i* with land capability subclass 'shallow' or 'dry' under the capability classes II, III, or IV.
Q_i^{wet}	% soils in county *i* with land capability subclass 'poor drainage' or 'wet' under the capability classes II, III, or IV.

Crop-specific growing seasons are presented in table 3.

Table 2. Palmer Z's characterization of wetness and droughts

Category	Palmer Z
Extreme Wetness	≥ 3.50
Severe Wetness	[2.50, 3.49]
Mild to Moderate Wetness	[1.00, 2.49]
Near Normal	[-1.24, 0.99]
Mild to Moderate Drought	[-1.99, -1.25]
Severe Drought	[-2.74, -2.00]
Extreme Drought	≤ -2.75

Table 3. Growing seasons and temperature thresholds for corn, soybean, spring wheat and alfalfa

Commodity	Growing Season	Temperature Thresholds
CORN	May-August	$GD \in [7^o C, 26^o C]; SD \geq 30^o C$
SOYBEANS	May-August	$GD \in [6^o C, 26^o C]; SD \geq 32^o C$
SPRING WHEAT	April-July	$GD \in [6^o C, 20^o C]; SD \geq 27^o C$
ALFALFA	April-July	$GD \in [6^o C, 22^o C]; SD \geq 27^o C$

Table 4. Decadal summaries of monthly weather variables.

Variable	1950-'60	1961-'70	1971-'80	1981-'90	1991-'00	2001-'10
CORN						
GD	756.95	955.39	1004.25	1010.28	999.30	940.07
SD	22.80	32.07	38.73	36.91	19.87	27.93
DRYZ	0.60	0.35	1.02	1.09	0.18	0.65
WETZ	0.84	1.51	0.79	0.77	2.46	1.61
SOYBEANS						
GD	1094.79	1178.12	1193.75	1112.84	1100.46	1004.54
SD	16.05	15.32	18.26	15.46	6.90	8.45
DRYZ	0.44	0.29	1.04	1.12	0.12	0.45
WETZ	0.66	1.50	0.76	0.74	2.14	1.87
SPRING WHEAT						
GD	588.16	727.66	767.87	778.83	748.36	715.90
SD	32.84	43.54	53.91	52.63	29.21	39.98
DRYZ	0.64	0.24	1.06	1.30	0.16	0.68
WETZ	0.63	1.55	0.87	1.07	2.44	1.40
ALFALFA						
GD	629.36	773.23	784.41	762.82	783.07	773.17
SD	33.77	43.54	44.85	35.22	29.06	42.91
DRYZ	0.68	0.241	0.97	1.61	0.13	0.66
WETZ	0.58	1.55	1.02	0.78	2.02	1.51

Table 5. The (parsimonious) yields regression model. Dependent Variables: Yields (bu./ac.)

	CORN	SOYBEANS	SPRING WHEAT	ALFALFA
Variable	**Estimate**	**Estimate**	**Estimate**	**Estimate**
Intercept	24.145***	23.848***	24.696***	25.872***
t	0.833***	0.209***	0.654***	-0.064
t65	1.081***	0.385***	-0.230***	1.463***
t80	-0.858***	-0.230***	-0.292***	-1.322***
t95	1.370***	0.133***	0.654***	0.565***
GD	0.003***	0.002***	0.002***	0.004***
$t \times GD$	0.0002***	0.000001	0.00002	0.0002***
SD	-0.147***	-0.065***	-0.055***	-0.106***
$t \times SD$	-0.005***	-0.001***	0.0004*	0.00003
DRYZ	-3.638***	-1.351***	-2.015***	-5.384***
$t \times DRYZ$	-0.120***	-0.006	-0.031***	-0.091***
$DRYZ \times SD$	0.026***	0.010***	0.004***	0.017***
WETZ	-0.077	0.012	-0.292***	2.112***
$t \times WETZ$	-0.034***	-0.009***	-0.015***	-0.018***
$WETZ \times SD$	0.024***	0.028***	-0.001	0.013***
$Q_i^{dry} \times SD$	-0.0002	0.002*	0.000	0.0001
$Q_i^{dry} \times DRYZ$	-0.0594***	0.003	-0.010	-0.094***
$Q_i^{wet} \times WETZ$	-0.0100	-0.006	-0.034***	-0.021
R^2	0.7974	0.7805	0.7242	0.7374
N	6,935	2,911	7,067	6,123

****p<0.01, **p<0.05, *p>0.1*

Table 6. Marginal impacts of isolated and consecutive incidence of the SDs (heat stress). Full regression in the SM, see table S7.

	CORN	SOYBEAN	SPRING	ALFALFA
Variable	**Estimate**	**Estimate**	**Estimate**	**Estimate**
SD^{1}	-0.071	0.194***	0.053	-0.339***
SD^{23}	-0.210	-0.176**	0.068	-0.331**
SD^{4+}	-1.964***	-0.507***	-1.469***	-2.729***

****p<0.01, **p<0.05, *p>0.1*

Table 7. Yields-weather elasticities (Crop Competitiveness)

Variable	CORN (59 bu./ac.)	SOYBEANS (22 bu./ac.)	SPRING WHEAT (27 bu./ac.)	ALFALFA (55 bu/ac)
GD	0.043	0.119	0.055	0.055
SD	-0.076	-0.039	-0.089	-0.077
DRYZ	-0.042	-0.037	-0.053	-0.063
WETZ	0.002	0.001	-0.015	0.051

Table 8. IV Regressions for Government Payments Variables

Regressors	Crop Insurance Subsidy			Disaster Payments	Farm Subsidies
	Corn	Soybeans	Wheat		
Intercept	5.89***	-19.30***	11.68***	2.15	14.997***
Trends				0.62***	
Corn Price	0.76***				
Soy Price		0.32***			
Wheat Price			0.35***		
Average Price				-1.09***	-0.17***
GD	-0.001*	-0.001	-0.001**	-0.005**	
SD	0.01***	0.05	0.001	0.14***	
DRYZ	0.58***	0.73	0.44***	2.49***	
WETZ	0.62***	1.30***	0.15***	1.41***	
Fixed Effects	Yes	-0.001	-0.001	Yes	Yes
R^2	0.73	0.82	0.89	0.14	0.86
N	2,111	2,111	2,023	2,088	2,044

****p<0.01, **p<0.05, *p>0.1*

Table 9. Marginal effects of the change in exogenous variables on land use shares for Dakotas' counties east of the Missouri River where soybean yields are reported, see equation (11). Standard errors (in parentheses) are calculated using the delta method.

	CORN	SOY	SPRING WHEAT	ALFALFA	GRASS
Coefficient	**Estimate**	**Estimate**	**Estimate**	**Estimate**	**Estimate**
π^{c}	0.0004[a]	0.0004[b]	0.0006[a]	-0.0002[a]	-0.001[a]
	(0.00008)	(0.0002)	(0.00009)	(0.00003)	(0.0002)
$\pi^{c} \mid W,Q$	-9.63E-10[a]	3.71E-09[a]	-3.85E-10[a]	-1.93E-10[a]	-1.88E-09[a]
	(2.42E-10)	(9.32E-10)	(9.68E-11)	(4.84E-11)	(4.72E-10)
π^{s}	0.001[a]	-0.0004	-0.002[a]	0.0002[a]	0.001[b]
	(0.00014)	(0.0002)	(0.0004)	(0.00004)	(0.0003)
$\pi^{s} \mid W,Q$	2.08E-04[a]	2.4E-04[a]	-0.001[a]	0.00004[a]	0.0004[a]
	(7.48E-05)	(8.61E-05)	(0.0003)	(0.000015)	(0.0002)
π^{w}	-0.001[a]	0.00005	0.003[a]	-0.0002[a]	-0.001[a]
	(0.0001)	(0.0002)	(0.0002)	(0.00003)	(0.0002)
$\pi^{w} \mid W,Q$	-5.02E-04[a]	-5.77E-04[a]	0.002[a]	-0.0001[a]	-0.001[a]
	(4.07E-05)	(4.68E-05)	(0.0002)	(8.16E-06)	(0.0001)
π^{a}	0.002[a]	0.003[a]	0.001[a]	-0.0001	-0.005[a]
	(0.0002)	(0.0004)	(0.0003)	(0.0001)	(0.0005)
$\pi^{a} \mid W,Q$	0.002[a]	0.002[a]	0.001[a]	-0.0002[b]	-0.004[a]
	(0.0002)	(0.0004)	(0.0003)	(0.00008)	(0.0005)
π^{cow}	0.001[a]	0.004[a]	0.002[a]	-0.001[a]	-0.006[a]
	(0.0003)	(0.0005)	(0.0003)	(0.0001)	(0.0006)
π^{fallow}	-0.001[a]	-0.001	-0.0005	0.001[a]	0.002[b]
	(0.0005)	(0.0009)	(0.0005)	(0.0002)	(0.0011)
π^{CRP}	-0.001[b]	-0.0004	-0.002[a]	0.0003[b]	0.002
	(0.0004)	(0.0008)	(0.0005)	(0.0001)	(0.0010)
			Crop Insurance Subsidy		
$G^{c}_{ins.subsidy}$	0.085[a]	-0.013	-0.024[a]	-0.001	-0.041[a]
	(0.0035)	(0.0066)	(0.0036)	(0.0011)	(0.0076)
$G^{s}_{ins.subsidy}$	-0.028[a]	0.089[a]	0.006	0.002	-0.059[a]
	(0.0047)	(0.0088)	(0.0050)	(0.0015)	(0.0103)
$G^{w}_{ins.subsidy}$	-0.035[a]	-0.044[a]	0.063[a]	-0.007[a]	0.020[a]
	(0.0024)	(0.0045)	(0.0025)	(0.0008)	(0.0052)
			Other Government Payments		
$G_{disaster\text{-}payments}$	-0.007[a]	0.001	0.004[a]	-0.002[a]	0.004
	(0.0011)	(0.0021)	(0.0012)	(0.004)	(0.0025)
$G_{oth.\,farm\ subsidy}$	-0.022[a]	-0.017[a]	-0.022[a]	0.001	0.053[a]
	(0.0031)	(0.0059)	(0.0033)	(0.0004)	(0.0068)
$Q_{\%LCC\leq 2}$	0.172[a]	0.257[a]	0.030	-0.051[a]	-0.354[a]
	(0.0214)	(0.0399)	(0.0220)	(0.0069)	(0.0464)
R^2	0.5947	0.8282	0.9910	0.4849	n/a
N	651	651	651	651	651

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

Notes: These marginal effects were calculated using the expression in equation (7), see regression estimates in the supplementary material.

Table 10. Elasticity of land use shares with regards to own- and cross-profits, i.e. $\mathrm{E}(s^u_{i,t}, \pi^v_{i,t|W,Q})$. Standard errors (in parentheses) are calculated using the delta method.

Variable	Corn Shares	Soy Shares	Spring Wheat Shares	Alfalfa Shares	Grass Shares
π^c	0.31[a]	0.31 [b]	0.46[a]	-0.15[a]	-0.77[a]
	(0.06)	(0.15)	(0.07)	(0.02)	(0.15)
$\pi^c \mid W,Q$	-7.4E-7[a]	2.9E-6[a]	-3.0E-7[a]	-1.5E-7[a]	-1.4E-6
	(1.9E-7)	(7.2E-7)	(7.4E-8)	(3.7E-8)	(3.6E-7)
π^s	0.77[a]	-0.31[b]	-1.54[a]	0.15[a]	0.77[a]
	(0.11)	(0.15)	(0.31)	(0.03)	(0.23)
$\pi^s \mid W,Q$	0.16[a]	0.18[a]	-0.77[a]	0.03[a]	0.31[b]
	(0.06)	(0.07)	(0.23)	(0.01)	(0.15)
π^w	-1.43[a]	0.07	4.28[a]	-0.29[a]	-1.43[a]
	(0.14)	(0.29)	(0.29)	(0.04)	(0.14)
$\pi^w \mid W,Q$	-0.72[a]	-0.82[a]	2.85[a]	-0.14[a]	-1.43[a]
	0.06	(0.07)	(0.29)	(0.01)	(0.14)
π^a	3.70[a]	5.55[a]	1.85[a]	-0.19	-9.25[a]
	(0.37)	(0.74)	(0.56)	(0.19)	(0.93)
$\pi^a \mid W,Q$	3.70[a]	3.70[a]	1.85[a]	-0.37[a]	-7.40
	(0.37)	(0.74)	(0.56)	(0.15)	(0.93)

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

Table 11. Marginal effects of the change in exogenous variables on land use shares for Dakotas' counties west of the Missouri River where soybean yields are not reported, see equation (11). Standard errors (in parentheses) are calculated using the delta method.

	CORN	SPRING WHEAT	ALFALFA	GRASS
Variable	**Estimate**	**Estimate**	**Estimate**	**Estimate**
π^{c}	0.00006	-0.0008[a]	-0.0001[a]	0.0008[a]
	0.00005	(0.0003)	(0.00002)	(0.0002)
$\pi^{c}\mid W,Q$	0.00004	-0.0003	0.00001	0.0002
	0.00005	(0.0003)	(0.00001)	(0.0002)
π^{w}	-0.0002[a]	0.0011[a]	0.0001	-0.0009[a]
	(0.00005)	(0.0003)	(0.00008)	(0.0003)
$\pi^{w}\mid W,Q$	-0.0001[b]	0.0004	0.00001	-0.0003
	(0.00006)	(0.0003)	(0.00006)	(0.0003)
π^{a}	0.0002[a]	0.0013[a]	0.0001	-0.0015[a]
	(0.00007)	(0.0004)	(0.00008)	(0.0004)
$\pi^{a}\mid W,Q$	0.00005	0.0012[a]	-5.31E-06	-0.0011[a]
	(0.00007)	(0.0004)	(0.0001)	(0.0004)
π^{cow}	0.0005[a]	0.0018[b]	0.0002[b]	-0.0022[a]
	(6.3E-05)	(0.00009)	(6.2E-05)	(0.0003)
π^{fallow}	0.0004[a]	0.0011	0.0007[a]	-0.0019
	(0.0001)	(0.0006)	(0.0002)	(0.0006)
π^{CRP}	-0.0006[a]	-0.0014[a]	-0.0004[a]	0.0021[a]
	(0.0001)	(0.0005)	(0.00015)	(0.0006)
$G^{c}_{ins.subsidy}$	0.0115[a]	0.0076[a]	0.0051[a]	-0.0216[a]
	(0.0004)	(0.0021)	(0.0006)	(0.0022)
$G^{w}_{ins.subsidy}$	0.0002	0.0013	-0.0002	-0.0012[a]
	(0.00014)	(0.0008)	(0.0002)	(0.0008)
$G_{disaster\text{-}payments}$	-0.0017[a]	0.0051[a]	0.0006	-0.0036[a]
	(0.0002)	(0.0011)	(0.0003)	(0.0012)
$G_{oth.\ farm\ subsidy}$	-0.0088[a]	-0.0151[a]	-0.0066[a]	0.0273[a]
	(0.0005)	(0.0029)	(0.0008)	(0.0029)
$Q_{\%LCC\leq 2}$	0.0449[a]	0.4530[a]	-0.0253[a]	-0.4225[a]
	(0.0036)	(0.0199)	(0.006)	(0.0206)
R^2	0.9711	0.8978	0.9572	n/a
N	645	645	645	

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

Notes: These marginal effects were calculated using the expression in equation (7), see regression estimates in the supplementary material.

Table 12. Elasticity of land use shares with regards to own- and cross-profits, i.e., $\mathrm{E}(s^u_{i,t}, \pi^v_{i,t|W,Q})$, for Dakotas' counties on west of the Missouri River. Standard errors (in parentheses) are calculated using the delta method.

Variable	Corn Shares	Spring Wheat Shares	Alfalfa Shares	Grass Shares
π^c	0.46	-6.16[a]	-0.77[a]	6.16[a]
	(0.39)	(2.31)	(0.15)	(1.54)
$\pi^c \mid W,Q$	0.0002[a]	-2.31	-0.08	1.54
	(0.00002)	(2.31)	(0.08)	(1.54)
π^w	-0.25[a]	1.39[a]	0.13[a]	-1.14[a]
	(0.06)	(0.38)	(0.10)	(0.38)
$\pi^w \mid W,Q$	-0.13	0.51	0.01	-0.38
	(0.08)	(0.38)	(0.08)	(0.38)
π^a	0.37[a]	2.41[a]	0.19	-2.78[a]
	(0.13)	(0.74)	(0.15)	(0.74)
$\pi^a \mid W,Q$	0.09[a]	2.22[a]	-0.01	-2.04
	(0.13)	(0.74)	(0.19)	(0.74)

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

Table 13. Projection of the evolution of the Dakotas' production systems by 2031-'60 relative to the 1996-2013 levels under the A1B emissions scenario of the IPCC.

Commodity	**% Change in Acreage Shares (Eastern Counties)**	**% Change in Acreage Shares (Western Counties)**
CORN	-3.2	1.0
SOYBEANS	-3.6	n/a
SPRING WHEAT	-21.2	1.4
ALFALFA	-0.4	20.4
GRASS	0.8	-1.4

FIGURES

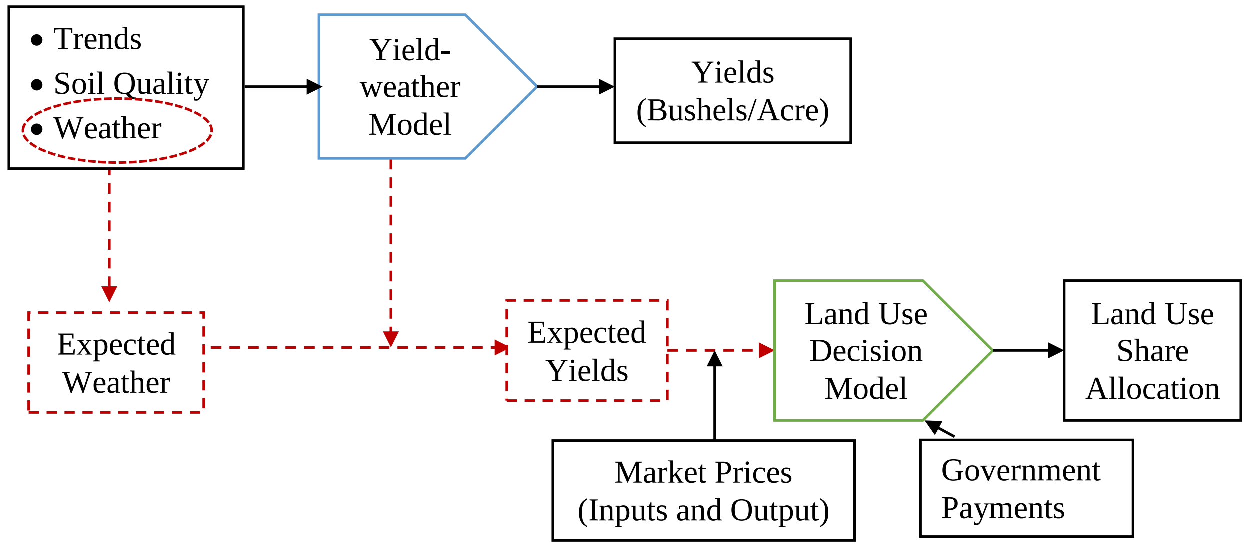


Figure 1. Conceptual framework to assess the regional impact of weather outcomes on land use.

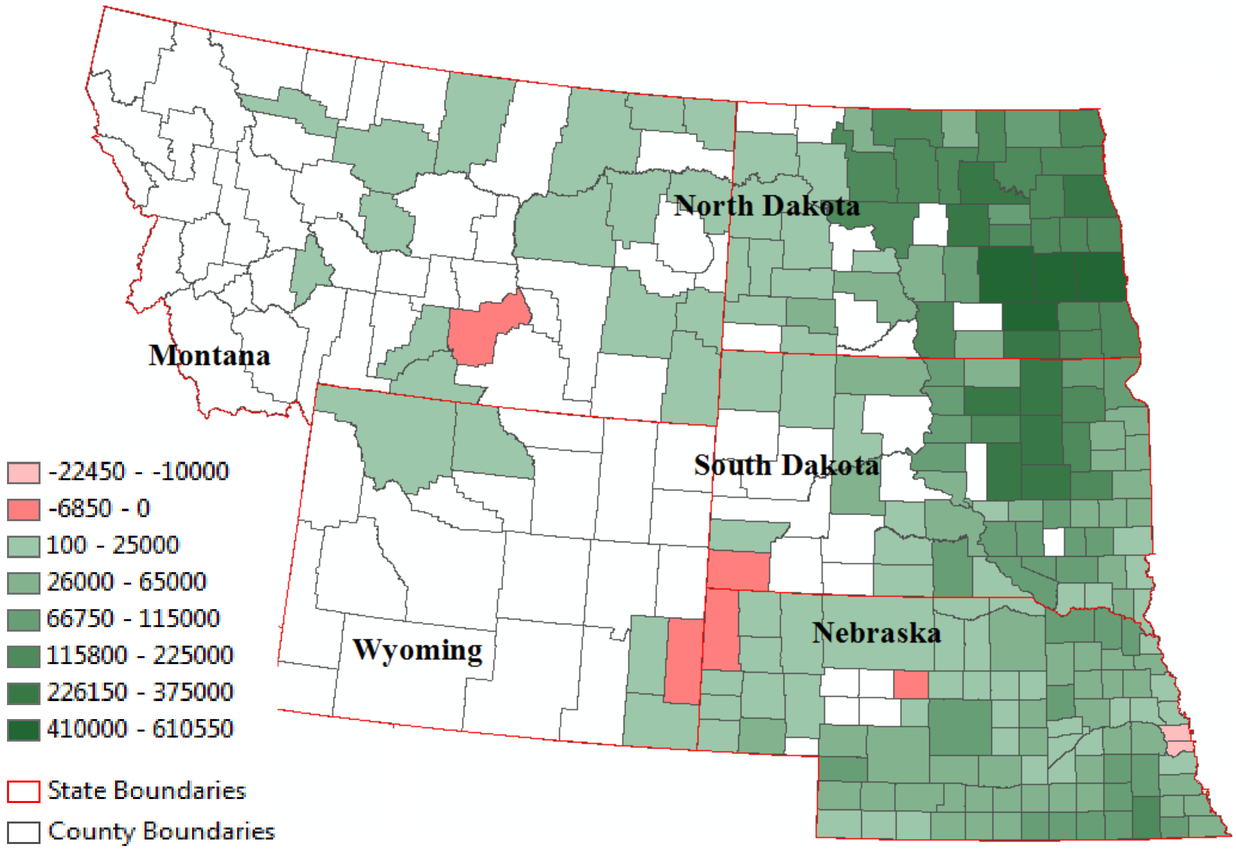


Figure 2. Change in corn and soybeans acreage in the U.S. Northern Great Plains states between 1994-95 and 2014-15. No color signifies missing values in either years.

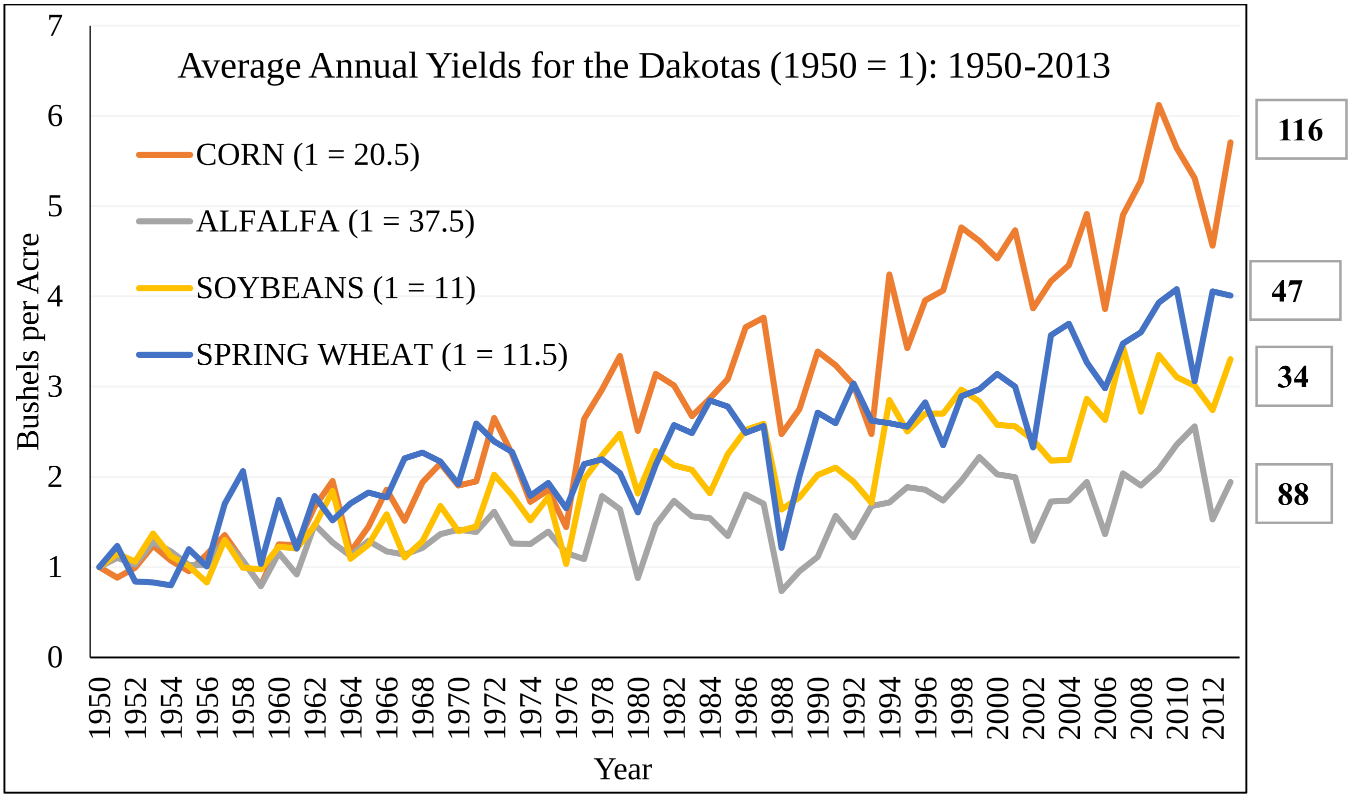


Figure 3. Historical Yields for the Dakotas' major crops, i.e. corn, alfalfa, soy and spring wheat.

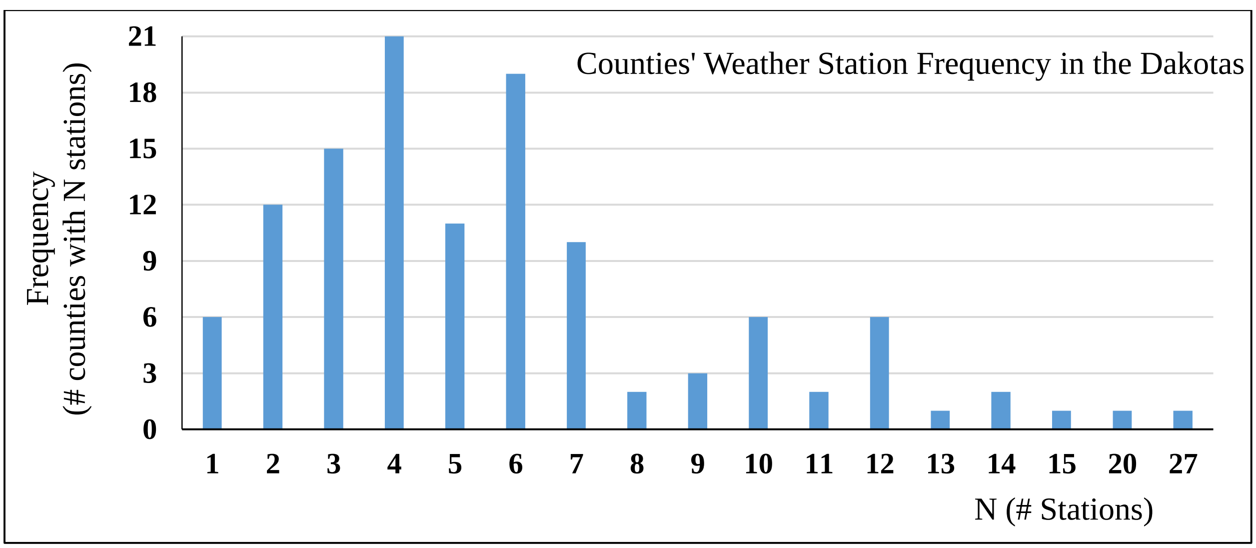


Figure 4. Weather Station Frequency across 119 counties in North and South Dakota.

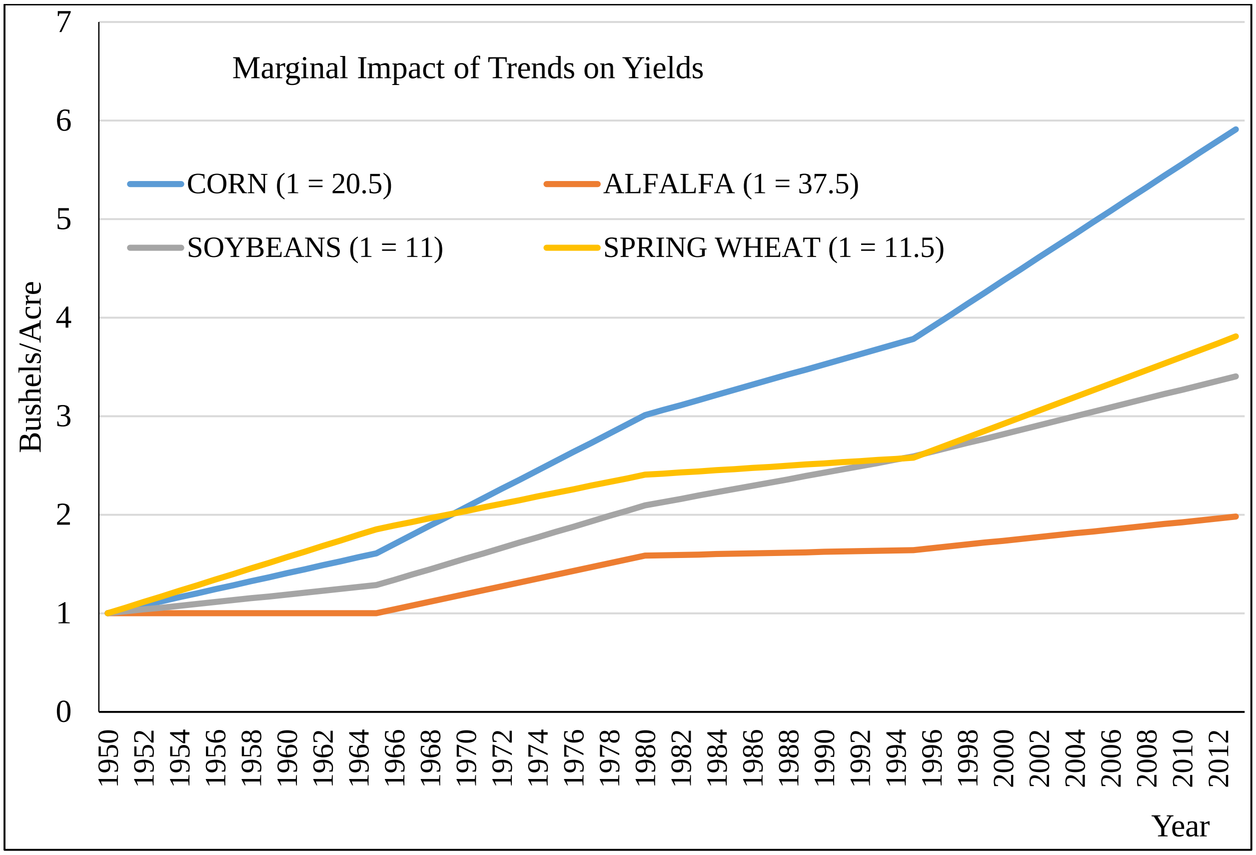
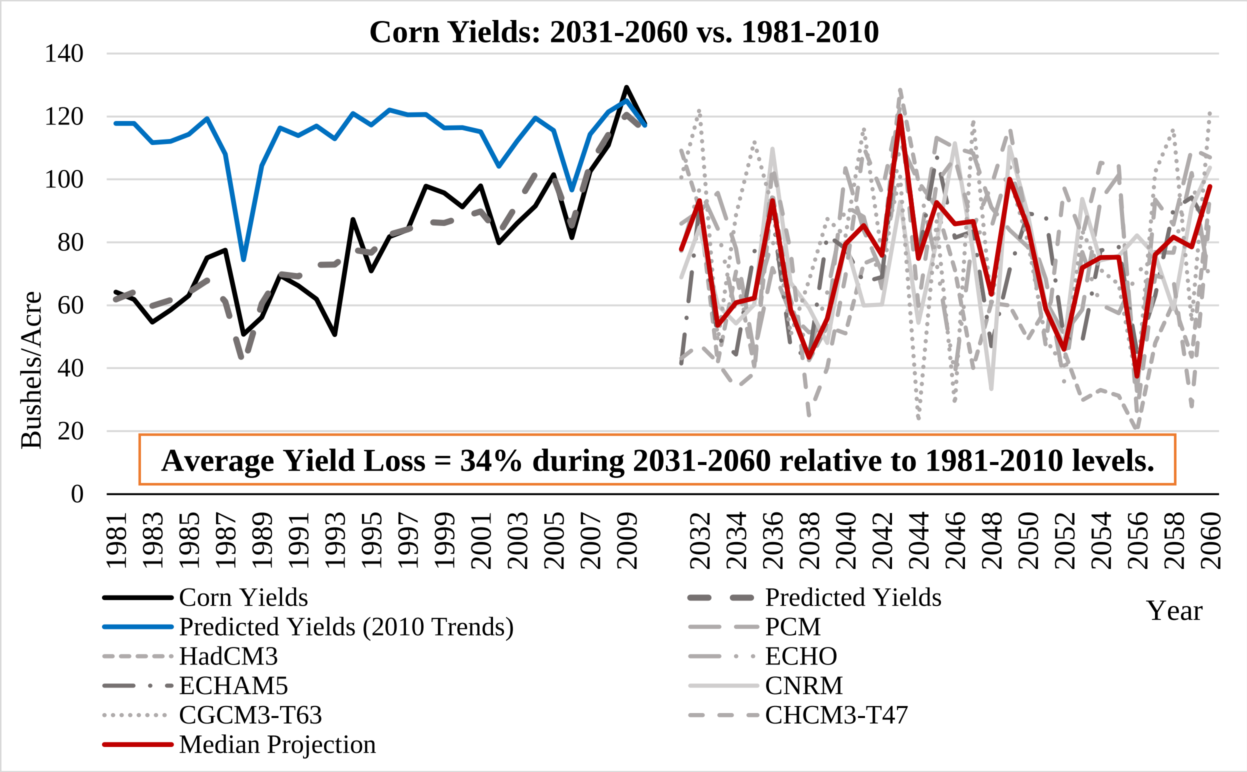
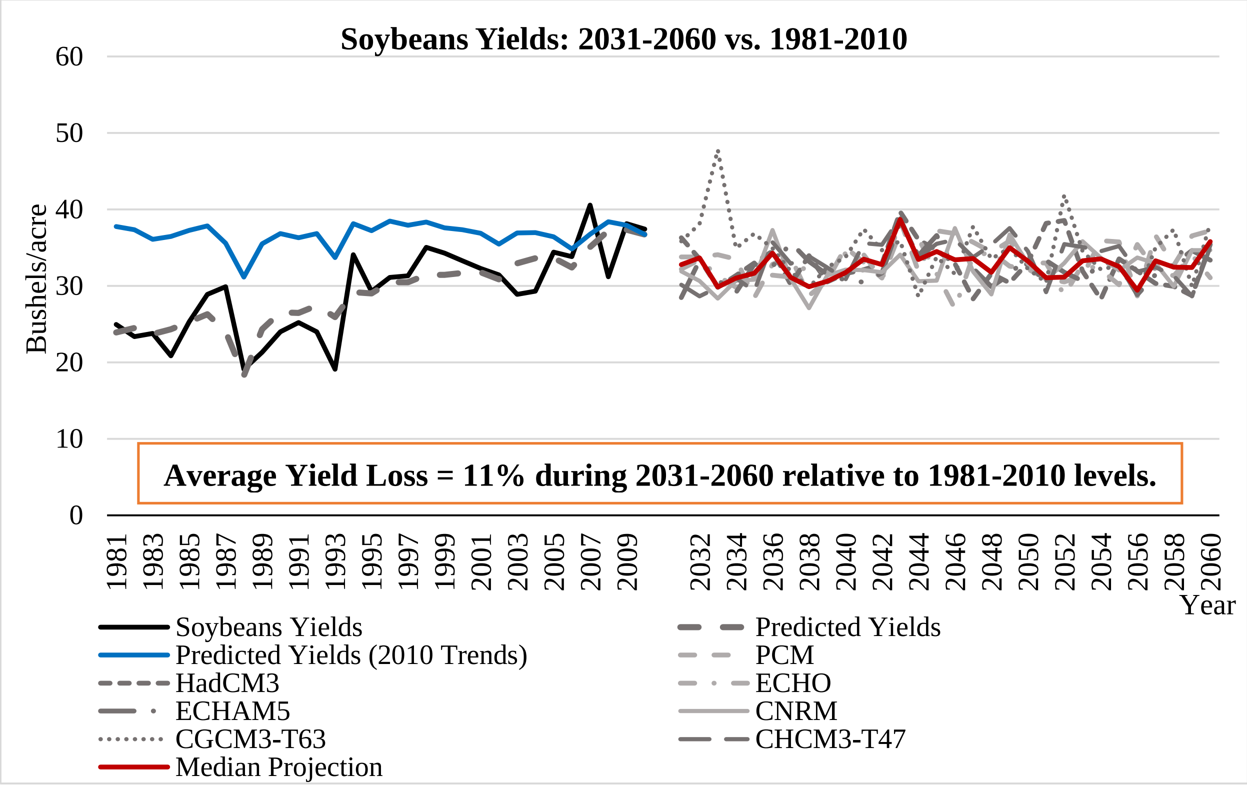
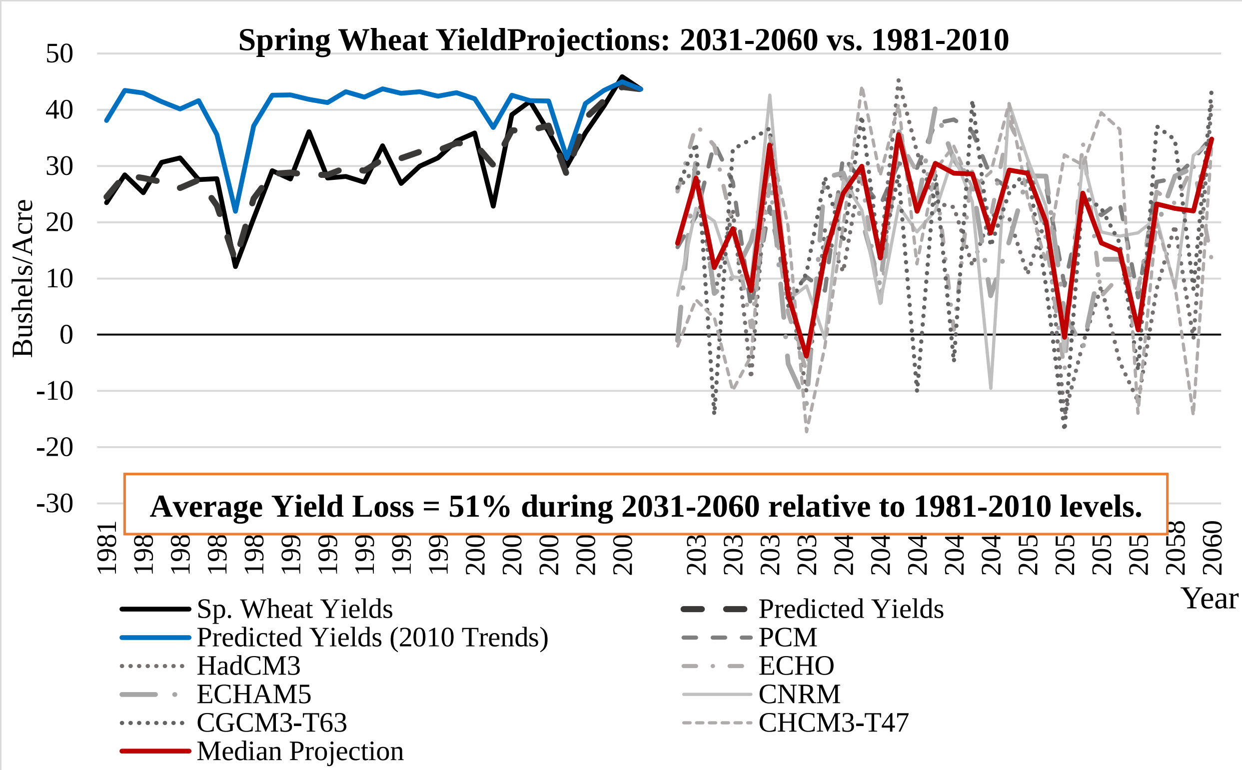
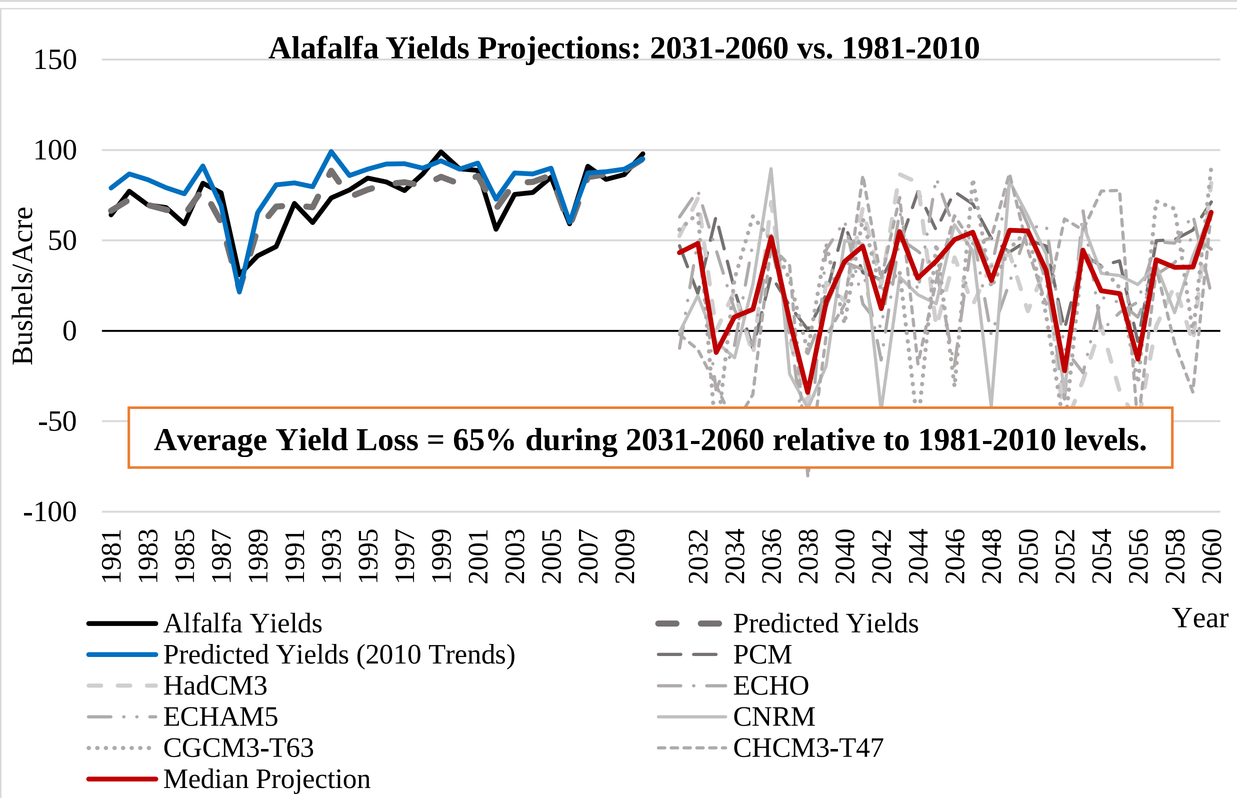


Figure 5. Marginal Trend Impacts on Crop Yields. The 1950 values are standardized to equal 1.


Corn Yields: 2031-2060 vs. 1981-2010
Bushels/Acre
Average Yield Loss = 34% during 2031-2060 relative to 1981-2010 levels.
Year
Corn Yields
Predicted Yields (2010 Trends)
HadCM3
ECHAM5
CGCM3-T63
Median Projection
Predicted Yields
PCM
ECHO
CNRM
CHCM3-T47


Soybeans Yields: 2031-2060 vs. 1981-2010
Bushels/acre
Average Yield Loss = 11% during 2031-2060 relative to 1981-2010 levels.
Year
Soybeans Yields
Predicted Yields (2010 Trends)
HadCM3
ECHAM5
CGCM3-T63
Median Projection
Predicted Yields
PCM
ECHO
CNRM
CHCM3-T47





Figures 6-9. Predicted yields for individual crops during 2031-'60 relative to the historical yields during 1981-2010.

REFERENCES

Burke, M., Miguel, E., Satyanath, S., Dykema, J., Lobell, D. 2015. "Incorporating climate uncertainty into estimates of climate change impacts," *Review of Economics and Statistics*, 97(2):461-71.

Butler, E., Huybers, P. 2012. "Adaptation of U.S. maize to temperature variations," *Nature Climate Change*, 3:68-72.

Collins, M., Knutti, R., Arblaster, J., Dufresne, J.L., Fichefet, T., Friedlingstein, P., Gao, X., Gutowski, W.J., Johns, T., Krinner, G., Shongwe, M., Tebaldi, C., Weaver, A.J., Wehner, M. 2013. "Long-term Climate Change: Projections, Commitments and Irreversibility," In Stocker, T.F., Qin, D., Plattner, G.K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M. (eds.), Ch. 12, pp. 1029-1136, *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. Available at http://www.ipcc.ch/pdf/assessment-report/ar5/wg1/WG1AR5_Chapter12_FINAL.pdf

Claassen R., Carriazo, F., Cooper, J.C., Hellerstein, D., Ueda, K., 2011b. "Grassland to Cropland Conversion in the Northern Plains: The Role of Crop Insurance, Commodity, and Disaster Programs," *Economic Research Report* #ERR-120, USDA ERS, Washington, DC.

Deschenes, O., Greenstone, M. 2007. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather," *American Economic Review*, 97(1): 354-385.

Environmental Working Group, Farm Subsidy Database. Available at: www.ewg.org/farm.

Falk, B., Lee, B. 1998. "Fads versus fundamentals in farmland prices," *American Journal of Agricultural Economics*, 80(4): 696-707.

Griliches, Z. 1960. "Hybrid Corn and the Economics of Innovation," *Science*, 132(3422):275-280.

Intergovernmental Panel on Climate Change. 2012 "IPCC Special Report Emission Scenarios: Summary for Policymakers", A Special Report of IPCC Working Group III. Available at https://www.ipcc.ch/pdf/special-reports/spm/sres-en.pdf.

Johnston CA. 2014. "Agricultural expansion: land use shell game in the U.S. Northern Plains," *Landscape Ecology* 29(1):81-95.

Karl, T.R. 1986. "The Sensitivity of the Palmer Drought Sensitivity Index and Plamer's Z-Index to their Calibration Coefficients Including Potential Evapotranspiration," *Journal of Applied Meteorology and Climatology*, 25:77-86.

http://scenarios.globalchange.gov/sites/default/files/NOAA_NESDIS_Tech_Report_142-4-Climate_of_the_U.S.%20Great_Plains_0.pdf)

Massetti, E., Mendelson, R. 2016. "How do Heat Waves, Cold Waves, Droughts, Hail and Tornadoes affect U.S. Agriculture," paper presented at the *ASSA Meetings*, January 4-6, 2016, San Francisco C.A.

Mendelsohn, R., Nordhaus, W.D., Shaw, D. 1994. "The Impact of Global Warming on Agriculture: A Ricardian Approach," *American Economic Review*, 84(4): 753-771.

Miao, R., Hennessy, D.A., Feng, H. 2014. "Sodbusting, crop insurance, and sunk costs," *Land Economics* 90(4): 601-622.

Miller, D.J., Plantinga, A.J. 1999. "Modelling Land Use Decisions with Aggregate Data," *American Journal of Agricultural Economics*, 81(1):180-194.

National Resource Inventory 2010. U.S. Department of Agriculture – National Resource Conservation Service.

Quicktats 2.0. National Agricultural Statistical Service, USDA. http://quickstats.nass.usda.gov/

Shafer, M., Ojima, D., Antle, J.M., Kluck, D., McPherson, R.A., Petersen, S., Scanlon, B., Sherman, K. 2014. "Climate Change Impacts in the United States: The Third National Climate Assessment," Melillo, J.M., Richmond, T.C., Yohe, G.W. (eds.) Ch.19: Great Plains pp. 441-461, *U.S. Global Change Research Program*. doi:10.7930/J0D798BC.

Schlenker W., Hanemann W.M., Fisher AC. 2005. "Will U.S. Agriculture Really Benefit from the Global Warming? Accounting for Irrigation in the Hedonic Approach," *American Economic Review* 95(1): 395-406.

Schlenker W., Hanemann W.M., Fisher AC. 2006. "The impact of global warming on U.S. agriculture: An econometric analysis of optimal growing conditions," *Review of Economics and Statistics*, 88(1):113-125.

Schlenker W., Roberts M.J. 2009. "Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change," *Proc. Nat. Acad. Sci. USA*, 106:15594-15598.

Statistical Methods Branch, National Agricultural Statistical Service, USDA. 2012. "The Yields Forecasting Program of NASS", NASS Staff Report No. SMB 12-01. Available at: http://www.nass.usda.gov/Publications/Methodology_and_Data_Quality/Advanced_Topics/

Tack J., Barkley A., Nalley L.L. 2015. "Effect of warming temperatures on U.S. wheat yields," *Proceedings of the National Academy of Sciences USA*, 112:6931-6936.

Thompson, L.M. 1975. "Weather and technology in production of corn in the U.S. Corn Belt," *Agronomy Journal*, 188(4188):535-541.

Thompson, L.M. 1969. "Weather variability, climate change and grain production," *Science*, 61(3):453-456.

U.S. Department of Agriculture-Economic Research Service. 2011. "Major Land Uses in the United States," available at: http://www.ers.usda.gov/data-products/major-land-uses/.aspx

U.S. Department of Agriculture-Economic Research Service. 2016. "Commodity Costs and Returns," available at: http://www.ers.usda.gov/data-products/commodity-costs-and-returns.aspx.

Wright, CK, Wimberly MC. 2013. "Recent land use change in the Western Corn Belt threatens grasslands and wetlands," *Proc. Nat. Acad. Sci. USA*, 110:4134-4139.

Xu, Z., Hennessy, D.A., Sardana, K., Moschini, G. 2013. "The Realized Yield Effect of Genetically Engineered Crops: U.S. Maize and Soybean," *Crop Science*, 53:735-45.

Yu, T., Babcock, B.A. 2010. "Are U.S. Corn and Soybeans Becoming More Drought Tolerant," *American Journal of Agricultural Economics*, 92(5):1310-1323.

Wu, J., Segerson, K. 1995. "The impact of Policies and Land Characteristics on Potential Groundwater Pollution in Wisconsin," American Journal of Agricultural Economics, 77(4): 1033-1047.

APPENDIX B
[SUPPLEMENTARY MATERIAL]

Crop-specific yields-weather relationship

Data and Explanatory Variables

Land Capability Subclasses: Definitions and the NRI's nomenclature

The land capability classification assigns progressively unsuitable soils into higher classes. Soils of higher land capability categories require more intense management practices to mitigate intrinsic limitations towards agricultural production. Typically, class I soils can be readily subject to cropping; class II, III & IV lands require some additional remedies before they can be cropped; and categories (V-VIII) are usually inappropriate for cropping. The extent and type of remedies required for class II, III & IV lands depends on the type of impediment(s). Land capability classes II-VIII are further sub-categorized by the soil's dominant impediments. These sub-categories are vulnerability to erosion, excess wetness (or poor drainage), root-zoning limitations (dry, shallow soils) and climatic limitations. The NRI follows a hierarchical nomenclature in assigning these sub-categories if multiple impediments are present. 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 limitations 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 towards cropping. The data does 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. We constrain our analysis to land capability classes II-IV as they support about 85-90% of crop acreage in the Dakotas. In our yield models, we include soil-weather interactions. In particular, we use percent land in a county under *[S]*, denoted Q_i^{dry}, and interact it with *SD*, *GD*, *DRYZ* and *WETZ*. These interactions are expected to reveal whether specific soil limitations could mitigate or aggravate heat/moisture impact 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 worsened on soils under *[W]* sub-category.

Robustness (The yield-weather model)

We conduct robustness tests on our corn yield model estimates. For this purpose, we either break that spatially into: north vs. south and east vs. west, or we utilize weighted regressions with average crop-acreage share for each county as weights.

A. East of the 100th Meridian vs. West of the 100th Meridian (see Table S1-S2): 100th meridian cuts the U.S. mainland into two type of agricultural land, i.e. the eastern half is generally rain-fed and the west needs irrigation for growing crops. Now the 100th meridian cuts the Dakotas into halves and thus the western portion of the states is really at the non-irrigated/irrigated margin considering the total east-west expanse of the United States. However, if the western Dakotas are significantly irrigated then the impact of dry seasons and/or *SD*s may be undermined in our regressions. This is why these robustness test are important. We find discrepancies in the weather dependence patterns in eastern Dakotas from the west. While *WETZ* is found to be negative for eastern county corn yields, its impact is positive, significant towards the west. Also, the *SD*, *GD* impact is insignificant for western Dakotas' corn yields. This may be because a different thresholds may be more optimal to define these regressors in this portion of the states.

B. North Dakota vs. South Dakota (see Table S3-S4): South Dakota is warmer than its northern counterpart and may be better for agriculture through richer spatio-temporal yields data driving the results. However, we find our model estimates to be robust, except for soil quality.

C. Weighted Regressions (Table S5): Since the respondent density is affected by crop failures, county-level yield estimates reposted by NASS are also prone to measurement errors. This issue is dealt with using weighted least squares regressions where the weights are various functional variations of county-level crop acreage shares. Weights may be time-invariant in this study. Only trends and trend-weather interactions are problematic, rest are robust. The issue with trends arises due to the loss of monotonicity when multiplied by non-monotonic weights.

D. Spatial Correlation among weather variables (Table S6): Auffhammer et al. (2013) pointed towards pitfalls of using climate data. The one relevant to our study is the potential spatial correlation among weather variables. We utilize Conley's (1999) procedure to control for spatial autocorrelation in the errors. Specifically, we define a cutoff along the x-axis and the y-axis such that each county has at least one neighbor. Among the counties whose coordinates lie within these cutoffs are designated spatially connected. A sandwich variance-covariance matrix is estimated, that is the weighted sum of covariance among spatially-connected neighbors. The weight used is the inverse of the squared Euclidean distances among spatially connected counties. We find that inference will not change upon controlling for spatial autocorrelation in the errors.

SD categorization

To differentiate yield impacts by the intensity of heat stress, we disaggregate the stress degree-days into isolated or single-day events (SD^1), and 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 with an indicator variable that equals 1 on an isolated hot day or 0 otherwise. SD^{23} and SD^{4+} are constructed in the similar fashion. Now, 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 them 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. We describe our normalization factors and the underlying concept that ensures comparable coefficients across disaggregated *SD* categories.

Consider a snapshot of a representative county *i*'s in year *t*. Our modelling approach asserts that the yields in *i* would increase given an additional *GD* and decrease given 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 divide the total quantum of heat accumulated in *SD*s into various categories and want to test whether an additional unit of *SD* in one category is more or less harmful than in the other category.

For a mathematical representation of this hypothesis, we specify a hypothetical and simplified situation where $SD \geq 32^{o}C$ and they accumulate either as isolated single-day events or as consecutive 2-day events during the year *t*'s growing season. If we let I_1 and I_2 be the total frequency of single-day and 2-day *SD* events, then 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, so $m_1 = \left(I_1\right)^{-1} \sum_{d \in I_1} (T_d - 32)$, and $m_2 = \left(2I_2\right)^{-1} \sum_{d \in I_2} (T_d - 32)$. So, $SD^1 = q_1 I(1)$ and $SD^2 = 2q_2 I(2)$. We can re-write our yields-weather model as

$$\begin{aligned} Yields_{i,t} &= \beta_0 + \beta_1 SD^1_{i,t} + \beta_2 SD^2_{i,t} + \text{ other controls..} \\ &= \beta_0 + \beta_1 q_1 I(1) + 2\beta_2 q_2 I(2) + \ .. \end{aligned} \tag{S1}$$

Recall that the equation (S1) is essentially a cross-sectional regression specified for a snapshot of a 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 (q_1 *vs.* q_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, if $q_2 = k_q q_1$ and $I_2 = k_I I_1$ then we can re-write the regression equation (S1) as:

$$\begin{aligned} Yields_{i,t} &= \beta_0 + \beta_1 q_1 I_1 + 2k_q k_I \beta_2 q_1 I_1 + \ .. \\ &= \beta_0 + \beta_1 SD^1_{i,t} + 2k_q k_I \beta_2 SD^1_{i,t} + \ .. \end{aligned}$$

(S2)

Equation (6) is essentially 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 of yields, the coefficients β_1 and $2k_q k_I \beta_2$ are directly comparable. An alternative way to achieve this is to divide SD^2 by a normalization factor

$2k_q k_I$. It is important to realize that the factor $2k_q k_I$ captures disproportionate heat intensity across *SD* categories.

Within the context of this study, we find continuous *SD*s to be much less frequent as compared to the isolated ones, and that they could accumulate higher *or* lower average heat per day (*q*). However, this is purely an empirical issue and fixed normalization factors, of say 2 for SD^2 or 3 for SD^3, may not correctly represent the differences across categories.

Now, we only considered a simplified snapshot of a representative county in a given year. For conceptual illustration. However, in reality the normalization factors, i.e. $2k_q k_I$ above, may vary spatially (across counties) as well as temporally (year-by-year). We designate the overall mean of SD^1s, SD^{23}s and SD^{4+}s during 1950-2013 as a proxy for the normalization factors. We do so to keep the interpretation of the resulting variables simple, 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 S7, S8). Early-season *SD*s are beneficial towards spring wheat and soybean yields, mainly because isolated *SD* events mostly occur in the mid-April to mid-June period. For spring wheat, even late-season *GD*s are found to be damaging when early-season *SD*s are beneficial. This, with relatively low *GD* and *SD* thresholds for spring wheat (table 2), suggests seasonal temperature effects rather than the usual thresholds-based characterization. Further, Tack *et al.*, 2015 found that higher spring-time wetness to mitigate the impact of heat-stress on spring wheat yields based on field-trials. We too find such an impact for county-level alfalfa yields from $WETZ \times SD$ in April-May, although it is positive but insignificant for spring wheat yields. Interestingly, we find that droughty-conditions are relatively more detrimental to yields late in the growing season for all commodities. Further, the late-season humidity (*WETZ*×*SD*) is beneficial to corn and soybean yields but its impact is insignificant early in the growing season.

Weather Realizations, Crop Competitiveness and Land Use Change

Re-estimating the yield-weather model to allow for yield decomposition

We assume $\beta_{tW}=0$ in equation (3) of the main text to allow for profits decomposition into a weather-driven component and a trends-driven component. However, this assumption can bias the estimates of other coefficients in model. We therefore re-estimate the model with the restriction $\beta_{tW}=0$ to calculate weather-driven and trends-driven profit components. We present the new estimation results in table S10.

Weather Outcome Predictions: Econometric Considerations and Results

Consider an AR(4) (panel) time-series process for the *GD*s with $E(GD_{i,t})=\gamma_i+\gamma_t t$:

$$GD_{i,t}=(1-\sum_{k=1}^{4}\gamma_k)\gamma_t t+\sum_{k=1}^{4}\gamma_k GD_{i,t-k}+(1-\sum_{k=1}^{4}\gamma_k)\gamma_i+\nu_{i,t}, \qquad \text{(S3)}$$

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 in order for the above process to be estimable. The counterpart of stationarity of an autoregressive process is its invertibility. So to test stationarity of our panel data series for weather we conduct unit-root tests for the AR process by following a procedure proposed by Breitung and Meyer (1994). The corresponding t-test relies upon transforming equation (S3) such that the test statistic for the null hypothesis of a unit root, i.e. $\sum_{k=1}^{4}\gamma_k=1$, is asymptotically normally distributed, also termed as the "unbiased test-statistic".[36] Specifically, Breitung and Meyer (1994) suggest the following transformation of (S3) using the first value of the process $GD_{i,0}$,

$$GD_{i,t} - GD_{i,0} = \gamma_t(1 - \sum_{k=1}^{4}\gamma_k)t + \sum_{k=1}^{4}\gamma_k(GD_{i,t-k} - GD_{i,0}) + v_{i,t} - (1 - \sum_{k=1}^{4}\gamma_k)(GD_{i,0} - \gamma_i) \qquad \text{(S4)}$$

See that the impact of individual means vanishes under this transformation under the null, $\sum_{k=1}^{4}\gamma_k = 1$, making regular t-test viable. We implement Breitung and Meyer's (1994) test procedure for individual weather series ($GD_{i,t}, SD_{i,t}, DRYZ_{i,t}, WETZ_{i,t}$) in SAS's panel model procedure – "Unbiased t-test". Results are presented in tables S11-S14. We find $GD_{i,t}, SD_{i,t}$, $WETZ_{i,t}$ and $DRYZ_{i,t}$ to be time and cross-section stationary for all the commodities.

Annual Futures contract price versus regional crop prices

We utilized the annual February prices for December/November futures contracts for corn and spring wheat/soybeans to control for landowner expectations of their harvest's future market valuation. However, alfalfa is not traded with such contracts and we utilize regional-level prices for alfalfa instead. Here, compare the regional counterparts of corn, soybeans and spring wheat's future contract prices to ascertain whether regional-level prices are a viable candidate for landowners' expectations of actual market valuations of these commodities. We plot the annual soybean's November futures prices, and corn and spring wheat's December futures prices with

[36] 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 the Dickey-Fuller test of Fuller (1976), although the latter proposed a bias-corrected test-statistic with critical values differing from a normally distributed t-statistic.

the corresponding regional level prices made available by ERS's 'Commodity Costs and Returns 2016 dataset'. See our plots in figure S5. We find that the futures prices for South and North Dakota to be highly correlated with the ERS prices. We thereby conclude that regional-level alfalfa prices are indeed viable to control for landowners' pre-planting expectation of this crop's actual market price after harvest.

Calculating Marginal Effects for the multinomial logit model

We have specified crop u's shares as $s_{i,t}^{u} = \exp[\bar{\beta}^{u} X_{i,t} + \bar{\varepsilon}_{i,t}^{u}] / \left(1 + \sum_{v \in \bar{U}} \exp\left[\bar{\beta}^{v} X_{i,t} + \bar{\varepsilon}_{i,t}^{v}\right]\right)$ where $\bar{\beta}^{u} = \beta^{u} - \beta^{g}$ and $u \in \bar{U} \in \{c, s, w, a\}$ as defined earlier. We calculate the marginal effect of a variable $x_{i,t} \in X_{i,t}$ using the division rule of differentiation below.

$$M(s_{i,t}^{u}, x_{i,t}) = \frac{\partial s_{i,t}^{u}}{\partial x_{i,t}} = \frac{\bar{\beta}^{u} \exp[\bar{\beta}^{u} X_{i,t} + \bar{\varepsilon}_{i,t}^{u}]\left(1 + \sum_{v \in \bar{U}} \exp\left[\bar{\beta}^{v} X_{i,t} + \bar{\varepsilon}_{i,t}^{v}\right]\right)}{\left(1 + \sum_{v \in \bar{U}} \exp\left[\bar{\beta}^{v} X_{i,t} + \bar{\varepsilon}_{i,t}^{v}\right]\right)^{2}} - \frac{\exp[\bar{\beta}^{u} X_{i,t} + \bar{\varepsilon}_{i,t}^{u}] \sum_{v \in \bar{U}} \bar{\beta}^{v} \exp\left[\bar{\beta}^{v} X_{i,t} + \bar{\varepsilon}_{i,t}^{v}\right]}{\left(1 + \sum_{v \in \bar{U}} \exp\left[\bar{\beta}^{v} X_{i,t} + \bar{\varepsilon}_{i,t}^{v}\right]\right)^{2}}$$

$$= s_{i,t}^{u}\left[\bar{\beta}_{x}^{u} - \sum_{v \in \bar{U}} \bar{\beta}_{x}^{v} s_{i,t}^{v}\right].$$

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 a physical relationship specified by Karl (1986). That is, monthly Zs depend upon monthly precipitation, evapotranspiration and soil's water holding capacity. 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). Based on this information, we specify the following model for predicting the Z index

$$Z_{k,t} = \beta_0 + \sum_{\gamma=1,2,..,6} \beta_{Z,\gamma} Z_{k,t-\gamma} + \beta_1 \overline{\overline{P}}_{k,t} + \beta_2 \overline{\overline{P}}_{k,t}^{\,2} + \beta_3 \overline{\overline{P}}_{k,t} \overline{\overline{T}}_{k,t} + \sum_M \beta_M T_{k,t} 1_M + \sum_k \lambda_k 1_k, \tag{S5}$$

where k: Climate Division k,

t: date (Year*100+Month),

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

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

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

1_M: Month-dummy,

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

Here, $\sigma(.)$ is the standard deviation operator. Our primary objective in estimating equation (S5) is to maximize regression fit so that our projections for Z are trusted. The data used range from 1895-2014 for the 18 climate divisions in North and South Dakota. Climate divisional dummy variables are expected to control for soil's water holding capacity. Monthly dummy variables, and their interaction with temperature are expected to control for the heat accumulated due to average days-length in a month. We observe high multicollinearity when higher order functions are used for monthly temperature and precipitation. We find that standardized temperature and precipitation modelled as lower order polynomials reduce multicollinearity (motivated from Kim and Dong-Ku, 1999). Specifically, we include quadratic precipitation and precipitation-temperature interaction term to control for the non-linear relationship to some extent. The R-squared achieved in the process is 0.91. Table S19 presents the estimation results. The future projections for Z are computed by multiplying coefficients in equation (S7) to our constructed weather projections

Acquiring climate projections

The climate projections data are acquired from the U.S. Geological Survey's Geo-Data Portal (GDP; Blodgett, 2013).[37] The GDP provides spatially rescaled outputs from Global Climate Models' (GCM) at the level of finer grids, referred to as statistical downscaling. We utilize "Eighth degree Contiguous US Statistical Asynchronous Regional Regression" algorithm to project the grid-level daily climate projections to area-weighted climate projections for the Dakotas' 18 climate divisions.[38,39]

Monthly-average and Annual Average Mean-shifts

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

$$\begin{aligned} &\text{a) } \Delta F^{monthly}_{k,y',y,m} = \frac{\sum_{d \in m} \Delta F_{k,y',y,m,d}}{\sum_{d \in m} 1} \\ &\text{b) } \Delta F^{annual}_{k,y',y} = \frac{\sum_{m,d \in y} \Delta F_{k,y',y,m,d} 1_{(m \in [4,8])}}{\sum_{m,d \in y} 1_{(m \in [4,8])}} \end{aligned} \qquad \text{(S6)}$$

[37] http://cida.usgs.gov/gdp/

[38] One-eighth degree grid is roughly 3 km along the latitude (Y-axis) and 5 km along the longitude (X-axis).

[39] Downloading projections is time-intensive with restrictions on the maximum size of vector polygon files that can be processed. Given the size restriction, we were able to process three climate divisions at a time.

Clearly, in equations (S6 a-b), $\Delta F_{k,y',y,m}^{monthly}$ varies monthly and is constant for all days within a month, and $\Delta F_{k,y',y}^{annual}$ varies annually and is constant for all days in a year. Based on these, the future weather variables for a representative county *i* is given as

$$\begin{aligned} &\text{a) } F_{i,y',m}^{monthly} = F_{i,y,m} + \Delta F_{i,y',y,m}^{monthly} \\ &\text{b) } F_{i,y'}^{annual} = F_{i,y} + \Delta F_{i,y',y}^{annual} \end{aligned} \tag{S7}$$

In equation (S7 a-b), variables $F_{i,y',m}^{monthly}$ and $F_{i,y'}^{annual}$ are the county-level projections that we use to describe climate change relative to past weather during the 1981-2010 period. Recall that we evaluated equations (S6) and (S7) for seven distinct sets of climate projections.

We present comparative plots of historical and projected temperature distribution using two climate model-specific outputs in figure 5.

Climate Change in the Dakotas – 2031-’60 vs. 1981-2010

We compare the historical weather realizations (1981-2010) with our future projections during 2031-’60. We present comparisons monthly weather projections derived from seven climate model outputs in tables S20-S21. Average temperature and total precipitation will increase for all growing season months during this period. The highest increase in average temperature is projected in April (33%) and May (18%), and least increase in July (12%). August precipitation will increase the most (15%). Figure 6 a-b suggests the average monthly *Z* will become more negative in future, primarily driven by higher future temperatures. To gain an understanding of the projected changes in weather variables using in our regression analysis we tabulate the state-wise changes from 1981-2010 to 2031-’60 in our weather regressors, i.e. *GD*, *SD*, *DRYZ*, *WETZ*. Table S22 show a stark increase (decrease) in projected *DRYZ* (*WETZ*) in both states. However, the droughty conditions, as measured by *DRYZ*, will be relatively more intense in South Dakota by 2060. Although *GD* and *SD* will increase, *SD* will almost double by 2060 and *GD* will increase by 15%-18%. Note that the impact of projected weather will depend on individual crop yield responsiveness to weather stressors, as measured by yield-weather elasticities.

TABLES (SUPPLEMNTARY MATERIAL)

Table S1. Variable Summaries for counties that are located east and west of the 100th Meridian.

Variable	East	West
GD	962.15	894
SD	27.70	29.84
DRYZ	0.59	0.75
WETZ	1.30	1.36
%lcc234[S]	10.15	6.77
%lcc234[W]	9.48	1.44

Table S2. Corn yield models for counties that are located east and west of the 100th Meridian.

CORN	EAST	WEST
Variable	**Estimate**	**Estimate**
Intercept	66.30***	28.10***
t	0.81***	0.87***
t65	0.85***	1.04***
t80	-0.15	-1.70
t95	1.24***	1.26***
GD	0.005***	0.00004
t×GD	0.0001**	0.0001
SD	-0.17***	-0.03
t×SD	-0.005***	-0.001*
DRYZ	-4.43***	-2.87***
t×DRYZ	-0.14***	-0.06***
DRYZ×SD	0.03***	0.01***
WETZ	-0.46***	0.62***
t×WETZ	-0.05***	0.02*
WETZ×SD	0.03***	0.02**
%lcc234[S]×SD	-0.002*	-0.001
%lcc234[S]×DRYZ	-0.031	-0.02
%lcc234[W]×WETZ	-0.012	-0.05
R^2	0.8634	0.6958
N	3,899	2,251

***p<0.01, **p<0.05, *p>0.1

Table S3. Variable Summaries for North and South Dakota counties.

Variable	North Dakota	South Dakota
GD	843.8	1005.79
SD	14.09	39.83
DRYZ	0.78	0.58
WETZ	1.46	1.26
%lcc234[S]	7.22	10.10
%lcc234[W]	7.09	5.47

Table S4. Corn yield models for North and South Dakota counties.

CORN	NORTH DAKOTA	SOUTH DAKOTA
Variable	**Estimate**	**Estimate**
Intercept	37.84***	24.18***
t	0.75***	0.77***
t65	1.13***	1.04***
t80	-1.12***	-0.67***
t95	1.49***	1.28***
GD	0.002	0.002**
$t \times GD$	0.0003***	0.0001*
SD	-0.086***	-0.16***
$t \times SD$	-0.002	-0.006***
DRYZ	-3.05***	-5.23***
$t \times DRYZ$	-0.09***	-0.11***
$DRYZ \times SD$	0.02***	0.04***
WETZ	-0.19	-0.04
$t \times WETZ$	-0.01	-0.04***
$WETZ \times SD$	0.05***	0.02***
$\%lcc234[S] \times SD$	-0.003	-0.0003***
$\%lcc234[S] \times DRYZ$	-0.009	0.02
$\%lcc234[W] \times WETZ$	-0.04***	0.03*
R^2	0.7917	0.8106
N	2,907	4,028

****p<0.01, **p<0.05, *p>0.1*

Table S5. Weighted Regressions.

CORN	*WT*	*SQWT*	*SQMWT*	*WTBAR*
Variable	**Estimate**	**Estimate**	**Estimate**	**Estimate**
Intercept	4.26***	7.59***	39.09***	2.20***
t	1.76***	1.25***	1.41***	1.12***
t65	-0.51***	0.10	-0.13	0.50***
t80	1.05***	0.76***	0.33**	0.26***
t95	0.57***	0.71***	0.75***	1.16***
GD	0.01***	0.01***	0.01***	0.002***
$t \times GD$	0.0005***	0.0004***	-0.00001	0.001***
SD	-0.07***	-0.12***	-0.23***	-0.13***
$t \times SD$	-0.03***	-0.02***	-0.003***	-0.03***
DRYZ	-6.85***	-5.39***	-3.90***	-5.07***
$t \times DRYZ$	-0.21***	-0.17***	-0.03***	-0.41***
$DRYZ \times SD$	0.19***	0.08***	0.02***	0.14***
WETZ	-1.97***	-1.17***	0.02	-1.23***
$t \times WETZ$	0.06***	-0.004	-0.01***	-0.05***
$WETZ \times SD$	0.10***	0.05***	0.01***	0.11***
%lcc234[S] $\times$ *SD*	0.02***	0.001	-0.01***	-0.004
%lcc234[S] $\times$ *DRYZ*	0.04	-0.01	0.03	0.11
%lcc234[W] $\times$	0.04	0.01	0.02***	0.04
$\mathbf{R^2}$	0.9710	0.9591	0.9110	0.9707
N	6,935	6,935	6,935	6,935

****p<0.01, **p<0.05, *p>0.1*

Notes: *WT* signifies that the regression weight $s_{i,t}^{corn}$, which is acreage share of corn in county i and year t. Similarly, *SQWT*, *SQMWT* and *WTBAR* signify $\sqrt{s_{i,t}^{corn}}$, $\sqrt{s_{i,t}^{corn} / \mu(s_{i,t}^{corn})}$ *and* $\mu(s_{i,t}^{corn})$ *respectively where* $\mu(s_{i,t}^{corn}) = (IT)^{-1} \sum_i \sum_t s_{i,t}^{corn}$.

Table S6. OLS regression, no intercept. *WHITE S.E* (1st row) vs. *S.E. corrected for spatial dependence* (2nd row).
Variable Transformation for F.E.: Demeaned Y & X variables w.r.t their county-level counterparts.

	CORN	SOYBEANS	SPRING WHEAT	ALFALFA
Variable	**Estimate**	**Estimate**	**Estimate**	**Estimate**
t	0.831 (0.072)*** (0.091)***	0.209 (0.037)*** (0.031)***	0.654 (0.026)*** (0.036)***	-0.064 (0.065) (0.124)
t65	1.081 (0.116)*** (0.159)***	0.385 (0.058)*** (0.064)***	-0.230 (0.041)*** (0.056)***	1.463 (0.113)*** (0.166)***
t80	-0.858 (0.105)*** (0.242)***	-0.230 (0.048)*** (0.070)***	-0.292 (0.038)*** (0.050)***	-1.322 (0.116)*** (0.152)***
t95	1.370 (0.104)*** (0.160)***	0.133 (0.043)*** (0.066)***	0.654 (0.039)*** (0.069)***	0.565 (0.105)*** (0.156)***
GD	0.0026 (0.0009)*** (0.0017)*	0.002 (0.0003)*** (0.0003)***	0.002 (0.0005)*** (0.0009)***	0.004 (0.001)*** (0.002)***
$t \times GD$	0.0002 (0.00003)*** (0.00008)***	-0.000001 (0.00001) (0.00001)	0.00002 (0.00002) (0.00005)	0.0002 (0.00004)*** (0.00014)*
SD	-0.148 (0.012)*** (0.026)***	-0.065 (0.011)*** (0.014)***	-0.055 (0.003)*** (0.006)***	-0.106 (0.009)*** (0.013)***
$t \times SD$	-0.005 (0.0004)*** (0.001)***	-0.0014 (0.0004)*** (0.0005)***	-0.0002 (0.0001)* (0.0003)	0.00003 (0.0003) (0.001)
DRYZ	-3.637 (0.161)*** (0.277)***	-1.351 (0.079)*** (0.098)***	-2.015 (0.058)*** (0.084)***	-5.384 (0.163)*** (0.259)***
$t \times DRYZ$	-0.120 (0.010)*** (0.019)***	-0.006 (0.0054) (0.0051)	-0.031 (0.004)*** (0.005)***	-0.091 (0.009)*** (0.015)***
$DRYZ \times SD$	0.026 (0.003)*** (0.004)***	0.010 (0.003)*** (0.002)***	0.004 (0.001)*** (0.001)***	0.017 (0.002)*** (0.004)***

Table S6 continued

WETZ	-0.078 (0.114) (0.160)	0.012 (0.056) (0.038)	-0.292 (0.041)*** (0.064)***	2.112 (0.106)*** (0.193)***
$t \times WETZ$	-0.034 (0.005)*** (0.007)***	-0.009 (0.002)*** (0.002)***	-0.015 (0.002)*** (0.003)***	-0.018 (0.005)*** (0.008)***
$WETZ \times SD$	0.024 (0.004)*** (0.004)***	0.028 (0.004)*** (0.004)***	-0.0008 (0.0010) (0.0013)	0.013 (0.003)*** (0.003)***
$\%lcc234[S] \times SD$	0.0002 (0.001) (0.003)	0.002 (0.0010)* (0.0009)***	-0.0003 (0.0003) (0.001)	0.0001 (0.001) (0.002)
$\%lcc234[S] \times DRYZ$	-0.059 (0.021)*** (0.023)***	0.003 (0.009) (0.009)	-0.010 (0.007) (0.009)	-0.094 (0.026)*** (0.044)***
$\%lcc234[W] \times WETZ$	-0.010 (0.012) (0.015)	-0.006 (0.004) (0.005)	-0.034 (0.005)*** (0.007)***	-0.021 (0.012)* (0.025)
R^2	0.761	0.758	0. 6728	0.555
N	6935	2911	7067	6123

****p<0.01, **p<0.05, *p>0.1*

Table S7. Marginal impacts of isolated and consecutive incidence of the SDs (heat stress)

	CORN	SOYBEAN	SPRING WHEAT	ALFALFA
Variable	**Estimate**	**Estimate**	**Estimate**	**Estimate**
Intercept	24.182***	23.193***	24.916***	25.747***
t	0.769***	0.206***	0.663***	-0.069
t65	1.075***	0.387***	-0.247***	1.464***
t80	-0.855***	-0.223***	-0.280***	-1.314***
t95	1.370***	0.116***	0.642***	0.564***
GD	0.002*	0.002***	0.001*	0.005***
$t \times GD$	0.0001***	-0.00002	0.00001	0.0002***
SD^{1}	-0.071	0.194***	0.053	-0.339***
$t \times SD^{1}$	-0.005	0.009***	0.003	-0.007
SD^{23}	-0.210	-0.176**	0.068	-0.331**
$t \times SD^{23}$	-0.006	-0.002	0.001	0.017**
SD^{4+}	-1.964***	-0.507***	-1.469***	-2.729***
$t \times SD^{4+}$	-0.063***	-0.012***	-0.009**	-0.004
DRYZ	-3.654***	-1.375***	-2.004***	-5.363***
$t \times DRYZ$	-0.121***	-0.006	-0.030***	-0.089***
$DRYZ \times SD$	0.026***	0.011***	0.005***	0.017***
WETZ	-0.084	0.021	-0.296***	2.108***
$t \times WETZ$	-0.035***	-0.009***	-0.014***	-0.018***
$WETZ \times SD$	0.023***	0.027***	-0.001	0.013***
%lcc234[S] × *SD*	-0.0004	0.001	-0.0004	0.00002
%lcc234[S] × *DRYZ*	-0.059***	0.001	-0.009	-0.096***
%lcc234[W] ×	-0.010	-0.005	-0.035***	-0.020
R^2	0.7978	0.7828	0.7260	0.7382
N	6,935	2,911	7,067	6,123

****p<0.01, **p<0.05, *p>0.1*

Table S8. Within-season weather Impacts: Corn and Soybeans

Growing Season: May-August	**CORN**	**SOYBEAN**
Variable	**Estimate**	**Estimate**
Intercept	24.458***	22.729***
t	0.758***	0.181***
t65	1.078***	0.441***
t80	-0.901***	-0.295***
t95	1.672****	0.248***
GD_MAY_JUN	0.016***	0.007***
t×GD_MAY_JUN	0.001***	0.001***
GD_JUL_AUG	-0.008***	-0.001
t×GD_JUL_AUG	-0.001***	-0.0004***
SD_MAY_JUN	0.144***	0.054
t×SD_MAY_JUN	0.008***	0.003*
SD_JUL_AUG	-0.177***	-0.073***
t×SD_JUL_AUG	-0.007***	-0.002***
DRYZ_MAY_JUN	-2.329***	-0.984***
t×DRYZ_MAY_JUN	-0.116***	0.020
DRYZ×SD_MAY_JUN	0.039**	0.009
DRYZ_JUL_AUG	-5.642***	-1.857***
t×DRYZ_JUL_AUG	-0.140***	-0.029***
DRYZ×SD_JUL_AUG	0.025***	0.011**
WETZ_MAY_JUN	-0.182	-0.327***
t×WETZ_MAY_JUN	-0.032***	-0.003
WETZ×SD_MAY_JUN	0.039	0.036
WETZ_JUL_AUG	0.305*	0.445***
t×WETZ_JUL_AUG	-0.038***	-0.017***
WETZ×SD_JUL_AUG	0.056***	0.069***
%lcc234[S]×SD	-0.0002	0.002
%lcc234[S]×DRYZ	-0.046**	0.001
%lcc234[W]×WETZ	-0.012	-0.004
$\mathbf{R^2}$	0.8061	0.7930
N	6,935	2,911

****p<0.01, **p<0.05, *p>0.1*

Table S9. Seasonal Weather Impacts: Spring Wheat and Alfalfa

Growing Season: April-July	**SPRING WHEAT**	**ALFALFA**
Variable	**Estimate**	**Estimate**
Intercept	26.117***	27.763***
t	0.709***	0.010
t65	-0.349***	1.265***
t80	-0.187***	-1.069***
t95	0.643***	0.420***
GD_APR_MAY	0.021***	0.005
t×GD_APR_MAY	-0.00003	-0.0002
GD_JUN_JUL	-0.010***	0.005**
t×GD_JUN_JUL	0.00003	0.0003***
SD_APR_MAY	0.038**	-0.177***
t×SD_APR_MAY	0.012***	0.020***
SD_JUN_JUL	-0.059***	-0.104***
t×SD_JUN_JUL	-0.001***	-0.002***
DRYZ_APR_MAY	-1.625***	-3.961***
t×DRYZ_APR_MAY	-0.035***	-0.088***
DRYZ×SD_APR_MAY	-0.024***	0.048**
DRYZ_JUN_JUL	-2.417***	-6.137***
t×DRYZ_JUN_JUL	-0.019***	-0.074***
DRYZ×SD_JUN_JUL	0.007***	0.021***
WETZ_APR_MAY	0.094	2.731***
t×WETZ_APR_MAY	-0.014***	-0.048***
WETZ×SD_APR_MAY	0.003	0.086**
WETZ_JUN_JUL	-0.407***	1.605***
t×WETZ_JUN_JUL	-0.012***	0.005
WETZ×SD_JUN_JUL	-0.001	0.012***
%lcc234[S]×SD	-0.0004	0.00001
%lcc234[S]×DRYZ	-0.005	-0.086***
%lcc234[W]×WETZ	-0.034***	-0.021*
R^2	0.7438	0.7420
N	7,067	6,123

****p<0.01, **p<0.05, *p>0.1*

Table S10. The (parsimonious) yields regression model with $\beta_{tW} = 0$.

	CORN	SOYBEANS	SPRING WHEAT	ALFALFA
Variable	Estimate	Estimate	Estimate	Estimate
Intercept	25.265***	24.200***	24.623***	24.774***
t	0.878***	0.232***	0.667***	-0.142**
t65	0.943***	0.354***	-0.234***	1.564***
t80	-0.771***	-0.210***	-0.300***	-1.315***
t95	1.243***	0.124***	0.653***	0.527***
GD	0.003***	0.002***	0.002***	0.005***
SD	-0.153***	-0.058***	-0.056***	-0.110***
DRYZ	-3.880***	-1.383***	-2.077***	-5.550***
DRYZ☓ *SD*	0.016***	0.007***	0.003***	0.013***
WETZ	-0.325***	-0.046	-0.347***	2.078***
WETZ☓ *SD*	0.016***	0.025***	-0.001	0.015***
$Q_i^{dry} \times SD$	0.0004	0.002**	-0.0003	-0.0001
$Q_i^{dry} \times DRYZ$	-0.043**	0.006	-0.008	-0.081***
$Q_i^{wet} \times WETZ$	-0.012	-0.006	-0.033***	-0.019
R^2	0.7870	0.7777	0.7204	0.7317
N	6,935	2,911	7,067	6,123

******p<0.01, **p<0.05, *p>0.1*

Table S11. Unit Root Regressions for **Corn**'s seasonal Weather Outcomes. $H_o : \sum_{k=1}^{4} \gamma_k = 1$

Regressors	*GD*	*SD*	*DRYZ*	*WETZ*
Trend	-0.20*	-0.05***	-0.002*	0.02***
$W_{i,t-1}$	0.69***	0.38***	0.04***	-0.01
$W_{i,t-2}$	0.06***	0.05***	-0.06***	0.11***
$W_{i,t-3}$	0.07***	0.08***	0.04***	-0.04***
$W_{i,t-4}$	0.03***	0.12***	0.07***	-0.06***
Fixed-Effects	Yes	Yes	Yes	Yes
R^2	0.86	0.63	0.02	0.06
N	7,051	7,051	7,051	7,051
Unbiased t-test	-3.85***	-8.66***	-8.29***	-22.19***

******p<0.01, **p<0.05, *p>0.1*

Table S12. Unit Root Regressions for **Soybean**'s seasonal Weather Outcomes. $H_o : \sum_{k=1}^{4} \gamma_k = 1$

Regressors	*GD*	*SD*	*DRYZ*	*WETZ*
Trend	-0.24*	-0.04***	-0.002*	0.02***
$W_{i,t-1}$	0.69***	0.34***	0.04***	-0.01
$W_{i,t-2}$	0.06***	0.02*	-0.06***	0.11***
$W_{i,t-3}$	0.07***	0.08***	0.04***	-0.04***
$W_{i,t-4}$	0.03***	0.11***	0.07***	-0.06***
Fixed-Effects	Yes	Yes	Yes	Yes
R^2	0.86	0.56	0.02	0.06
N	7,055	7,055	7,055	7,055
Unbiased t-test	-3.88***	-9.55***	-8.31***	-22.24***

****p<0.01, **p<0.05, *p>0.1*

Table S13. Unit root regressions for **Spring Wheat**'s weather outcomes. $H_o : \sum_{k=1}^{4} \gamma_k = 1$

Regressors	*GD*	*SD*	*DRYZ*	*WETZ*
Trend	-0.26***	-0.04*	-0.001	0.02***
$W_{i,t-1}$	0.66***	0.41***	0.12***	-0.05***
$W_{i,t-2}$	0.04**	0.06***	-0.10***	0.10***
$W_{i,t-3}$	0.12***	0.08***	0.02**	-0.07***
$W_{i,t-4}$	0.03***	0.11***	0.06***	-0.07***
Fixed-Effects	Yes	Yes	Yes	Yes
R^2	0.84	0.65	0.04	0.05
N	7,025	7,025	7,025	7,025
Unbiased t-test	-4.06***	-10.69***	-8.37***	-17.58***

****p<0.01, **p<0.05, *p>0.1*

Table S14. Unit root regressions for **Alfalfa**'s weather outcomes. $H_o: \sum_{k=1}^{4} \gamma_k = 1$

Regressors	*GD*	*SD*	*DRYZ*	*WETZ*
Trend	-0.28***	-0.04*	-0.001	0.02***
$W_{i,t-1}$	0.66***	0.41***	0.12***	-0.05***
$W_{i,t-2}$	0.03**	0.06***	-0.10***	0.10***
$W_{i,t-3}$	0.12***	0.08***	0.02**	-0.07***
$W_{i,t-4}$	0.03***	0.11***	0.06***	-0.07***
Fixed-Effects	Yes	Yes	Yes	Yes
R^2	0.84	0.66	0.04	0.05
N	7,029	7,029	7,029	7,029
Unbiased t-test	-4.19***	-10.96***	-10.44***	-19.78***

****p<0.01, **p<0.05, *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 S15. Models for Corn's Seasonal Weather Outcomes

Regressors	$GD_{i,t}$	$SD_{i,t}$	$DRYZ_{i,t}$	$WETZ_{i,t}$
Trend	-0.30**	-0.10***	0.001	0.02***
$GD_{i,t-1}$	0.70***	0.02***	0.0005***	-0.001***
$GD_{i,t-2}$	0.07***	-0.01***	-0.001***	0.001***
$GD_{i,t-3}$	0.05***	-0.004*	-0.0002	-0.0002
$GD_{i,t-4}$	0.03**	0.003	0.0003***	-0.0002
$SD_{i,t-1}$	-0.01	0.33***	0.004***	-0.01***
$SD_{i,t-2}$	0.06	0.08***	0.001	0.003*
$SD_{i,t-3}$	0.16	0.05***	-0.003***	-0.002
$SD_{i,t-4}$	-0.03	0.10***	-0.001	0.004***
$DRYZ_{i,t-1}$	-5.31***	-2.08***	-0.01	-0.02
$DRYZ_{i,t-2}$	-4.96***	-1.68***	-0.08***	-0.07***
$DRYZ_{i,t-3}$	2.64*	-0.14	0.03**	-0.09***
$DRYZ_{i,t-4}$	-0.87	-0.35	0.07***	0.05**
$WETZ_{i,t-1}$	5.98***	0.24*	-0.03***	-0.04***
$WETZ_{i,t-2}$	2.31**	0.22*	-0.03***	0.11***
$WETZ_{i,t-3}$	-1.75*	-0.60***	-0.08***	-0.05***
$WETZ_{i,t-4}$	-0.44	0.63***	0.01	-0.06***
Fixed-Effects	**Yes**	**Yes**	**Yes**	**Yes**
R^2	0.86	0.66	0.05	0.08
N	7,051	7,051	7,051	7,051

****p<0.01, **p<0.05, *p>0.1*

Table S16. Models for Soybean's Seasonal Weather Outcomes

Regressors	$GD_{i,t}$	$SD_{i,t}$	$DRYZ_{i,t}$	$WETZ_{i,t}$
Trend	-0.36***	-0.06***	0.001	0.02***
$GD_{i,t-1}$	0.69***	0.01***	0.0005***	-0.001***
$GD_{i,t-2}$	0.08***	-0.003**	-0.001***	0.001***
$GD_{i,t-3}$	0.05***	-0.003*	-0.0002	-0.0001
$GD_{i,t-4}$	0.03**	0.002*	0.0003***	-0.0001
$SD_{i,t-1}$	0.01	0.30***	0.01***	-0.02***
$SD_{i,t-2}$	0.01	0.04***	0.001	0.01***
$SD_{i,t-3}$	0.32*	0.05***	-0.003**	-0.01**
$SD_{i,t-4}$	-0.10	0.08***	-0.002	0.01***
$DRYZ_{i,t-1}$	-5.76***	-1.23***	-0.01	-0.01
$DRYZ_{i,t-2}$	-5.10***	-1.08***	-0.08***	-0.07***
$DRYZ_{i,t-3}$	2.59	-0.08	0.03**	-0.08***
$DRYZ_{i,t-4}$	-0.74	-0.14	0.07***	0.05**
$WETZ_{i,t-1}$	6.36***	0.03	-0.03***	-0.04***
$WETZ_{i,t-2}$	2.49**	0.03	-0.03***	0.11***
$WETZ_{i,t-3}$	-1.85*	-0.38***	-0.08***	-0.05***
$WETZ_{i,t-4}$	-0.56	0.39***	0.01	-0.06***
Fixed-Effects	**Yes**	**Yes**	**Yes**	**Yes**
R^2	0.86	0.59	0.05	0.08
N	7,055	7,055	7,055	7,055

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

Table S17. Models for Spring Wheat's Seasonal Weather Outcomes

Regressors	$GD_{i,t}$	$SD_{i,t}$	$DRYZ_{i,t}$	$WETZ_{i,t}$
Trend	-0.36***	-0.11***	0.0002	0.02***
$GD_{i,t-1}$	0.65***	0.04***	0.0001	-0.0002
$GD_{i,t-2}$	0.07***	-0.002	-0.001***	0.001***
$GD_{i,t-3}$	0.05***	-0.01***	0.0005***	-0.00002
$GD_{i,t-4}$	0.05***	-0.001	-0.0001	-0.0004*
$SD_{i,t-1}$	0.18***	0.34***	0.004***	-0.01***
$SD_{i,t-2}$	-0.09	0.09***	0.001	-0.002
$SD_{i,t-3}$	0.35***	0.08***	-0.001*	-0.002**
$SD_{i,t-4}$	-0.20***	0.10***	-0.001	0.004***
$DRYZ_{i,t-1}$	-3.54***	-1.66***	0.09***	-0.09***
$DRYZ_{i,t-2}$	-7.73***	-2.46***	-0.08***	-0.06***
$DRYZ_{i,t-3}$	1.16	-0.86***	0.01	-0.10***
$DRYZ_{i,t-4}$	0.24	-0.41	0.06***	-0.06***
$WETZ_{i,t-1}$	7.54***	1.28***	-0.00005	-0.10***
$WETZ_{i,t-2}$	1.66**	1.18***	0.04***	0.07***
$WETZ_{i,t-3}$	-3.56***	-0.95***	-0.07***	-0.08***
$WETZ_{i,t-4}$	-0.27	0.73***	-0.03***	-0.08***
Fixed-Effects	**Yes**	**Yes**	**Yes**	**Yes**
R^2	0.83	0.68	0.06	0.08
N	6,760	6,760	6,760	6,760

****p<0.01, **p<0.05, *p>0.1*

Table S18. Models for Alfalfa's Seasonal Weather Outcomes

Regressors	$GD_{i,t}$	$SD_{i,t}$	$DRYZ_{i,t}$	$WETZ_{i,t}$
Trend	-0.36	-0.11	0.0002	0.02
$GD_{i,t-1}$	0.65	0.04	0.0001	-0.0002
$GD_{i,t-2}$	0.07	-0.002	-0.001	0.001
$GD_{i,t-3}$	0.05	-0.01	0.0005	-0.00002
$GD_{i,t-4}$	0.05	-0.001	-0.0001	-0.0004
$SD_{i,t-1}$	0.18	0.34	0.004	-0.01
$SD_{i,t-2}$	-0.09	0.09	0.001	-0.002
$SD_{i,t-3}$	0.35	0.08	-0.001	-0.002
$SD_{i,t-4}$	-0.20	0.10	-0.001	0.004
$DRYZ_{i,t-1}$	-3.54	-1.66	0.09	-0.09
$DRYZ_{i,t-2}$	-7.73	-2.46	-0.08	-0.06
$DRYZ_{i,t-3}$	1.16	-0.86	0.01	-0.10
$DRYZ_{i,t-4}$	0.24	-0.41	0.06	-0.06
$WETZ_{i,t-1}$	7.54	1.28	-0.0005	-0.10
$WETZ_{i,t-2}$	1.66	1.18	0.04	0.07
$WETZ_{i,t-3}$	-3.56	-0.95	-0.07	-0.08
$WETZ_{i,t-4}$	-0.27	0.73	-0.03	-0.08
Fixed-Effects	**Yes**	**Yes**	**Yes**	**Yes**
R^2	0.83	0.68	0.06	0.08
N	6,760	6,760	6,760	6,760

****p<0.01, **p<0.05, *p>0.1*

Table S19. Palmer Z model regressions

Variable	Estimate	Variance Inflation Factor
Intercept	2.65***	0
$\overline{\overline{P}}$	2.91***	4.5
$\overline{\overline{P}}^{2}$	-0.11***	3.0
$\overline{\overline{PT}}$	-0.31***	3.4
Z_{t-1}	0.18***	1.1
Z_{t-2}	0.10***	1.2
Z_{t-3}	0.06***	1.2
Z_{t-4}	0.03***	1.2
Z_{t-5}	0.03***	1.2
Z_{t-6}	0.03***	1.1
$T \cdot 1_{JAN}$	-0.01***	1.3
$T \cdot 1_{FEB}$	-0.01***	1.4
$T \cdot 1_{MAR}$	-0.05***	1.7
$T \cdot 1_{APR}$	-0.07***	2.3
$T \cdot 1_{MAY}$	-0.08***	2.5
$T \cdot 1_{JUN}$	-0.09***	2.3
$T \cdot 1_{JUL}$	-0.06***	2.1
$T \cdot 1_{AUG}$	-0.05***	2.1
$T \cdot 1_{SEP}$	-0.05***	2.3
$T \cdot 1_{OCT}$	-0.04***	2.1
$T \cdot 1_{NOV}$	-0.03***	1.6
Fixed Effects	**YES**	
R^2	0.9122	
N	26,136	

****p<0.01, **p<0.05, *p>0.1*

Table S20. Monthly changes in temperature: Historical realizations during 1981-2010 vs. Projected (31-day M.A.) weather during 2031-'60.

Month	Degree C (1981-2010)	Degree C (2031-2060)	%Change
April	5.7	7.6	33
May	11.0	13.0	18
June	15.2	17.3	13
July	17.9	20.1	12
August	17.3	19.6	13
Annual (Average)	13.4	15.5	15

Table S21. Monthly changes in precipitation: Historical realizations during 1981-2010 vs. Projected (31-day M.A.) weather during 2031-'60.

Month	Hundreds of mm (1981-2010)	Hundreds of mm (2031-2060)	%Change
April	53.4	59.2	11
May	85.1	96.0	13
June	103.4	116.8	13
July	85.8	96.3	12
August	66.7	76.8	15
Annual (Total)	394.3	445.2	13

Table S22. Projected average change in growing-season weather: Historical realizations during 1981-2010 vs. Projected (31-day M.A.) weather during 2031-'60.

Crop	**Variable**	**1981-2010 (Realized)**	**2031-2060 (Projected)**	**% Change**
NORTH DAKOTA				
CORN	*GD*	902.10	1070.77	18.70
	SD	15.53	39.27	152.93
	DRZ	0.80	6.57	721.38
	WETZ	1.57	0.02	-98.82
SOY	*GD*	998.80	1175.16	17.66
	SD	6.69	21.27	217.94
	DRZ	0.64	6.57	926.56
	WETZ	1.84	0.02	-98.91
SPW	*GD*	692.46	816.94	17.98
	SD	18.96	41.07	116.61
	DRZ	0.79	7.10	798.73
	WETZ	1.52	0.02	-98.68
ALFALFA	*GD*	722.59	874.57	21.03
	KD	3.94	12.62	220.30
	DRZ	0.79	7.10	798.73
	WETZ	1.54	0.02	-98.70
SOUTH DAKOTA				
CORN	*GD*	1076.15	1243.15	15.52
	SD	38.96	79.51	104.07
	DRZ	0.53	7.15	1249.23
	WETZ	1.64	0.02	-99.04
SOY	*GD*	1179.71	1352.89	14.68
	SD	19.74	48.57	146.05
	DRZ	0.47	7.15	1421.28
	WETZ	1.54	0.02	-98.70
SPW	*GD*	812.01	937.96	15.51
	SD	44.76	81.65	82.42
	DRZ	0.65	7.43	1043.08
	WETZ	1.75	0.04	-97.71
ALFALFA	*GD*	886.65	1048.21	18.22
	KD	12.80	31.81	148.52
	DRZ	0.50	7.43	1386.00
	WETZ	1.51	0.04	-97.35

Notes: Median climate model outputs are used to represent weather projections during 2031-'60.

Table S23. Average price, yields, costs, profits and land use shares for each crop type during 1996-2013.

	CORN	SOYBEANS	SPRING WHEAT	ALFALFA
Av. Price ($/bushels)	3.52	7.92	5.34	1.81
Av. Yields (bushels/acre)	97.66	33.71	35.33	82.80
Av. Direct Cost ($/acre)	189.60	90.29	74.65	75.46
Av. Profit ($/acre)	154.16	176.69	114.01	74.41
Av. Land Share (West Counties)	0.02	-	0.09	0.04
Av. Land Share (East Counties)	0.20	0.23	0.08	0.04

FIGURES (SUPPLEMENTARY MATERIAL)

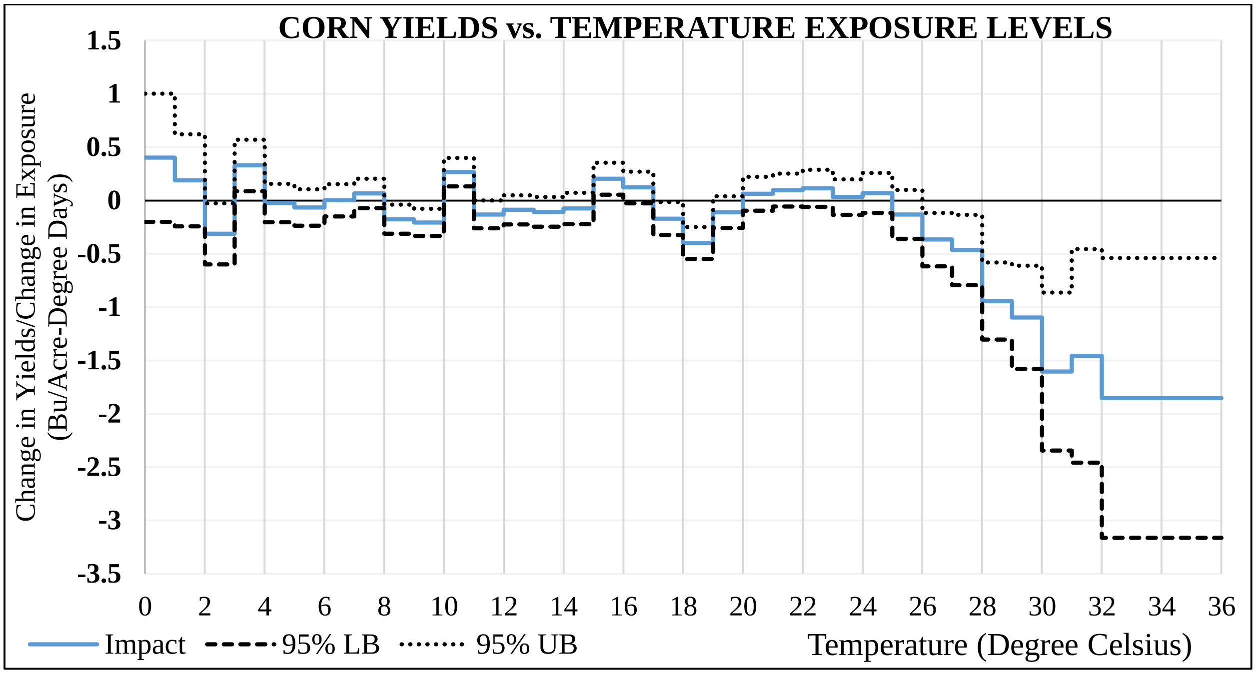


Figure S1. Corn Yields vs. Number of Days in Each Degree-Celsius Bin

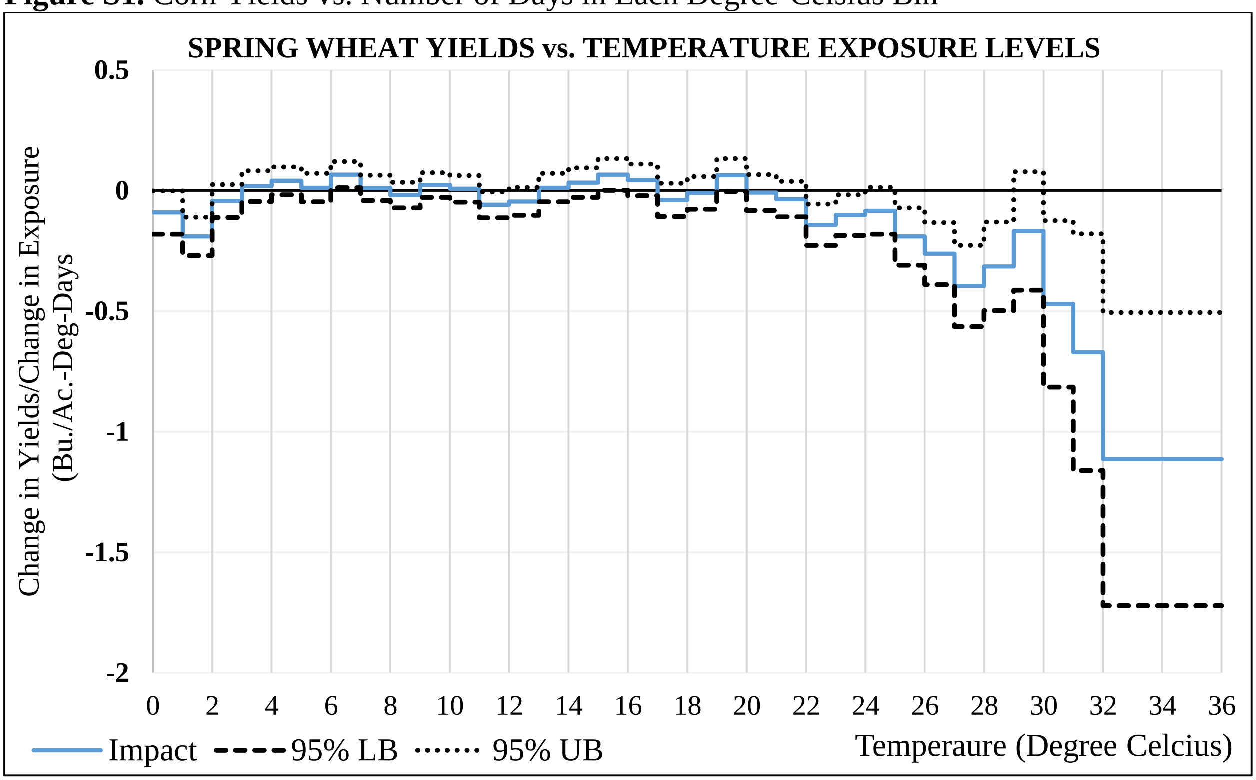


Figure S2. Spring Wheat Yields vs. Number of Days in Each Degree-Celsius Bin

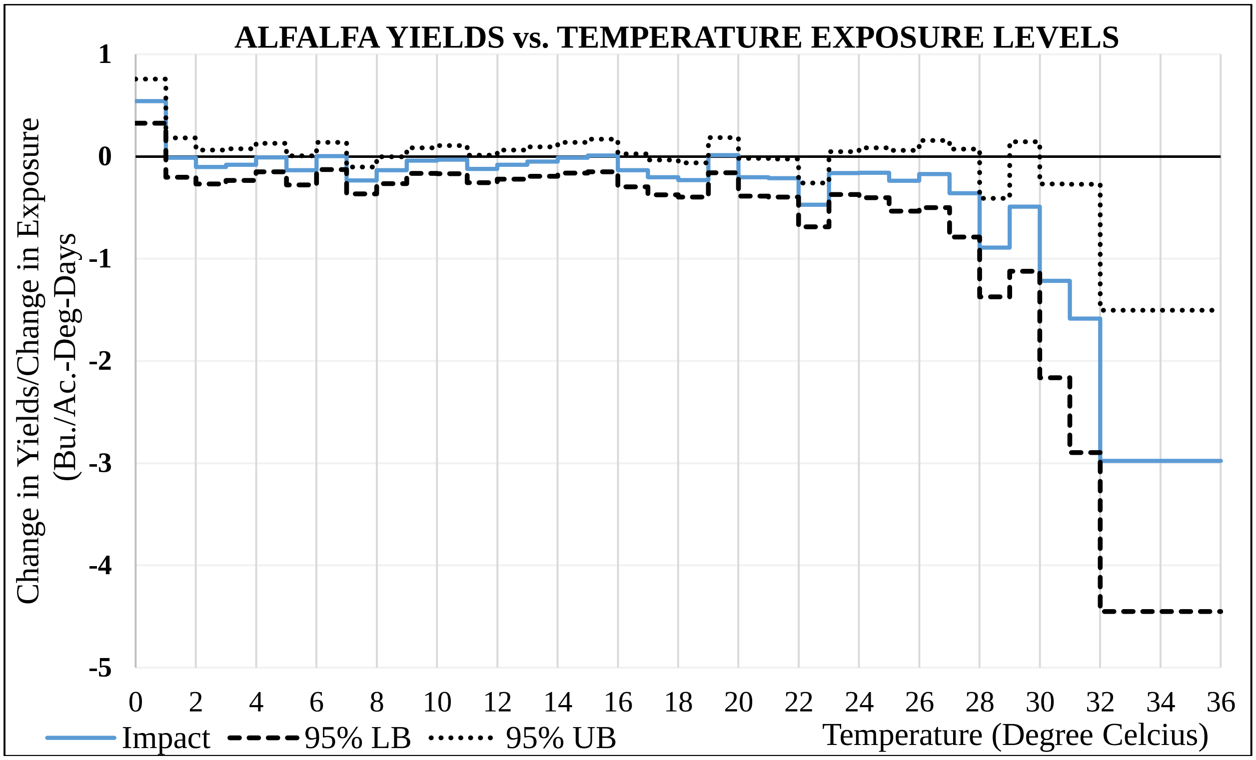


Figure S3. Alfalfa Yields vs. Number of Days in Each Degree-Celsius Bin

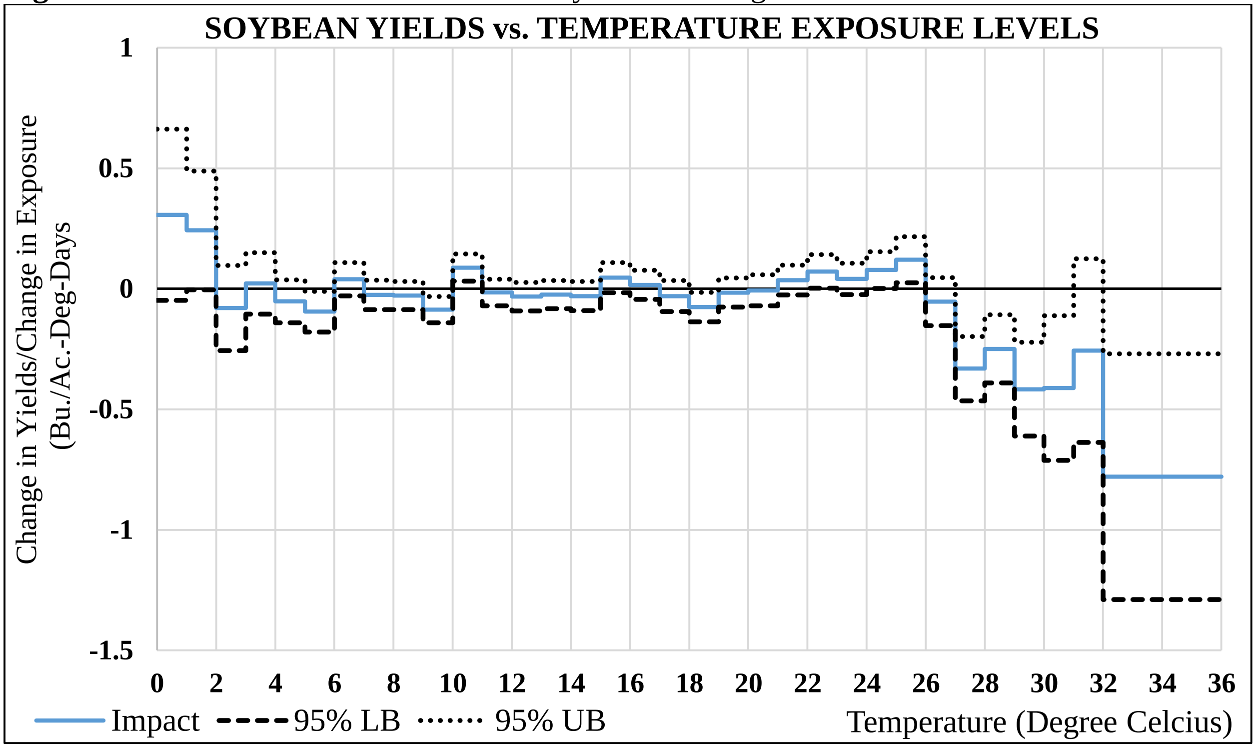


Figure S4. Soybean Yields vs. Number of Days in Each Degree-Celsius Bin

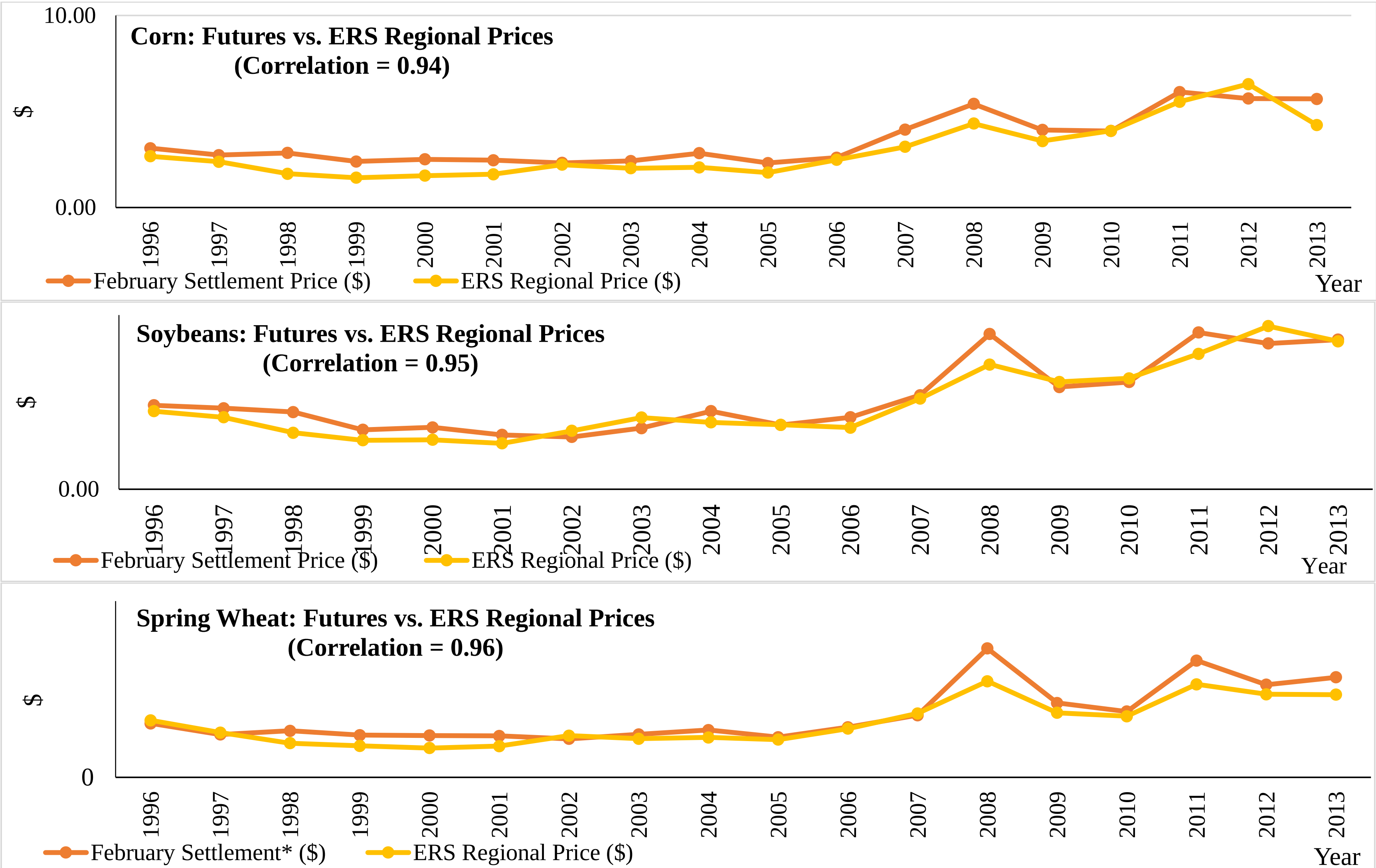
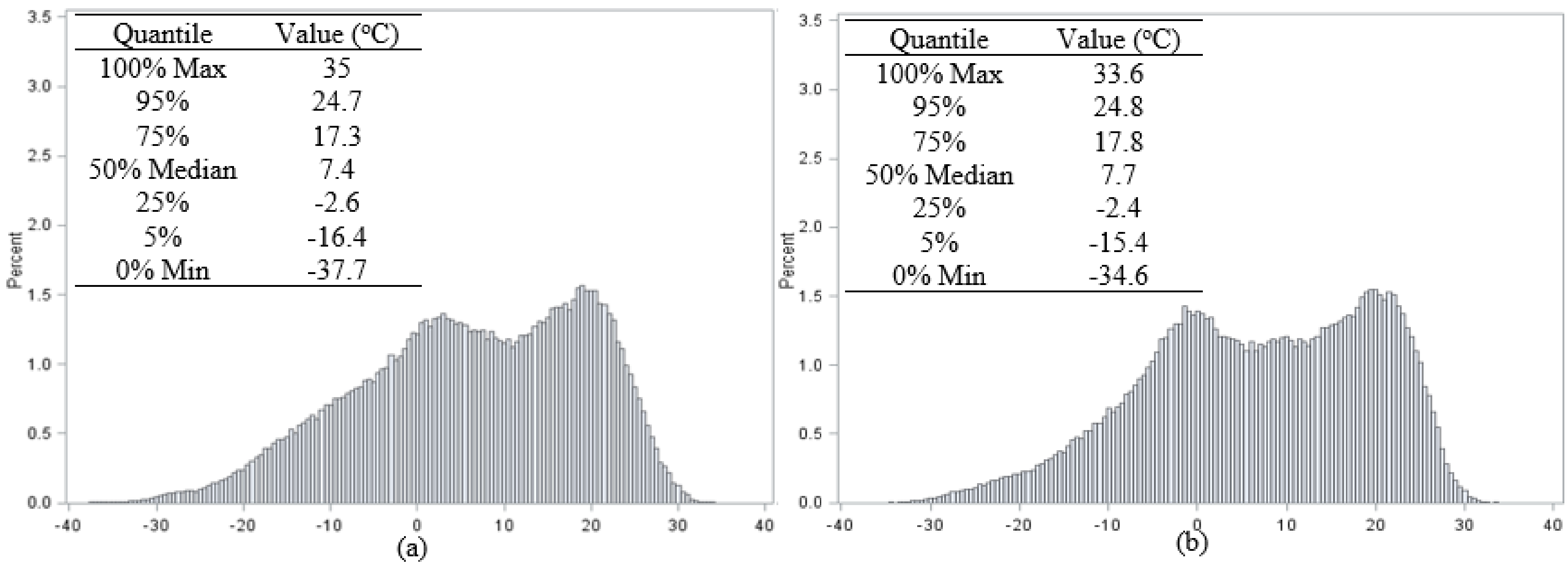
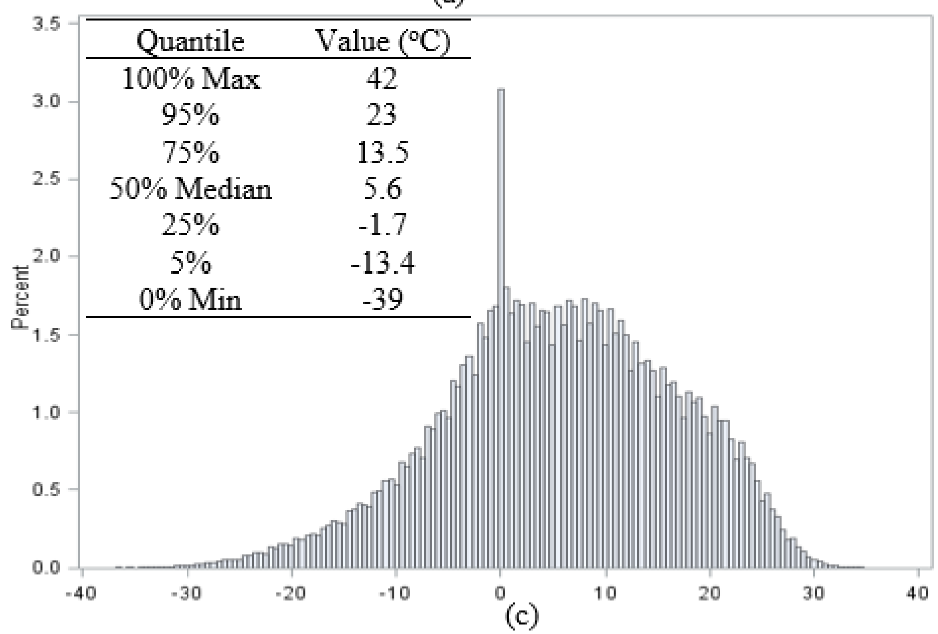
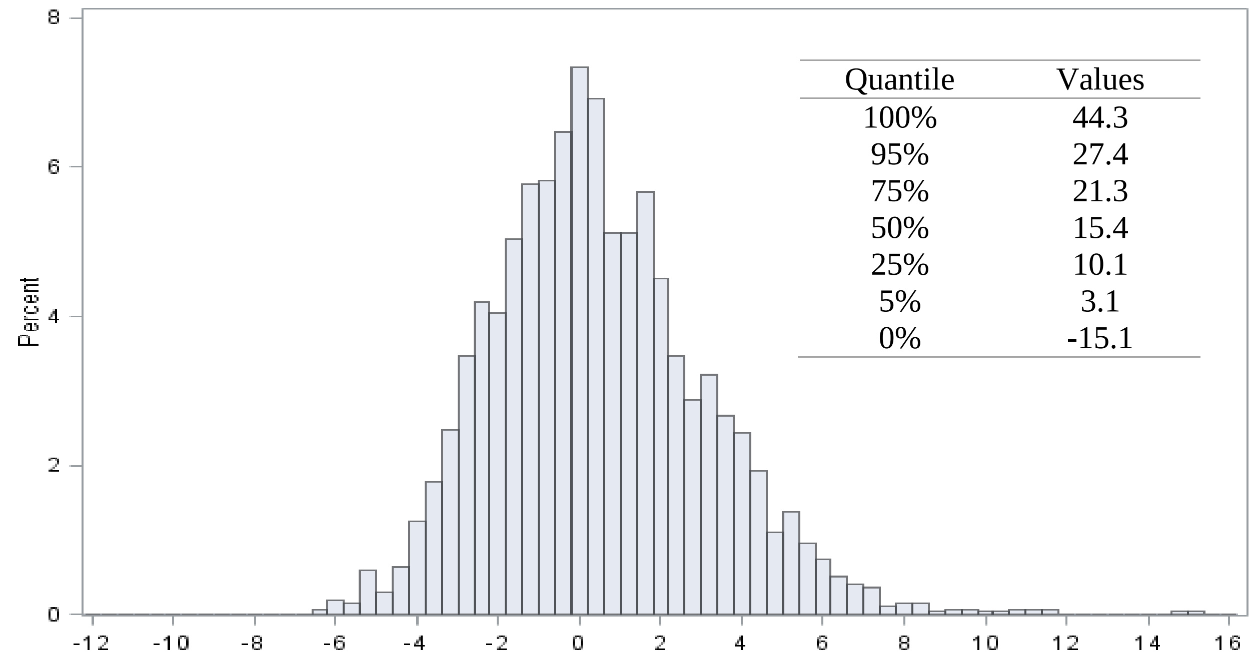


Figure S5. Comparative plots of ERS prices and futures prices for each crop type. All prices are in dollars. * denotes that Spring Wheat's settlement prices were calculated as daily averages of 'Open' and 'Last' prices from the Minneapolis Grain Exchange.

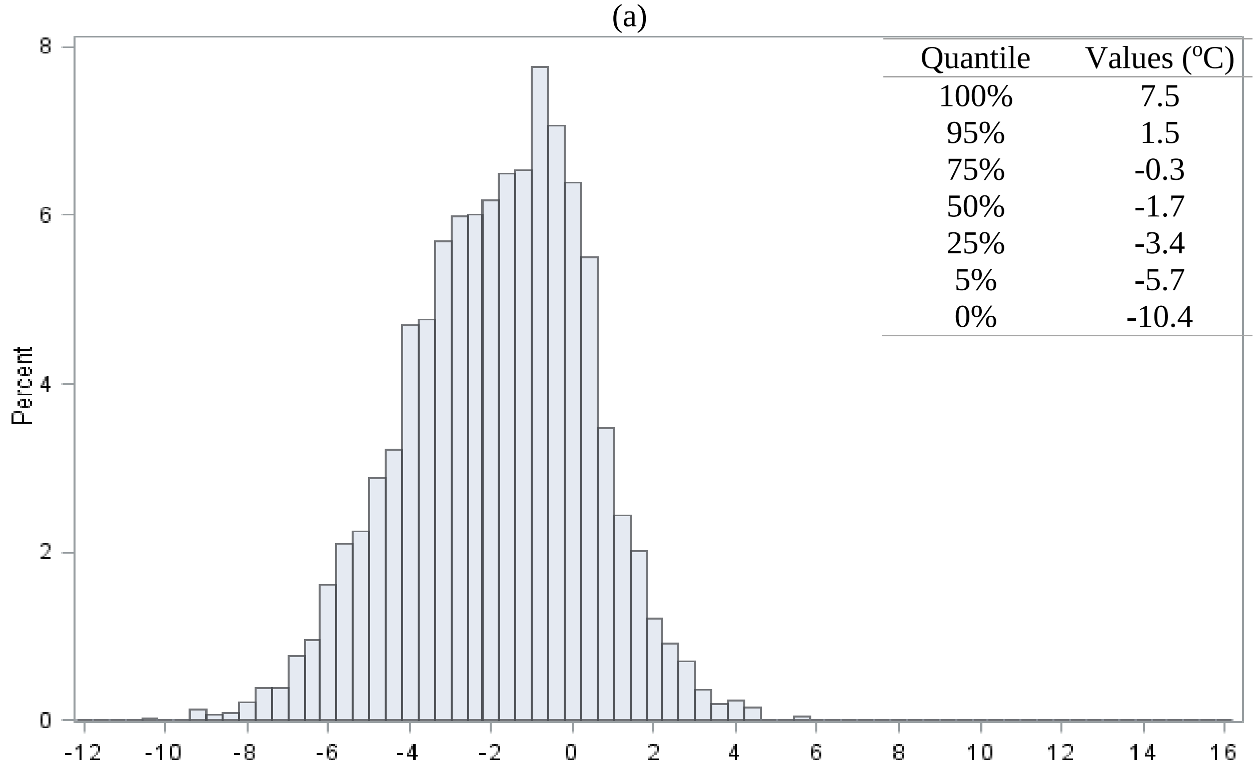




Figures S6 a-c. Comparative histograms for temperature (°C) from projections data and actual station-level realizations during 1981-2010. The data in figure 8 a-b are climate projections from HadCM3 and CNRM climate models respectively. Figure 8c presents actual temperature realizations as observed at the weather stations.



(a)



(b)

Figure S7 a-b. Change in growing season (April-August) *Z*: 2030-’60 vs. 1981-2010. Panel (a) shows historical temperature distribution, 1981-2010; and panel (b) shows the distribution of median temperature projections based on the 31-day moving average mean-shifts from the seven climate models during 2030-’60.

REFERENCES (SUPPLEMENTARY MATERIAL)

Auffhammer, M., Hsiang, S.M., Schlenker, W., Sobel, A. 2013. "Using Weather Data and Climate Model Output in Economic Analyses of Climate Change," *Review of Environmental Economics and Policy*, 7(2):181-198.

Breitung, J., Meyer, W. 1994. "Testing for unit roots in panel data: are wages on different bargaining levels cointegrated?," *Applied Economics*, 26(4): 353-61.

Blodgett, D.L. 2013. "The U.S. Geological Survey Climate Geo Data Portal: an integrated broker for climate and geospatial data," *U.S. Geological Survey Fact Sheet* 2013–3019, 2 p. http://pubs.usgs.gov/fs/2013/3019.

Conley, T.G. 1999. "GMM estimation with cross sectional dependence," *Journal of Econometrics*, 92:1-45.

Falk, B., Lee, B. 1998. "Fads versus fundamentals in farmland values," *American Journal of American Economics*, 80(4): 696-707.

Karl, T.R. 1986. "The Sensitivity of the Palmer Drought Sensitivity Index and Plamer's Z-Index to their Calibration Coefficients Including Potential Evapotranspiration," *Journal of Applied Meteorology and Climatology*, 25:77-86.

Kim, D., Dong-Ku, S. 1999. "A Standardization Technique to Reduce the Problem of Multicollinearity in Polynomial Regression Analysis," *Bulletin of the International Statistical Institute, 52nd Session Proceedings*, Finland. Available at https://www.stat.fi/isi99/proceedings/arkisto/varasto/kim_0574.pdf.

National Resource Inventory 2010. U.S. Department of Agriculture – National Resource Conservation Service.

Tack J., Barkley A., Nalley L.L. 2015. "Effect of warming temperatures on U.S. wheat yields," *Proc. Nat. Acad. Sci. USA*, 112:6931-6936.

Thornthwaite, C.W. 1948. "An Approach toward a Rational Classification of Climate," *Geographical Review*, 38(1): 55-94.

CHAPTER 4

CHARACTERIZING DAKOTAS LAND USE CHANGES USING HISTORICAL SATELLITE SENSOR DATA: 1984-2014

(PAPER III)

by

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ABSTRACT

We design and implement a robust, phenology-based satellite image classification algorithm to identify historical cropland allocation within the eastern portions of South Dakota and North Dakota since 1984. We identify five major crops (corn, soybeans, wheat, alfalfa, and grass) using archived Landsat-5 surface reflectance data and achieve accuracy levels similar to those reported for the annual Cropland Data Layer (CDL) raster products. We contribute by efficiently generating CDL-compatible raster products that predate the initial CDL availability by 13 and 22 years in ND and SD, respectively. We analyze both our pre-CDL image data in combination with existing CDL products and also CDL alone to better document and understand regional cropland use changes on the western edge of the U.S. Corn Belt. Summaries of land use trends calculated using pre-CDL + CDL and CDL alone for this region show that the restricted historical depth of the CDL tends to exaggerate the rate of land use change across crop and non-crop categories.

Introduction

In this study, we describe an intuitive, phenology-based approach for identifying and classifying dominant agricultural crop types (corn, soybeans, wheat, alfalfa, and native grass) using multi-temporal Landsat sensor data. We apply these methodologies for the purpose of extending the temporal depth of the existing Cropland Data Layer (CDL) archive back to 1984 for eastern portions of North Dakota and South Dakota. The aim of the study is to provide spatially explicit raster products commensurate with CDL to enable a longer, more detailed analysis of land use change trends within the western edge of the U.S. Corn Belt.

The Cropland Data Layer (CDL) effort provides annual geo-referenced information on U.S. crop cover based on analysis of multiple dates and seasons of satellite sensor data (primarily Landsat) that capture crop-specific phenology. These raster CDL products are then made available for the continental United States via the U.S. Department of Agriculture (USDA) National Agricultural Statistical Service's (NASS) 'CropScape' portal (https://nassgeodata.gmu.edu/CropScape/). The CDL raster products also include non-crop categories including developed/built-up areas, grasslands, wetlands, forests and water based on the 2001 and 2006 National Land Cover Data (NLCD: Homer et al. 2007, Homer et al. 2015) products. The main satellite sensors used in the production of CDL products (past and current) include the 30m Landsat sensors (Landsat-5 Thematic Mapper (TM), Landsat-7 Enhance TM Plus (ETM+), and Landsat-8 Operational Land Imager (OLI)) and the 56m Indian Remote Sensing RESOURCESAT-1 (IRS-P6) Advanced Wide Field Sensor (AWiFS) sensor. The USDA implements a complex, decision tree image processing algorithm trained and validated via the use of Farm Service Agency's aerial imagery during the agricultural growing seasons (Fry et al. 2009; Boryan et al. 2011) and a variety of other ancillary image products. The prevailing spatial resolution of CDL data products is 30-m. Exceptions in spatial resolution (56m) occurred for a period between 2006 and 2009 when AWiFS sensor data were the primary source of inputs for the program.. It should be noted that extraction and analysis of these CDL data across this time span has been known to confound or complicate quantification of precise land use transitions in some studies (Arora et al. 2016a).

Nevertheless, the availability of CDL has allowed the study of fine-scale cropland dynamics that quantify the timing (when), area (how much), and location (where) of regional and national land use transitions (Wright and Wimberly 2013, Boryan et al 2012). Quantifying such metrics adds a rich spatial dimension to land use transitions analysis and the related policy-making process that was unavailable with traditional county-level land use data. However, two major challenges emerge when using these data for multi-year analyses.

First, the historical depth of these raster data is both limited and variable across the 48 contiguous U.S. states. The earliest year when CDL data are available for all lower 48 states is 2008. . As a consequence, the earliest possible countrywide land use analysis based on CDL products is likely to commence on or following this common date to maintain temporal consistency; even though earlier dates of CDL are available for some states (Lark et al. 2015). For instance, the North Dakota and South Dakota CDL archive begins in 1997 and 2006, respectively. This is a major restriction on evaluating the factors that may affect observed land use change trends, especially when such factors predate the CDL archive by years or decades and evolve gradually, such as climate change, infrastructure development, and agri-environmental policy (Arora et al. 2016b).

Second, land use type classification errors among the different years of CDL in the archive are considerable (Arora et al. 2016a). The CDL program provides state-specific accuracy levels for individual land cover types, which reveals regional discrepancy in the performance of their underlying land cover identification algorithm. Furthermore, Reitsma et al. (2016) identified within-state differences in cropland and grassland accuracy levels for the 2006 South Dakota image. Cropland and grassland accuracy levels were high in crop-dominant and grass-dominant areas, respectively. Arora et al. (2016a) identified numerous areas of illogical, multi-year, land use transitions for Iowa's Loess Hills region (e.g., water-corn-forest-soy), and implemented a multi-year despeckling procedure as a corrective strategy. Pixel-level spatial aggregation strategies of these CDL have also been used to mitigate such classification errors (Stephens et al. 2008, Arora et al. 2016b).

If care is taken in the data preprocessing phase of CDL time series analyses to screen out such errors, then great potential exists to accurately illuminate multiple driving forces behind observed trends in land use land cover change, especially in agricultural regions (Arora et al. 2016a). For example, Wright and Wimberly (2013) analyzed grass to corn/soy and corn/soy to grass transitions in the Dakotas between 2006 –the first year of CDL for SD— and 2011 following and concurrent with a period of sharp commodity price increases (Rashford et al. 2011, USDA 2017). They concluded that a net 271,000 ha of grassland were lost to corn/soy production within this five-year period. The authors expressed concerns about the apparent expansion of corn and soybean tillage replacing the region's native mixed-grass prairies (Wright and Wimberly 2013) because grasslands provide substantial ecosystem services as well as conserving and foster regional biodiversity (Stephens et al. 2008; Wright and Wimberly, 2013; Johnston 2014).

High commodity prices, agricultural risk management policies, technological innovations, and climate change have all been suggested as potential drivers of the recent land use changes on these privately-owned grass and croplands (Rashford et al. 2011, Claassen et al. 2011). As the CDL archive grows in concert with factors known to modify land cover type or land use decisions, the fine grain size of CDL products will become a powerful diagnostic tool for policy makers and resource managers; beyond that which was possible among county-level studies (Claassen et al. 2011, Wallander et al. 2011). However, due to CDL's relatively limited historical depth, the potential diagnostic power that may be gleaned from trend analysis declines substantially if suspected driving factors predate the CDL archive by years or decades. Examples of such factor include past agricultural policies (Lauck 2000, Anderson et al. 2001), improved management practices (Karlen et al. 2006, Cardwell 1982), crop genetics (Cardwell 1982), climate change (Phillips et al. 1996), and infrastructure (Baker and Zahniser, 2006).

As initially stated above, we strive in this effort to facilitate a longer, more detailed time-series analysis of regional cropland use change to better characterize trends related to various exogenous driving factors. While we do not report on the trend effects of exogenous driving factors in this paper, we do conclude by providing a complete summary of the historical land use trends in this area for the period between 1984 and 2015.

Materials and Methods

The location of our study area in the eastern Dakotas is shown in Figure 1. . This region was selected for our study based on known Corn Belt expansions between 2006 and 2011 (Wright and Wimberley 2013). Specifically, we focused on Worldwide Reference System (WRS) Landsat footprints path 31, rows 27-28 for North Dakota and path 30, rows 29-30 for South Dakota. We acquire Landsat surface reflectance data from the U.S. Geological Survey's (USGS) via their online archive (http://earthexplorer.usgs.gov/), which dates back to 1984 (as do our land use characterizations). Surface reflectance data are convenient as they have been corrected for reflectance variations due to terrain and atmospheric effects.

Below we describe only the classification algorithm used for the South Dakota portion of the study are (path 30, rows 29-30), as the algorithm used for North Dakota (path 31, rows 27-28) is nearly identical. Our search of the Landsat archives centered on two seasonal periods (late-July to mid-August and mid-September) to capture specific phenology information related to agricultural crops in this region, as well as availability of imagery with little or no cloud cover. These time periods were targeted for use as tools to discriminate reflectance differences between 1) corn and soybean fields and 2) between alfalfa, wheat, and native grass fields, respectively. The mid-growing season imagery, for instance, captures the green rows of mature corn plants, and their shadows, at a time when they completely cover the bare soil under the plants and between the rows. This is not the case for mature soybean fields in July/August, as sunlit soil between rows remains as a substantial component of the overall soybean signature at 30-m resolution. Here, the first shortwave infrared band (SWIR-1, B5) of the Landsat sensors (Landsat-5 and -7, 1.55 – 1.75 μm; Landsat-8, 1.56 – 1.66 μm) was chosen to discriminate corn and soybean fields because this region of the electromagnetic spectrum is known to be sensitive to shading characteristics generated by plant structural differences (Wolter et al. 2012).

Mid-September images were needed to capture reflectance differences between senescent corn/soy and other land cover types, such as alfalfa, wheat, and native grass. In this capacity, mid-September Landsat imagery is effective because, for example, while corn and soy fields are completely senescent (i.e., chlorophyll absent) alfalfa fields remain strongly photosynthetic. Hence, a discriminant applied to a rescaled version of the widely used normalized difference vegetation index (NDVI, Rouse et al., 1974; scale = [NDVI + 1]*100) easily distinguished vigorous, green alfalfa from all other crop types (NDVI > 175, Figure 4). Scaled NDVI values for wheat fields (NDVI 126-140) were intermediate to corn/soy (NDVI < 100) and alfalfa (NDVI > 175, Figure 4) during this time window, which enabled their discrimination. However, native grass fields were unique in this context because they were composed of a combination of green and dead/senescent grasses and forbs by mid-September. Because SWIR-1 (B5) is known to be sensitive to vegetation moisture content (Hunt and Rock 1989), we used SWIR-1 to uniquely discriminate native grass fields (Figure 4).

While we used September imagery to distinguish other green crops from senescent corn/soy fields, we should note that Landsat image dates extending into September were not considered optimal for the classifying corn from soybeans, and vice versa. Two reasons for this are that 1) prohibitive difference occur in the timing of initial corn and soybean senescence within and between these respective crops and fields that produce highly variable SWIR-1 signatures and 2) the onset of corn/soy harvesting (bare fields) precludes the use of NDVI or SWIR-based crop discrimination techniques. In this region, soybean harvest typically initiates ca. two weeks ahead of corn, but much variability exists (Table 2).

As is the case in any long-term study involving Landsat data, cloud cover was sometimes problematic and precluded acquisition of useable imagery. However, when cloud issues were limited to either the west or east sides of an image, we had an opportunity to substitute key imagery from neighboring Landsat paths --if it existed-- due the 70% total side lap at these latitudes (42.75^{o} – 48.86^{o}) between paths. However, in the event that neighboring, corrective imagery was not available in a particular year, we had to omit that year from our sample and designate the omitted year 'unavailable.' Consequently, out final multi-temporal land cover output is restricted to an intermittent time-series with some missing years due to 'unavailable' imagery.

As discussed above, our agricultural land use classification strategy utilizes each crop's unique phenology to determine best times of year for identification and discrimination from other crop types. To help track crop-wise developmental stage, we utilize the most active planting and harvest dates for cultivated land use types in the Dakotas (Table 2). Further, to assess accuracy levels using our classification algorithm (Figure 4, 5), we relied on traditional accuracy assessment techniques (Congalton, 1991) and visual quality assessments against the concurrent year (2015) of CDL imagery. For the former, we visited 265 sites across the study area in September or 2015 to determine crop type and to record the sample's location using Trimble Juno 3B GPS receiver (differentially corrected 2dRMS = 3 m). These points were then used to extract classified values from our 2015 results to quantify the user's (omission), producer's (commission), and overall accuracy of our classification algorithm's performance for 2015. We then qualitatively assessed (visual scans) our classified results against the CDL product for 2015 to check relative agreement and to check for obvious blunders.

Accuracy Analysis

As mentioned earlier, we designate the land cover identifying indices by cross-validation from CDL. An issue is that CDL's accuracy levels vary by land cover category, with mediocre accuracy for winter wheat, alfalfa and grass categories. So we perform an accuracy test on our AI's final output using ground-truth data from geo-coded field observations recorded on September 27th, 2015 in southeast South Dakota.

An issue in comparing Landsat 5 results directly with Landsat 8 sensor (2015 data), which is an advanced version of Landsat 5, is that band designations and scales differ across these two sensors. Figure 3 a-b presents a histogram for the range of intensity recorded from the 'Blue' band of original 2015 and 2009 data from the Landsat archive respectively. Clearly, the range recorded by this band in 2015, i.e., [48, 6069] is much different than that in 2009, i.e., [142, 4152]. Such discrepancy will lead to a biased identification of the region's land cover between 2009 and 2015, even though the data were acquired at the same time in both years. Therefore, we adjust each 2015 band to the respective scale of 2009 bands. As for our example for 'Blue' band above, 2015 image is rescaled to the intensity level of 2009 data by using the formula $\text{Blue}^{*}_{2015} = 0.67(\text{Blue}_{2015} - 48) + 142$. Here, * designates new (rescaled) 2015 band to 2009 level. A histogram in figure 3c shows the consequence of this adjustment. The remaining spectral differences are adjusted in the similar manner.

In order to document accuracy of our identification strategy we evaluate Type-I errors (false positives) and Type-II errors (false negatives) from our AI's land cover characterizations. We present the results in Table 5 and find that our algorithm achieved 96% accuracy in identifying wheat acres, followed by the combined Corn/Soybeans category (89%), alfalfa (87%) and grass (76%). CDL also provides accuracy levels for its 2015 land cover classification in South Dakota: corn at 97%, soybeans at 98%, spring wheat at 88% and alfalfa at 78%. These accuracy levels were much lower in 2006: corn at 83%, soybeans at 81%, spring wheat at 72% and alfalfa at 52%, indicating that the CDL data in the recent years is based on a better, more evolved AI. Recently, Reitsma (2016) also evaluated the accuracy for cropland and grassland classification in the 2006 South Dakota CDL. Our AI seems to have outperformed CDL's accuracy for grasses at 39% in southeast South Dakota as reported by Reitsma (2016). We achieved near-CDL accuracy for cropland in this region. Overall, these observations suggest that our identification strategy results in near-CDL accuracy but a longer time-series that dates back up to 1984. Further, harvested corn, soybean and wheat pixels are characterized as grass creating false positives for grass.

Dakotas' Historical Land Use Trends

We present land use trends from our AI for eastern South Dakota in table 6 and for eastern North Dakota in table 7. We include land cover statistics during 2006-2015 for South Dakota and during 1997-2015 for North Dakota from the CDL archive. Our intent is to compare the land use change inferences drawn from a narrow, medium-term time window from CDL, as also documented by Wright and Wimberly (2013), and from a longer time-series made available due to our land cover identification algorithm. Comparative land use trends are also provided from USDA National Agricultural Statistical Service's (NASS) and National Resource Conservation Service- National Resource Inventory's (NRI) county-level data. While the NASS data contain harvested acres for corn, soy, wheat and alfalfa, we utilize the NRI dataset to construct a Hay/Pasture/CRP category to proxy grasses. The counties that overlap with Landsat 5 swaths in North and South Dakota are identified using a map in Figure 6. Land use trends using NASS's county-level statistics are listed in tables 8 and 9, and those from the NRI data are listed in tables 10 and 11. We also plot these historical trends for South Dakota in figures 7-10 and for North Dakota in figures 11-13.

The land use trends for South Dakota imagery suggest a sustained increase in corn and soybean acreage, and decreasing wheat, alfalfa and grass acreage. These trends are consistent with the earlier findings of Wright and Wimberly (2013), although the inference on the rate of change will depend upon the choice of the change time-window. For example, combining our AI and the CDL archive suggests that corn acreage in eastern South Dakota increased by net 424,707 *ha*. between 1985 and 2011, by 199,247 *ha*. between 1997 and 2011, and by 223,120 *ha*.

between 2006 and 2011. Here, the long time series (1985-2011) suggests an average increase of 16,335 *ha*. corn acreage annually, the shorter series suggests an increase of 14,232 *ha*. corn acreage annually , while the short time-series (2006-2011) suggests that corn acreage increased by average 37,187 *ha*. Clearly, during 2006-2011 the rate corn acreage expansion in the area was much higher when compared to the rate of change due to the long time-series 1985-2011, which is attributed to biofuel expansion in the U.S. (Wright and Wimberley, 2013).

However, the average corn area in 1995-'97 (860,452 *ha*.) was even higher than in 2006 (755,825 *ha*.). This difference could likely be a consequence of the 1996 farm bill that disassociated government payments from cropping history thereby incentivizing cultivation of program crops. The inavailability of a longer time-series data from CDL would hinder a comparative analysis of the impacts of the Renewable Fuel Standards policy and that of the 1996 farm bill.

Table 5 also reveals that the rate of decline of grassland acres may be exaggerated if considered solely based on the CDL's narrow time-window. We find that grass acreage in eastern South Dakota declined by 786,730 *ha.* between 1987 and 2011, by 605,250 *ha.* between 1997 and 2011, and by 507,270 *ha*. between 2006 and 2011. Hence, the rate of grass conversion during 1987-2011 is equal to 31,469 *ha*. annually. Whereas the rate of grass conversion would be 43,232 *ha*. annually during 1997-2011 and 84,545 *ha*. annually during 2006-2011. Hence, the rate of conversion was close to three times when derived from 2006-2011 period rather than 1987-2011 period. This means that the extent of grassland losses in the area varies substantially depending upon the period of study. Using a longer time-series would be a value-added in better understanding grassland losses and identifying factors that would explain these changes. For example, in order to evaluate the impact of climate on the rate of grassland loss one would need several years of land use data primarily because climate change is a gradual phenomenon.

Our findings project the importance of using a longer time series for land use change analyses, a limitation faced by studies that solely rely upon the narrow time-window made available as CDL. Overall, we conclude that our identification outputs are a value-added to the CDL's narrow window of data availability to infer upon the extent of land use change and the factors that affect it.

We would like to caution our readers that despite carefully controlling for spectral differences across years our land use estimates for various categories are possibly erroneous. Based on cross-validations from NASS's county-level area, we find that our algorithm overstated corn (1993) and wheat (1987) and understated soybean (1987, 1993) for some years. We believe that these discrepancies in year-to-year identification are likely due to variability in crop phenology, an example of which would be adjustment in planting and harvesting dates by farmers from one year to the next.

Concluding Remarks and Future Work

We design and implement a robust satellite image processing algorithm based on each crop's phenology in the Dakotas to characterize historical land use changes in the region. We correct for any spectral differences and cloud cover across years for the raw Landsat-5 imagery. We utilize visual cross-validations from the existing CDL years and a ground-truth data that we collected in September 2015 to evaluate the accuracy of our outputs. Our identification strategy leads to CDL-like accuracy, thereby allowing us to extend the CDL data back to 1984. We summarize land use trends using our longer time-series and find that studies that solely rely upon the CDL data may exaggerate the rate of land use changes across crop and non-crop categories.

We find various discrepancies when comparing the output from our identification strategy and the same year's county-level land use statistics from NASS/NRI datasets. We attribute these differences to the varying phenology of crops across multiple years. In future, we will utilize the annual condition-of-crop reports from NASS, which document the state-wise progress of each crop's growth cycle, to reconcile our misidentified pixels.

In addition, we intend to utilize our new spatially-delineated data to identify land use transition zones in this region. Our longer time-series is hoped to provide an opportunity to better document the region's historical land use trends along with the spatial characteristics of these trends. Consequently, we also hope to identify factors that affect land use transitions in a more robust manner, including the impacts of agri-environmental policy.

TABLES

Table 4. Landsat TM Sensor's seven spectral bands and their wavelength ranges. B# means Band# of the TM's multi-spectral sensor.

Landsat 4-5	Name	Wavelength
B1	Blue	0.45-0.52
B2	Green	0.52-0.60
B3	Red	0.63-0.69
B4	Near Infrared	0.76-0.90
B5	Shortwave Infrared I	1.55-1.75
B6	Thermal Infrared	10.40-12.50
B7	Shortwave Infrared II	2.08-2.35

Table 5. Most Active Planting and Harvesting Dates in South Dakota

Crop Type	Planting Dates	Harvesting Dates
South Dakota		
Corn (Grain)	May 9 – May 25	Oct 10 – Nov 6
Soybeans	May 20 – Jun 6	Oct 1 – Oct 23
Spring Wheat	Apr 14 – May 2	Jul 27 – Aug 13
Winter Wheat	Sep 10 – Sep 23	Jul 15 – Jul 31
Alfalfa	Not Applicable	Jul 13 – Aug 19
North Dakota		
Corn (Grain)	May 2 – May 28	Oct 8 – Nov 19
Soybeans	May 14 – June 3	Sep 24 – Oct 21
Spring Wheat	Apr 24 – May 25	Aug 8 – Sep 13
Winter Wheat	Sep 10 – Sep 25	July 20 – July 29
Alfalfa	Not Applicable	June 10 – Sep 6

Source: USDA National Agricultural Statistics Service- Agricultural Handbook Number 628. Available from http://usda.mannlib.cornell.edu/usda/current/planting/planting-10-29-2010.pdf.

Table 6. Each spectral band's mean intensity across years for the designated AOIs reflecting spectral variances.

Imagery Date	B1	B3	B4	B5
	CONIFER AOI		WATER AOI	
South Dakota (Path 30)				
9/27/2015	249.5	217.3	120.7	61.6
9/26/2009	293.2	340.6	190.0	46.6
9/29/2004	304.7	364.9	138.6	36.6
9/25/1997	271.1	316.5	154.8	50.5
9/17/1994	267.9	330.3	151.3	47.9
9/30/1993	347.1	437.8	234.3	67.9
9/25/1991	326.2	414.9	315.4	205.2
9/30/1987	327.5	427.9	322.8	199.9
9/22/1986	348.0	463.0	321.0	148.1
North Dakota (Path 31)				
9/30/2008	341.2	493.2	167.9	47.6
9/27/1995	404.5	597.0	133.1	50.6
9/26/1989	410.0	581.1	190.5	69.1
9/23/1988	463.3	657.0	139.7	47.8
9/28/1984	499.8	802.6	262.1	91.3

Table 4. Land-Use Indices. B# means Band# of the TM's multi-spectral sensor.

Land-Use	Date Range	Index	Range
South Dakota (Path 30)			
Corn	24^{th} July-8^{th} Aug	B5/10	146-190
Corn/Soybeans	17^{th}-30^{th} Sept	I(C/S) = (B3/B3*90-40)+ (25,000/B5)	90-300
Wheat	17^{th}-30^{th} Sept	NDVI	126-140
Alfalfa	17^{th}-30^{th} Sept	NDVI	≥176
Grass	17^{th}-30^{th} Sept	B5/10	≥214
North Dakota			
Corn	17^{th}-30^{th} Sept	B5/10	115-190
Soybeans	17^{th}-30^{th} Sept	I(C/S) = (B3/B3*90-40)+ (25,000/B5)	148-200
Wheat	17^{th}-30^{th} Sept	NDVI	115-135
Alfalfa	17^{th}-30^{th} Sept	NDVI	≥176
Grass	17^{th}-30^{th} Sept	B5/10	146-162

Table 5. Accuracy Analysis

Ground-Reference Data

Our AI	Corn	Soybean	Wheat	Alfalfa	Grass/Pasture	Hay	Other Crops	Other	Harvested	*Total*	*User Acc.*
Corn/ Soybean	33				9					42	0.89
		43								43	
Wheat			31				1			32	0.97
Alfalfa	2	1		26		1				30	0.87
Grass		2	1	6	65	17	2		15	108	0.76
Other		1	1	2	2		3	1		10	0.10
Harvested										0	N/A
Total	35	47	33	34	76	18	6	1	15		
Prod. Acc.	0.93		0.94	0.76	0.87			1.00	0.00		

Table 6. Landsat derived land use areas (in hectares) for eastern South Dakota swath (1984-2005). CDL-derived areas for 2006 and 2011.

Year	Corn (*ha.*)	Corn/Soybeans (*ha.*)	Wheat (*ha.*)	Alfalfa (*ha.*)	Grass (*ha.*)
	Jul-Aug AI	**September AI**			
1985	554,238	-	-	-	-
1986	-	806,799	429,855	573,108	1,920,440
1987	418,452	349,943	1,528,380	126,564	1,874,820
1988	304,748	-	-	-	-
1990	653,842	-	-	-	-
1991	464,596	455,587	1,862,610	56,893	1,551,890
1993	1,173,850	500,406	857,720	135,156	2,414,760
1994	-	935,253	668,784	418,590	2,587,240
1995	840,758	-	-	-	-
1996	960,899	841,823	609,710	361,051	2,037,520
1997	779,698	1,197,120	538,514	302,220	1,738,960
1999	-	-	-	-	-
2001	750,506	-	-	-	-
2004	-	878,462	725,861	337,299	1,963,740
2006	755,825	1,544,657	371,264	109,555	1,640,980
2007	911,920	1,565,274	407,469	111,230	1,987,960
2008	781,000	1,552,735	370,826	96,009	2,087,100
2009	810,956	1,621,313	293,356	73,732	1,881,870
2010	816,249	1,680,358	238,794	95,889	1,734,390
2011	978,945	1,869,083	249,599	88,591	1,133,710
2012	1,137,950	2,095,204	166,729	87,343	1,054,860
2013	1,113,050	2,053,398	153,651	102,139	1,171,460
2014	1,076,650	2,136,950	161,358	107,532	1,037,170
2015	992,688	2,048,858	180,508	123,150	1,521,970

Notes: Missing values signify inavailability of good raw imagery for land use characterization. The September imagery for 1987 and 1991 (in red) had oddly different spectral signatures compared to the other years. Year 2003 is omitted because the paths of multiple tornadoes on June 24, 2003 intersected with most of western half of our study area in South Dakota.

Table 7. Landsat derived land use areas (in hectares) for eastern North Dakota swath (1984-1995). CDL-derived areas 1997 onward.

Year	Corn (ha.)	Soy (ha.)	Wheat (ha.)	Alfalfa (ha.)	Grass (ha.)
1984	71,681	207,527	1,194,965	6,369	845,531
1988	59,671	61,290	1,619,473	6,528	778,271
1989	54,721	90,803	1,665,513	29,529	1,013,801
1995	57,034	328,311	1,436,609	9,863	987,526
1997	98,860	117,615	1,048,384	0	1,186,050
1998	90,331	149,764	862,631	0	1,371,080
1999	84,778	115,275	876,094	0	1,719,940
2000	143,330	294,755	1,125,420	0	1,458,350
2001	111,466	277,264	722,843	0	1,253,470
2002	114,546	465,612	979,456	153,452	1,111,690
2003	158,077	818,619	681,985	114,968	1,472,470
2004	207,606	730,026	829,613	132,218	1,008,510
2005	241,657	650,836	769,395	86,092	1,396,700
2006	240,340	805,751	753,980	55,019	1,696,220
2007	414,292	599,091	623,274	34,848	1,575,080
2008	386,240	772,236	647,306	27,399	1,749,160
2009	316,754	799,215	637,284	31,553	1,578,320
2010	304,141	818,842	599,260	40,449	1,808,720
2011	385,640	929,556	649,681	62,856	1,270,030
2012	606,859	967,938	435,557	45,529	1,332,380
2013	637,966	1,052,520	372,592	43,951	1,256,890
2014	466,092	1,198,340	472,466	55,425	1,188,740
2015	448,223	1,091,880	544,222	53,201	1,229,480

Table 8. USDA NASS derives land use trends for South Dakota counties that approximately span the Landsat paths in figure 6 (red squares).

Year	Corn (ha.)	Soy (ha.)	Corn-Soy (ha.)	Wheat (ha.)	Alfalfa (ha.)
1984	541,809	169,371	711,180	457,853	0
1985	585,144	150,174	735,318	505,238	0
1986	548,411	169,938	718,349	505,440	0
1987	528,647	199,139	727,785	458,136	0
1988	481,667	280,341	762,008	404,838	0
1989	514,472	320,882	835,353	493,817	0
1990	591,138	310,554	901,692	562,869	0
1991	635,364	355,833	991,197	450,522	0
1992	642,938	361,058	1,003,995	598,671	0
1993	537,800	298,931	836,730	489,605	0
1994	671,895	401,558	1,073,453	464,738	0
1995	426,870	420,026	846,896	295,812	0
1996	723,735	480,776	1,204,511	574,088	327,645
1997	670,883	640,265	1,311,147	447,647	316,710
1998	694,170	709,682	1,403,852	388,557	311,445
1999	644,112	863,339	1,507,451	325,337	298,485
2000	768,488	958,797	1,727,285	298,890	337,365
2001	674,325	982,814	1,657,139	194,279	384,345
2002	617,463	883,062	1,500,525	267,989	385,560
2003	781,772	899,829	1,681,601	341,901	375,030
2004	838,512	886,626	1,725,138	371,466	346,680
2005	785,336	838,431	1,623,767	430,434	308,610
2006	599,036	854,793	1,453,829	409,415	282,690
2007	872,492	693,320	1,565,811	485,595	271,755
2008	849,204	895,982	1,745,186	379,850	247,050
2009	925,344	930,123	1,855,467	348,665	263,250
2010	826,929	905,175	1,732,104	243,527	235,305
2011	959,810	914,126	1,873,935	227,489	205,205
2012	963,617	1,010,151	1,973,768	150,802	138,364
2013	1,047,330	893,309	1,940,639	86,913	91,105
2014	937,778	1,067,661	2,005,439	164,074	84,993
2015	797,081	765,126	1,562,207	111,764	59,454

Table 9. USDA NASS derives land use trends for North Dakota counties that approximately span the Landsat paths in figure 6 (black squares).

Year	Corn (ha.)	Soy (ha.)	Wheat (ha.)	Alfalfa (ha.)
1984	80,069	62,127	847,625	178,889
1985	56,417	30,780	879,255	191,160
1986	66,258	24,300	1,005,453	176,378
1987	61,196	33,332	939,479	178,403
1988	38,678	65,489	704,255	118,463
1989	54,594	49,289	1,084,955	170,910
1990	52,448	27,216	1,206,536	165,645
1991	69,944	38,759	1,075,356	158,031
1992	67,028	45,846	1,382,225	155,723
1993	40,136	30,294	1,320,584	193,955
1994	57,794	31,023	1,320,786	161,555
1995	52,610	29,120	1,248,939	156,978
1996	69,255	50,706	1,428,435	183,060
1997	69,903	99,144	1,266,476	192,780
1998	113,076	177,512	926,235	150,255
1999	75,857	132,840	735,440	155,723
2000	136,688	265,680	876,339	142,965
2001	103,194	348,705	912,830	162,000
2002	165,038	505,076	780,273	168,075
2003	202,743	632,975	780,840	157,140
2004	184,559	806,598	738,072	161,190
2005	217,850	641,034	844,628	165,645
2006	268,070	878,040	719,442	153,293
2007	473,931	685,301	742,082	165,645
2008	459,068	869,697	759,254	170,910
2009	327,483	870,062	695,993	172,125
2010	375,354	940,127	698,706	155,925
2011	417,393	927,936	673,313	128,385
2012	691,295	1,004,319	382,413	79,664
2013	596,282	995,612	157,667	57,470
2014	355,914	1,131,489	420,593	42,606
2015	421,646	1,136,754	416,016	93,907

Table 10. NRCS NRI derived land use trends for South Dakota counties that approximately span the Landsat paths in figure 6 (red squares).

Year	**Corn** (*ha.*)	**Soy** (*ha.*)	**Corn-Soy** (*ha.*)	**Wheat** (*ha.*)	**Hay/Pasture/CRP** (*ha.*)
1984	838,958	131,544	970,502	428,531	888,692
1985	843,818	123,404	967,221	468,099	843,858
1987	668,412	200,151	868,563	498,960	863,379
1989	728,636	317,966	1,046,601	482,031	812,309
1990	701,582	292,653	994,235	570,605	803,925
1991	770,634	350,771	1,121,405	466,925	790,074
1992	840,578	361,220	1,201,797	541,931	984,555
1994	850,865	413,627	1,264,491	448,659	1,023,557
1995	608,391	470,246	1,078,637	287,145	1,047,614
1996	857,304	473,769	1,331,073	515,930	1,026,270
1997	756,621	713,367	1,469,988	407,471	1,030,766
1998	910,724	703,809	1,614,533	331,655	994,437
1999	814,739	827,334	1,642,073	311,040	1,004,927
2000	925,628	968,517	1,894,145	313,268	932,391
2001	858,357	1,054,418	1,912,775	179,861	919,958
2002	994,964	912,222	1,907,186	267,462	915,665
2003	955,841	942,192	1,898,033	335,300	921,740
2004	962,888	981,558	1,944,446	366,606	872,937
2005	979,736	873,018	1,852,754	454,532	871,722
2006	962,564	919,310	1,881,873	378,392	860,301
2007	1,075,437	849,690	1,925,127	430,191	847,584
2008	1,006,506	976,374	1,982,880	461,052	747,144
2009	1,001,444	1,026,716	2,028,159	386,249	751,154
2010	1,052,069	961,916	2,013,984	380,133	752,328

Notes: Corn-Soy (*ha.*) means corn hectares plus soybean hectares.

Table 11. NRCS NRI derived land use trends for South Dakota counties that approximately span the Landsat paths in figure 6 (black squares).

Year	**Corn** (*ha.*)	**Soy** (*ha.*)	**Wheat** (*ha.*)	**Hay/Pasture/CRP** (*ha.*)
1984	157,262	15,390	1,215,081	535,977
1985	170,789	9,882	1,146,879	538,691
1987	134,096	36,410	1,338,809	649,904
1989	121,743	48,762	1,380,686	492,683
1990	116,883	28,472	1,482,422	498,353
1991	119,799	34,628	1,238,409	481,100
1992	138,065	43,862	1,539,284	888,044
1994	114,777	31,226	1,495,463	878,769
1995	90,356	39,569	1,460,106	892,053
1996	112,631	33,494	1,567,431	869,130
1997	94,041	89,384	1,394,496	884,115
1998	193,671	159,813	1,234,319	882,657
1999	139,118	200,394	1,238,895	932,229
2000	155,561	293,423	1,156,397	954,383
2001	186,057	343,116	1,103,544	941,828
2002	200,921	567,689	1,024,407	927,045
2003	254,097	700,488	904,001	932,756
2004	447,525	775,899	752,976	922,712
2005	190,472	740,219	1,028,295	916,637
2006	341,982	1,049,031	732,038	903,272
2007	527,351	740,097	815,184	899,384
2008	616,977	882,941	735,480	857,426
2009	347,976	926,924	777,519	834,381
2010	449,024	925,911	809,231	797,202

Notes: Grass hectares were calculated from the sum of acreage under 'Hay', 'Pasture' and 'CRP' categories of the NRI dataset.

FIGURES

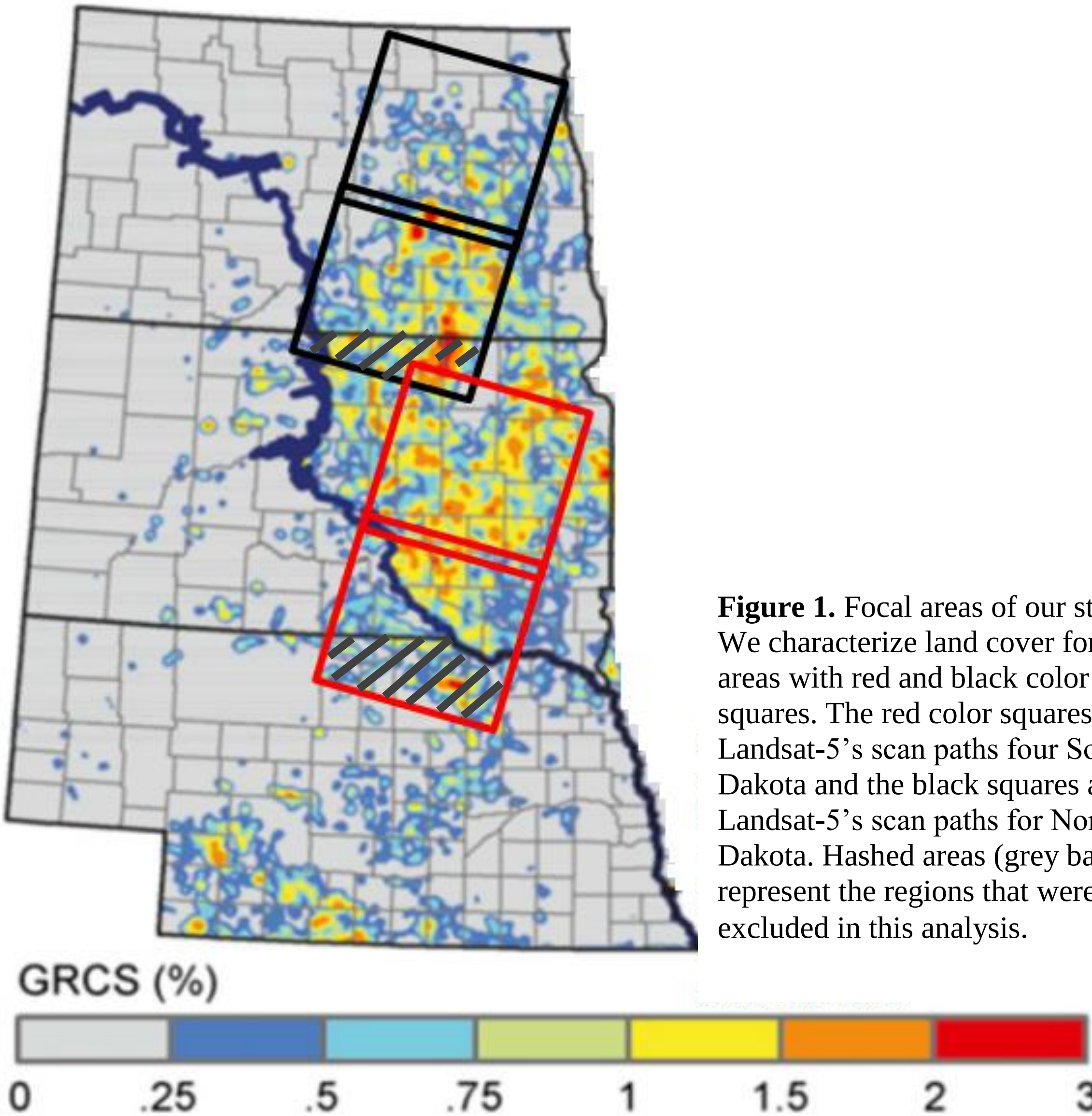


Figure 1. Focal areas of our study. We characterize land cover for areas with red and black color squares. The red color squares are Landsat-5's scan paths four South Dakota and the black squares are Landsat-5's scan paths for North Dakota. Hashed areas (grey bars) represent the regions that were excluded in this analysis.

Notes: This image has been adapted from Wright and Wimberly (2013). The color gradient provides heat maps to visualize absolute change from grass to corn/soy categories.

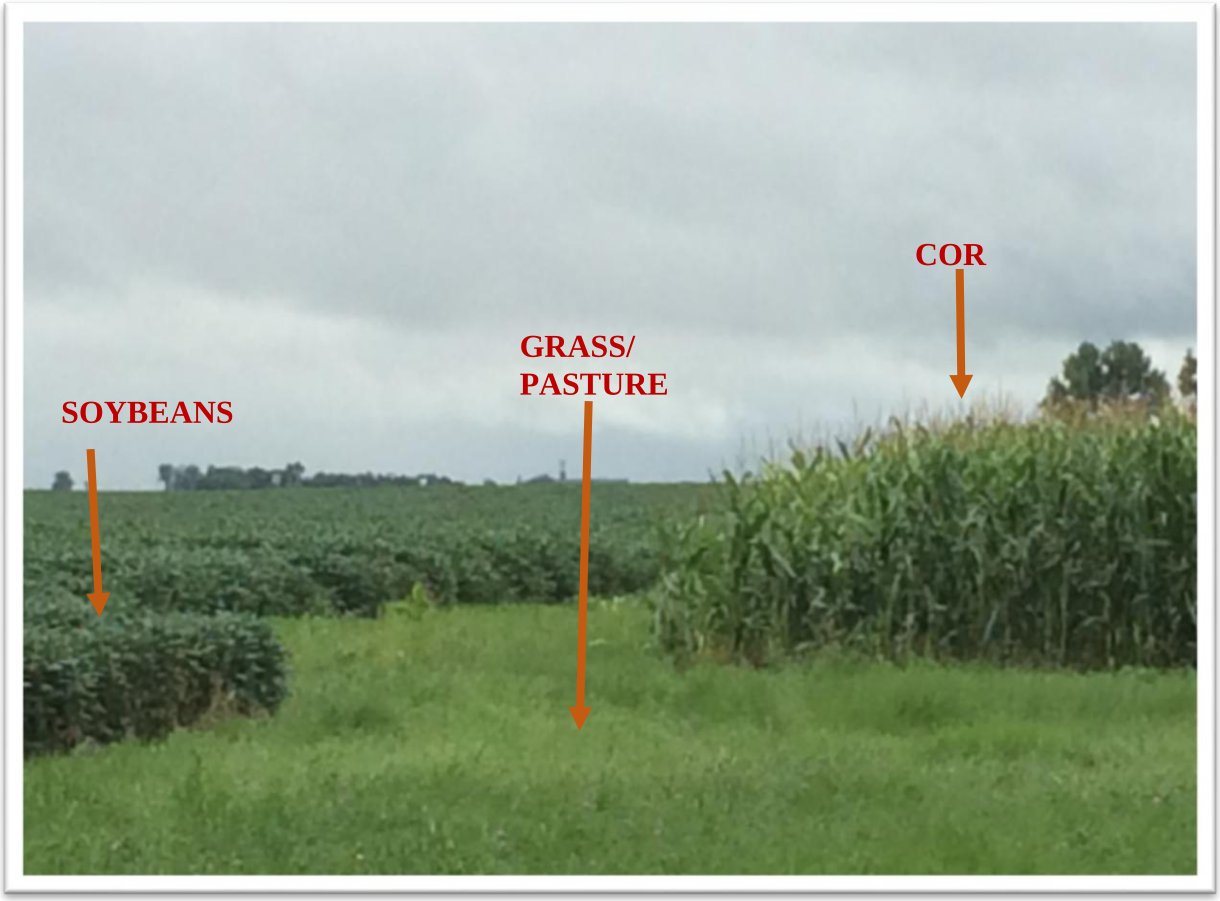
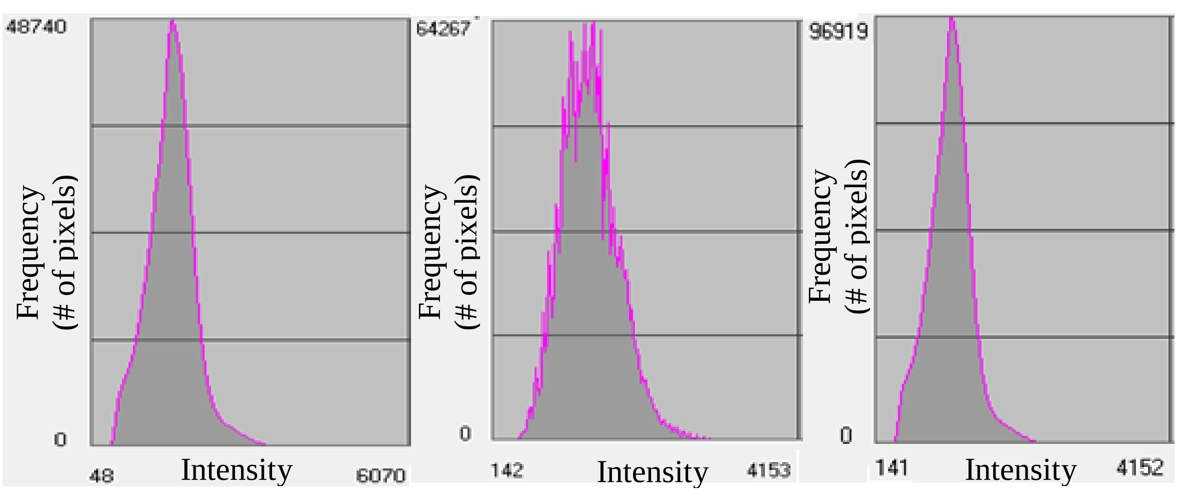
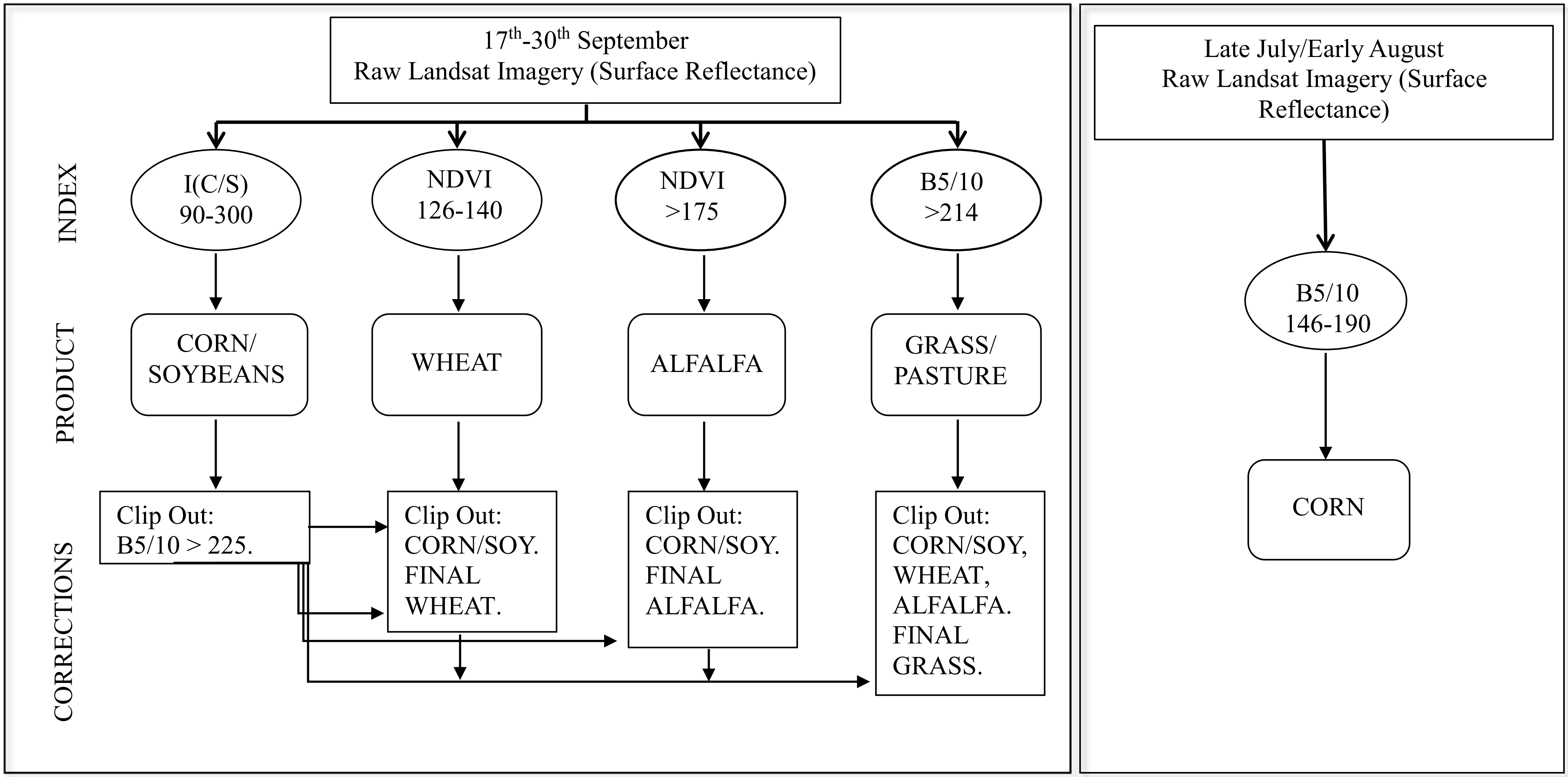


Figure 2. Near 276th Street, Lennox, SD on August 18, 2015. Photo Credits: Peter Wolter.



(a) **(b)** **(c)**

Figure 3. Histograms of the recorded intensity by **band B1** for: **(a)** raw Landsat-8 “9/27/2015” image; **(b)** raw Landsat-5 “9/26/2009” image; and **(c)** rescaled band intensity for Landsat-8 “9/27/2015” image to Landsat-5 “9/26/2009”’s level.



(a) **(b)**

Figure 4. (a) SD September Algorithm to classify Corn-Soybeans, Wheat, Alfalfa and Grass' **(b) SD July-August Algorithm** to classify Corn. We overlay developed lands, forest, wetlands, shrubs and surface water categories from NLCD 2006 to obtain the final product.

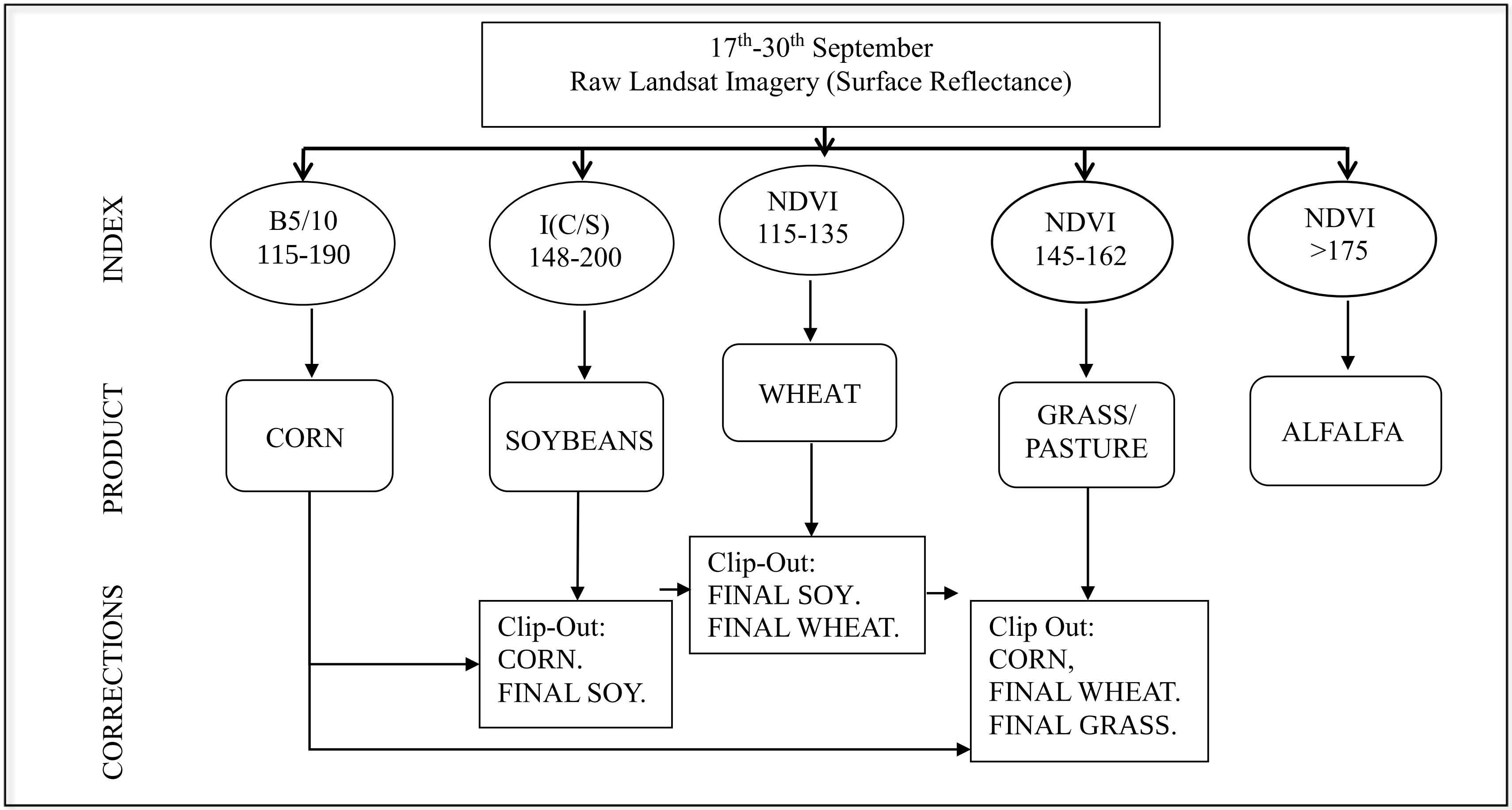


Figure 5. ND September Algorithm to classify Corn, Soybeans, Wheat, Alfalfa and Grass. We overlay developed lands, forest, wetlands, shrubs and surface water categories from NLCD 2006 to obtain the final product.

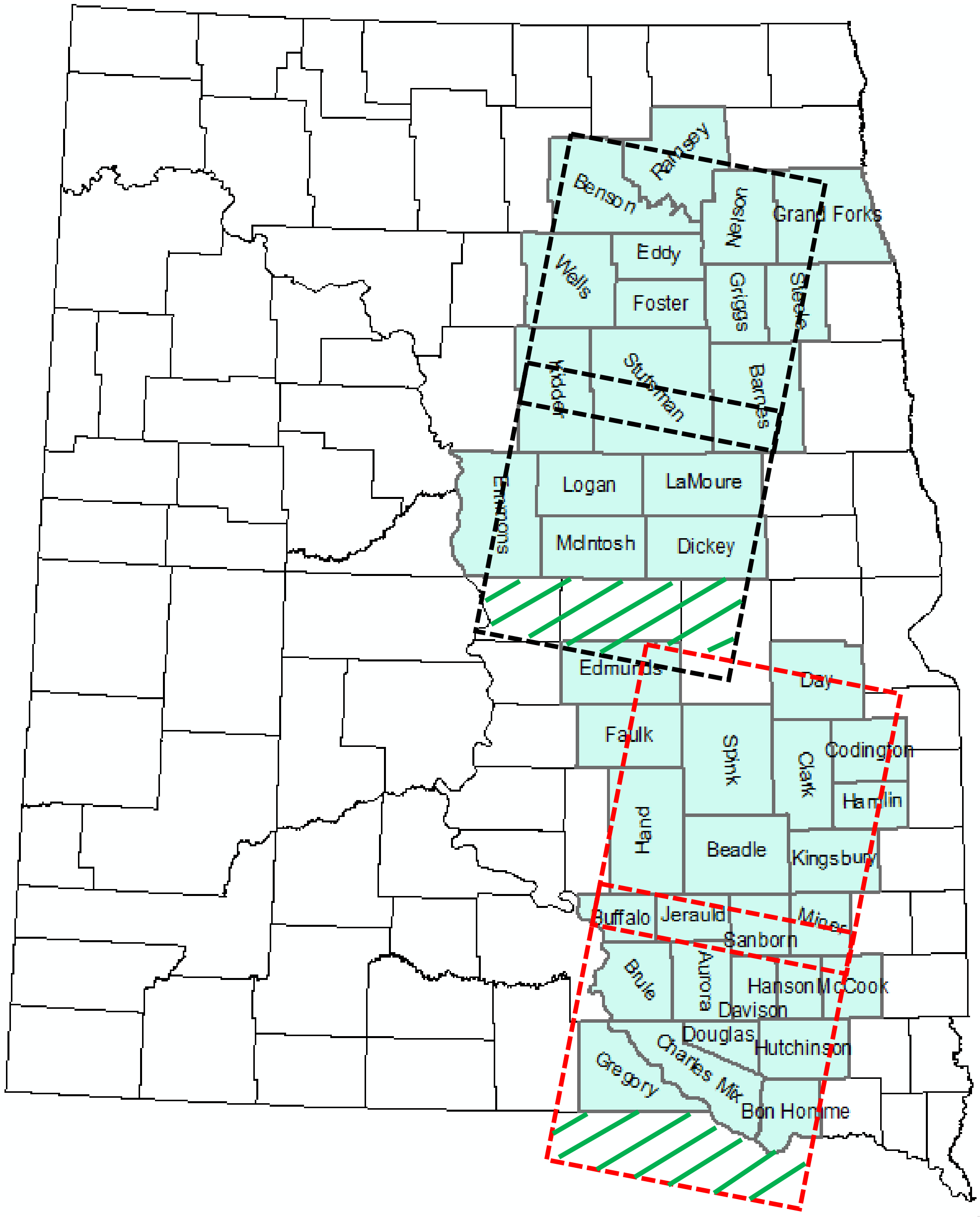
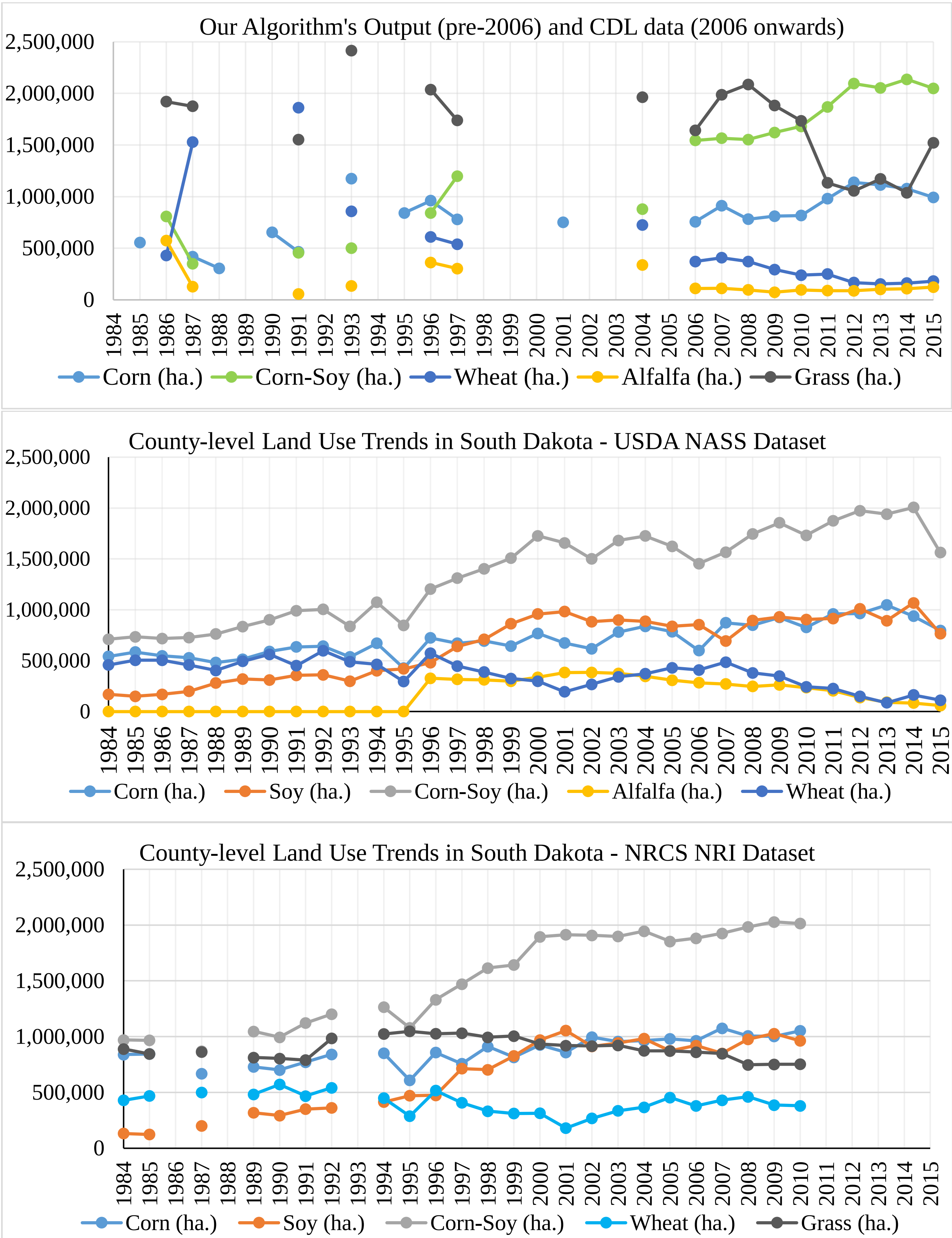
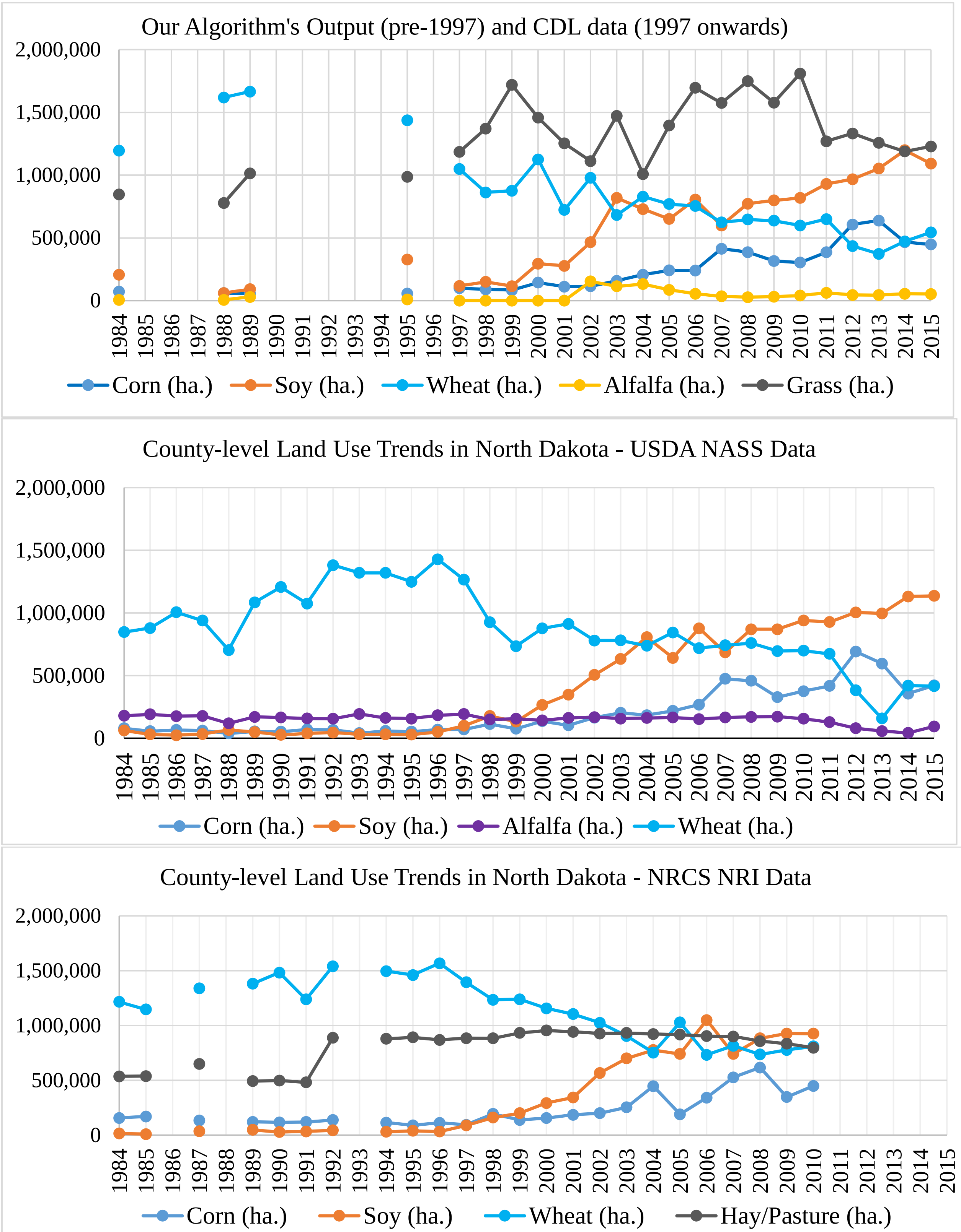


Figure 6. Dakotas' counties that (approximately) span the Landsat paths. Hashed areas (green bars) represent the regions that were excluded in this analysis.



Figures 7-9. Land Use Trends for South Dakota



Figures 10-12. Land Use Trends for North Dakota

REFERENCES

Anderson, D.P., Richardson, J.W., Smith, E.G. 2001. "Post-Freedom to Farm Shifts in Regional Production Patterns," Agricultural and Food Policy Center, Department of Agricultural Economics, Texas Agricultural Experiment Station, Texas Cooperative Extension, Texas A & M University.

Arora, G., Wolter, P.T., Feng, H., Hennessy, D.A. 2016a. "Land use and policy in Iowa's Loess Hills Region," *Sustainable Agriculture Research*, 5(4): 30-45.

Arora, G., Wolter, P.T., Feng, H., Hennessy, D.A. 2016b. "Role of ethanol plants in Dakotas land use change: incorporating flexible trends in difference-in-difference framework with remotely sensed data," *Center for Agricultural and Rural Development Working Paper* #16WP 564. http://www.card.iastate.edu/publications/synopsis.aspx?id=1250

Baker, A., Zahniser, S. 2006. "Ethanol reshapes the corn market," *Amber Waves*, 4(2), 30.

Boryan, C., Yang, Z., Di, L. 2012. "Deriving 2011 cultivated land cover data sets using USDA National Agricultural Statistics Service historic Cropland Data Layer," In *2012 IEEE International Geoscience and Remote Sensing Symposium* (pp. 6297-6300).

Boryan, C., Yang, Z., Mueller, R., Craig, M. 2011. "Monitoring US agriculture. The US Department of Agriculture, National Agricultural Statistics Service. Cropland Data Layer Program," *Geocarto International, 26*(5): 341-358.

Cardwell, V.B. 1982. "Fifty years of Minnesota corn production: Sources of yield increase," *Agronomy Journal*, 74(6): 984-990.

Claassen, R., Cooper, J.C., Carriazo, F. 2011. "Crop Insurance, Disaster Payments, and Land Use Change: The Effect of Sodsaver on Incentives for Grassland Conversion," *Journal of Agricultural and Applied Economics*, 43: 195-211.

Congalton, R.G. 1991. "A review of assessing the accuracy of classifications of remotely sensed data," *Remote sensing of environment*, 37(1): 35-46.

Fry, J.A., Coan, M.J., Homer, C.G., Meyer, D.K., Wickham, J.D. 2009. "Completion of the National Land Cover Database 1992-2001 land cover change retrofit product," *U.S. Geological Survey Open-File Report* #2008-1379, 18 p. http://www.mrlc.gov/nlcdrlc.php.

Homer, C., Dewitz, J., Fry, J., Coan, M., Hossain, N., Larson, C., Harold, N., McKerrow, A., VanDriel, J.N., Wickham, J. 2007. “Completion of the 2001 national land cover database for the conterminous United States.” *Photogrammetric Engineering and Remote Sensing*, 73(4): 337.

Homer, C.G., Dewitz, J.A., Yang, L., Jin, S., Danielson, P., Xian, G., Coulston, J., Herold, N., Wickman, J., Megown, K. 2015. “Completion of the 2011 National Land Cover Database for the conterminous United States-Representing a decade of land cover change information,” *Photogrammetric Engineering and Remote Sensing*, 81(5): 345-354.

Hunt, E.R., Rock, B.N. 1989. “Detection of changes in leaf water content using near-and middle-infrared reflectances”. *Remote sensing of environment*, 30(1): 43-54.

Johnston, C.A. 2014. “Agricultural expansion: land use shell game in the US Northern Plains,” Landscape ecology, 29(1): 81-95.

Karlen, D.L., Hurley, E.G., Andrews, S.S., Cambardella, C.A., Meek, D.W., Duffy, M.D., Mallarino, A.P. 2006. “Crop rotation effects on soil quality at three northern corn/soybean belt locations,” *Agronomy Journal*, 98(3), 484-495.

Lark, T.J., Salmon, J.M., Gibbs, H.K. 2015. “Cropland expansion outpaces agricultural and biofuel policies in the United States,” *Environmental Research Letters* 10(4):044003

Lauck, J. 2000. “After Deregulation: Constructing Agricultural Policy in the Age of Freedom to Farm,” *Drake J. Agric. L.*, 5, 3.

Phillips, D.L., Lee, J.J., Dodson, R.F. 1996. “Sensitivity of the US corn belt to climate change and elevated CO_2: I. Corn and soybean yields,” *Agricultural Systems*, 52(4): 481-502.

Reitsma, K.D., Clay, D.E., Clay, S.A., Dunn, B.H., Reese, C. 2016. “Does the U.S. Cropland Data Layer provide an accurate benchmark for land use change estimates?,” *Crop Economics, Production & Management*, 108(1): 266-272.

Rashford, B.S., Walker, J.A., Bastian, C. T. 2011. “Economics of grassland conversion to cropland in the Prairie Pothole Region,” *Conservation Biology*, 25(2): 276-284.

Rouse, J.W., Haas, R.H., Schell, J.A., Deering, D.W. 1974. “Monitoring vegetation systems in the Great Plains with ERTS,” *Proceedings of the 3rd ERTS Symposium* (pp. 1, 309–317), NASA SP-351 Washington D.C.: U.S. Government Printing Office.

Stephens, S.E., Walker, J.A., Blunck, D.R., Jayaraman, A., Naugle, D.E., Ringelman, J.K., Smith, A.J. 2008. “Predicting risk of habitat conversion in native temperate grasslands,” *Conservation Biology*, 22(5):1320-1330.

US Department of Agriculture, National Agricultural Statistics Service (2017). Quick Stats 2.0. Available at https://quickstats.nass.usda.gov/. Accessed January 7, 2017.

Wallander, S., Claassen, R., Nickerson, C. 2011. “The ethanol decade: an expansion of US corn production, 2000-09,” *USDA-ERS Economic Information Bulletin*, August (79).

Wright, C.K., Wimberly, M.C. 2013. “Recent land use change in the Western Corn Belt threatens grasslands and wetlands,” *Proceedings of the National Academy of Sciences of U.S.A*, 110:4134-4139.

CHAPTER 5

CONSERVATION EASEMENT ACQUISITIONS AMIDST LOCALIZED SPILLOVER EFFECTS IN GRASSLAND CONVERSIONS: ANALYSIS USING REMOTELY-SENSED DATA

(PAPER IV)

by

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ABSTRACT

We evaluate the efficiency of past conservation easement allocations in protecting the grasslands of the Prairie Pothole Region. We focus on the permanent grass conversions in eastern North Dakota during 1997-2015. Our spatio-temporal analysis suggests that the region's existing croplands and grasslands occur as large, contiguous tracts where permanent grass conversions occurred in proximity of the crop-intensive areas. We conjecture that localized spillovers exist in this region's land use decisions and present a game-theoretic framework of binary choices to evaluate easement allocations when strategic complementarities exist among private landowners. We find that that easement allocations are more cost-effective when acquired as contiguous tracts and on lands that provide weak cropping incentives, e.g. poor soils. We empirically validate our conjecture of localized spillovers by employing a duration modelling framework. We find that higher grass density inhibits the risk of conversion in its locality, and that easements are strategic complements to higher grass acres with regards to inhibiting conversion risks. The fact that past easements were acquired as relatively large tracts and on poorer quality soils is encouraging because our analytical findings would suggest that these easements were allocated in a cost-effective manner.

Introduction

The U.S. Prairie Pothole Region (PPR) is a biodiversity-rich ecosystem sustained by its mixed-prairie grasslands and wetlands. The perennial grasses generate ecosystem services, provide nesting and breeding habitat for the local waterfowl species, and allow for livestock production. On the east of the Missouri River in North and South Dakota there exists a grass-crop frontier along the western fringes of the Western Corn Belt (WCB, see figure 1). Grasslands enhance agricultural productivity of this region by sustaining its erosive soils. Dakota's grasslands are a valuable natural resource largely under private ownership and subject to conversion when crop returns are high. Almost 670,000 acres of grasslands were converted to corn/soy cultivation in these states between 2006 and 2011 (Wright & Wimberley 2013). Past economic analyses suggest that several factors drive grassland conversions in the PPR including commodity prices, soil quality (Rashford et al. 2010; Wang et al. 2016), neighborhood cropping-density (Stephens et al. 2008), technology and crop insurance policies (Wang et al. 2016). Incentive-based land retirement policies exist to motivate the PPR's private landowners to conserve their grasslands.

Acquiring conservation easements is a key policy tool of the U.S. Fish and Wildlife Service (FWS) and its partners to protect remaining grasslands in the PPR. Under this policy, landowners voluntarily enter a perpetual contract with the agency to give up their right to cultivate in lieu of a one-time payment, while still retaining ownership of the land. The FWS and its partner agencies raised Duck Stamp funds and acquired about 2.3 million acres of grassland easements since the 1950s (U.S. GAO, 2007), 80% of which lie in the Dakotas (FWS, 2011; Walker et al. 2013). The agencies plan to enroll additional 12 million acres in future in order to sustain the region's grassland bird habitat. However, at the current acquisition rate and insufficient funds could mean that the agency would not reach this goal for another 150 years (U.S. GAO, 2007). Such budget constraint impediments are even greater when land values are rising, as they have in the Dakotas where only 30% of lands could be eased during 2008-’12 relative to 1998-2012 with similar fund allocation (Walker *et al.* 2013). U.S. GAO (2007) recommended acquiring low cost, high-priority habitat, whereby, for example, FWS could have conserved 50% more land in 2006. Rashford et al. (2010) and Stephens et al. (2008) too made similar recommendations.

Various aspects of the incentive-based conservation policies, including the conservation easements, have been analyzed in the literature that are relevant for this study. Walker et al. (2013) recently reported that past easement acquisitions focused mainly on the abundance of waterfowl breeding pairs, visualized in figure 2, in the Dakotas’ PPR. The authors developed a spatially-delineated categorization of the remaining PPR’s grasslands based on the land’s ecological value, soils and acquisition costs. They ranked parcels into categories I-III to prioritize acquisition, with ‘highest duck-pair density, highest conversion risk and least costly’ lands in category-I to be acquired first. However, acquisitions based on this scheme would conserve a fragmented ecological reserve if all category-I lands are acquired first (see pp. 275 figure 7 in Walker et al. 2007). This is suboptimal for deriving ecological benefits as the conservation biology literature suggests that connected habitats are more beneficial to sustaining the supported species as compared to isolated habitats (Johnson et al. 2010; van Nouhuys, 2009).

Miao et al. (2016) recently developed a two-period model to evaluate landowners’ willingness to accept towards easing their lands in a dynamic setting of their conversion decisions. Their findings suggested that acquiring easements when landowners are uncertain about cropping/grazing returns should be avoided as their willingness to accept would be high in such a scenario even when their propensity to convert would be low.

Johnson et al. (2010) have identified large, contiguous patches of remnant prairie that would allow conserving the PPR's grassland bird population. The importance of conserving such contiguous spatial habitat arrangement for specie-protection has also been recognized in the economics literature. Economists have proposed agglomeration bonuses to promote voluntary conservation of contiguous parcels through land retirement policy. Drechsler et al. (2010) found that a policy that provides a premium towards newly retired lands that border previously conserved reserves generates efficiency gains relative to the spatially homogenous conservation payments. Parkhurst et al (2002) suggested that agglomeration bonus would enhance the chances of conserving contiguous habitat reserves, whereas a no-bonus scenario always lead to fragmented habitat reserves.

In this paper, we study grassland conversions and the role of easements therein when land use related returns (costs and benefits) are spatially dependent in a locality. We conjecture that local spillovers exist from the advent of more cropped land in an area such that the spatially connected cropland will provide higher cropping incentives than the same amount of spatially separated land. When more cropland emerges in a locality the cropping costs may decline as more agricultural services and related infrastructure like tillage equipment, tillage entrepreneurs and input suppliers enter the area. Similarly, higher density grassland in the area may inhibit conversions as the cost of grass-based production would be lower than crop-based production. So the strategically placed easements could complement grass acres in an area and disrupt the network of croplands to inhibit further conversion. In that sense, we extend the conservation targeting literature by examining the effectiveness of easement acquisitions when grassland conversions are dependent on the localized spillovers on a parcel's cost of conversion.

To the best of our knowledge, ours is the first study to consider the role of networks in conservation planning by easement acquisitions. We first develop a conceptual model with strategic complementarities among farmers who are deciding upon 'convert to crop' or 'stay in grass' options. We present analytical results as well as simulations of land use decisions when social spillovers are present in landowner payoff function. We compare the welfare effects of acquiring spatially connected easements from when the agency acquires easements in isolation. We then conduct an empirical analysis to test for the existence of social spillovers in the region's land use dynamics. We employ remote sensing tools and implement a hazard modelling framework to estimate the risk of permanent grass conversion to crop. We evaluate how the risk of conversion varies local grass-density and the presence of easements.

This paper is divided into several sections. We first discuss our empirical and economic basis for considering strategic complementarities in the Dakotas' land use decisions. We then present a game-theoretic model of permanent grassland conversions and the related analytical results on the role of easements, followed by simulation results. We then underline our empirical strategy, present our estimation results, and conclude with a brief discussion.

Spatial Spillovers in Grassland Conversions: Motivation

Our conjecture that localized spillovers exist in Dakotas' land use conversion decisions is based on an exploratory analysis of this region's past land use changes. We utilize the spatially-delineated pixel-level imagery from USDA's Cropland Data Layers (CDL) that characterize land use in North Dakota during 1997-2015. We condense the land uses in the longer time-series in North Dakota into two categories: crop (c) and grass (g). We then characterize all possible sequences of pixel-level transitions between *c* and *g* during 1997-2015. There are four possible land use switches between every consecutive year: *c* to *c*; *c* to *g*; *g* to *c*; and *g* to *c*, and so 2^{19} possible land use switching combinations for each 30m pixel during 1997-2015. To characterize long-term changes we focus on three specific combinations: always crop (C); always grass (G); and permanent grass to crop conversion (GC). The GC category represents pixels were *g* in 1997, underwent a single transition to *c*, and remained in *c* thereafter.

We map C, G, GC, and easement allocations during 1997-2015 in figure 3.[40] There are 759,043 permanent cropland acres located mostly on the east, 189,231 permanent grassland acres located mostly on the west of the study region. While C and G resemble large, contiguous tracts, GC switches occurred in proximity of permanent croplands. Moreover, easements seem to have been allocated near permanent grasslands, away from the observed conversions. This seems to suggest that easements were allocated in localities where lands did not convert anyway. These observations signify the scope in accounting for network effects in studying grassland conversions and evaluating the efficiency of existing easements.

The observed spatial conformity in landowner choices towards crops or grass and GC transitions being proximate to the existing croplands lead us to conjecture that these production systems exhibit strategic complementarity. That is, higher cropping density in an area seems to incentivize more cropping, and likewise higher grasses seem to have lowered the incentive to crop. The economic argument for such conformity is that strategic complementarity exists in the cost of production among neighboring landowners. To formally express cost complementarity we denote a price-taking farmer *i*'s profit from producing quantity q_i as $\pi_i = pq_i - C(q_i, q_j, w)$

[40] See National Conservation Easement Database http://www.conservationeasement.us/projects

where p is price of output, and $C(.)$ is the cost of production that depends on q_i, average local output q_j, and input price w. Crop complementarity exists when i's marginal cost is decreasing in local output level, i.e. $\partial^2 C / \partial q_i \partial q_j < 0$. The plausible scenarios of cost complementarity are when cropping attracts grain elevators, ethanol plants better roads, insurance agents and entrepreneurs, which in turn attract more cropping since costs are lowered as access to demand terminals and supporting services increases.

Model

Our conceptual framework is motivated from Brock and Durlauf's (2001) binary choice model with social interactions. The authors implemented a statistical mechanical structure to account for average group behavior in the utility maximization problem. This study drew a mathematical connection between the localized interactions among atoms on a lattice to produce a magnet and the interactions among decision-makers in a socioeconomic environment to determine their aggregate economic behavior (Durlauf, 1999). Brock and Durlauf (2001) adapted a mean-field version of the Curie-Weiss model that accounts for mean group behavior to analytically derive equilibrium decision in an interconnected population. The Curie-Weiss model is an advanced version of a simple and the more popular statistical mechanical model, known as the Ising model (Ellis, 1985 Ch. IV). The Ising model accounts for pairwise interactions among neighbors as opposed to average behavior in the Curie-Weiss model, and yet both models provide qualitatively similar results (Ellis, 1985). The mean-field version was specifically designed to facilitate analytical solution in case of the many-body systems on four-or higher dimensional lattices. We choose to adapt the Ising model to study grassland conversions because ours is a two-dimension lattice with heterogeneous grasslands distributed across the eastern

Dakotas. This approach also offers the following advantages over the Brock and Durlauf's (2001) framework.

While Brock and Durlauf (2001) provided equilibrium results for a single neighborhood designated as population, our framework will accommodate multiple neighborhoods that may interact though nodal agents to generate equilibrium strategies. In particular, social spillovers from an agent's actions are only localized and all of his/her designated neighbors may not be neighbors to each other. Furthermore, accounting for pairwise interactions will allow simulating the game's Nash equilibria using a simple algorithm on a standard statistical package. Our model extensions to incorporate heterogeneous agents and analyze easement allocations are more tractable with pairwise interactions among agents.

We model permanent grass conversions as a one-shot simultaneous move game among non-cooperative landowners to accommodate localized spillovers in grassland conversions. Formally, a representative agent *i* among *I* grassland owners chooses to either 'stay in grass' or 'convert to crop'. The binary choice set of each individual is denoted as $a_i \in \{-1,1\}$, where $-1 \triangleq$ stay in grass and $1 \triangleq$ convert to crop. We denote the game's strategy set as $a = \prod_{i \in I} a_i$, and the strategy set of all players other than i as $a_{-i} = (a_1, a_2, ..., a_{i-1}, a_{i+1}, ..., a_{I-1}, a_I)$. To study localized spillovers among neighbors we define set $N_i \in I$ that contains *i*'s neighbors with $\# N_i = n_i$. Finally, we denote the game's payoff function as $\pi(a) = (\pi_i(a_i, a_{-i}))_{i=1}^{I}$, where

$$\pi_i(a_i, a_{-i}) = \pi_i^{a_i} + \sum_j \sigma_{ij}^{a_i, a_j}; \; a_j \subseteq a_{-i}, \; j \in N_i, \; i, j \in I \tag{1}$$

The total payoff for individual *i* from action a_i in equation (1) is assumed to be the sum of a private payoff component, $\pi_i^{a_i}$, and a social payoff component from localized spillovers,

$\sigma_{ij}^{a_i,a_j}$. The private payoff component is most likely driven by the tract-level soil quality, expected weather, access to the region's transport infrastructure and demand-terminals. The social payoff component is derived from *i*'s pairwise-interaction with his/her neighbors as specified in equation (1). For strategic complementarity to hold *i*'s payoff function must satisfy the property of increasing differences in each neighbor's choice, i.e. $\sigma_{ij}^{1,1} - \sigma_{ij}^{-1,1} > \sigma_{ij}^{1,-1} - \sigma_{ij}^{-1,-1}$ $\forall j \in N_i,\ i, j \in I$. That is, the option 'convert to crop' will generate higher payoff when each neighbor chooses to 'convert to crop' as well. Similarly, there will be a penalty from choosing to convert when neighbors choose to 'stay in grass'.

Agent *i* will choose $a_i = 1$ or 'convert to crop' only if $\pi_i(1, a_{-i}) > \pi_i(-1, a_{-i})$, or

$$\pi_i^1 - \pi_i^{-1} > -\sum_j (\sigma_{ij}^{1,a_j} - \sigma_{ij}^{-1,a_j});\ j \in N_i,\ i, j \in I$$

(2)

To facilitate further insights on the agent's decision problem we define $\sigma_{ij}^{a_i,a_j} = \sigma_1$ if $a_i = a_j$ or σ_2 if $a_i \neq a_j$, where $\sigma_1 > \sigma_2$ satisfies the increasing differences property for strategic complementarity to hold. Hence, equation (2) becomes $\pi_i^1 - \pi_i^{-1} > -(\sigma_1 - \sigma_2)n_i$. An alternative specification $\sigma_{ij}^{a_i,a_j} = Ja_i a_j$ with $J = (\sigma_1 - \sigma_2)/2 > 0$ leads to identical ramifications for equation (2), only now with a single parameter *J* that is proportional to the difference in payoffs from conforming to (σ_1) and defecting from (σ_2) each neighbor's action. This alternative functional was proposed by Brock and Durlauf (2001) with J as the strength of strategic complementarity to account for average group-behavior, i.e. $\sigma_{ij}^{a_i,a_j} = Ja_i n_i^{-1} \sum_{j \in N_i} a_j$, in social payoffs. We too model social interactions with parameter *J* for notational simplicity.

We briefly discuss the existence and various properties of Nash equilibria. Generally for one-shot simultaneous move games pure N.E. exist when each player's strategy set is complete, finite and compact, and $\pi_i(a_i, a_{-i})$ is continuous in (a_i, a_{-i}) and quasiconcave in a_i for all $i \in I$ (MWG, 1995 Ch. 8 pp. 253). Vives (1990) analyzed the games with strategic complementarity using the lattice approach and reported that payoffs may not be quasiconcave for pure N.E. to exist. His analysis suggested that the set of pure N.E. is non-empty for such games when the payoff function is supermodular in the game's strategy set ($a = \prod_{i \in I} a_i$ for our study). The concept of supermodularity and increasing differences coincide when a is a product of ordered sets (Topkis, 1978 Theorems 3.1-3.2; Vives, 1990). We designated our game's payoff functions to have strictly increasing differences earlier and the sets a_i are too (trivially) ordered for all *i*. Hence, pure N.E. exist four our permanent conversion game. Note that we do not need $\pi_i^{a_i}$ to be linear in a_i unlike Brock and Durlauf (2001) to ensure the existence equilibria. Vives (1990) also found that the set of pure N.E. consisted of the smallest and largest element from the game's strategy set, see Theorem 4.2 (i). This means that in this study all farmers deciding to 'stay in grass' or 'convert to crop' will be candidate equilibria. Echenique (2003) showed that in the games of strategic complementarity when individual strategy spaces are one-dimensional mixed strategy equilibria exist. However, Echenique and Edlin (2003) found that mixed strategy equilibria are unstable and reduce to the game's extremal equilibria when player's beliefs about the opponents play are slightly wrong. We focus on pure strategy N.E. for our analysis.

We now turn to characterizing Nash equilibria (N.E.) for this game. We present simulations to illustrate the analytical results for a special case of I = 6 players that are placed on a torus with three neighbors each (figure 4). Players i = 1, 2 and 3 are placed on the upper ring of the torus and i = 4, 5 and 6 on the lower ring. A 3-D structure of interconnectedness among agents is hoped to provide richer illustrations of the game's equilibria than a circle, especially among heterogeneous players. A simple algorithm to simulate the pure N.E. for this game using a statistical software package is provided in an appendix.

We next analyze grassland conversions with spatial spillovers for players with same private payoff towards cropping and staying in grass, i.e. homogenous agents, followed by an extension to heterogeneous agents with differing private payoffs. We finally apply our framework to evaluate easement allocations amidst localized spillovers.

Homogeneous Players

Homogenous players are assumed to have same private costs towards each choice, i.e. 'convert to crop' and 'stay in grasses'. We know from equation (2) that agent i chooses action a_i if $(\pi^{a_i} - \pi^{-a_i}) / J > -2a_i \sum_j a_j;\ j \in N_i,\ i, j \in I$. For notational convenience we will denote $\pi^{a_i} - \pi^{-a_i} \triangleq \Delta\pi^{a_i,-a_i}$ hereafter.

A set of strategies are N.E. when none of the agents can improve their payoff by unilaterally updating their strategy. So here N.E. is the set of strategies $\{a_i^*\}_{i=1}^{I}$ that satisfy the following condition

$$\frac{\Delta\pi^{a_i^*,-a_i^*}}{J} > -2a_i^* \sum_j a_j^*\ \forall\ i, j \in I, j \in N_i \qquad (3)$$

Equation (3) here is the equilibrium characterizing equation where the only unknown for each agent i is the neighbors' choices. Hence, we have our first result for this case.

R1: *When strategic complementarities exist among players with binary choices the N.E. is characterized by a ratio of the difference in the individual player's private payoffs from the two choices* ***to*** *the strength of strategic complementarity between the player and his/her neighbors*.

An interesting implication of **R1** is that higher $\Delta\pi^{1,-1}$ will have a similar consequence for the game's N.E. as would weaker spillover effects, i.e. lower *J*.

The right-hand-side (R.H.S) of equation (3) is bounded, i.e. $-2a_i\sum_j a_j \in [-2n_i, 2n_i]$. This means that if the left-hand-side (L.H.S.) $> 2n_i$ in equation (3), then *i* will choose $a_i = 1$, and if L.H.S. $< -2n_i \;\forall\; i$ then $a_i = -1$ is *i*'s unique payoff maximizing choice. An interpretation is that, given *J*, the landowners choose to crop (stay in grass) when the private payoffs towards cropping (grass-based land use) are strong enough to overcome any losses due to defecting neighbors. Since the bounds of R.H.S. in equation (3) are increasing in n_i, we need $\Delta\pi^{1,-1} > \max_i(2n_i)$ for all agents to convert to crop. Similarly, we need $\Delta\pi^{1,-1} < \min_i(2n_i)$ for all agents to stay in grass.

In addition, when private payoffs are relatively weak this game may generate multiple equilibria. To see this let's consider a case where $0 < \Delta\pi^{1,-1} \leq 2n_i$ for all *i* given *J*. Clearly, $a_i = 1\, \forall i$ is still a N.E. as a unilateral deviation by any player would decrease his/her total payoff by choosing to 'stay in grass' due to losses from social spillovers as all neighbors convert and the private payoff from cropping is relatively higher. However, $a_i = -1$ could maximize the total payoff when all of his/her neighbors choose to stay in grass. This is because in this scenario conforming to his/her neighbors would earn player *i* a total payoff $2n_i - \Delta\pi^{1,-1}$ higher than from converting to crop. Since $2n_i - \Delta\pi^{1,-1} \geq 0$, to 'stay in grass' is as good or a better option that 'convert to crop' for earning a higher payoff. Consequently, if L.H.S. $\in[-2n_i, 2n_i]\ \forall i$ then $a_i = -1\ \forall i$ will also constitute an equilibrium where no player could deviate unilaterally to improve their payoffs. However, the equilibrium where $a_i = 1\ \forall i$ will generate higher total payoffs for all players compared to $a_i = -1\ \forall i$ due to the initial condition $\Delta\pi^{1,-1} > 0$. So, our next result on permanent grassland conversions in presence of localized spillovers is as under.

R2: *The one-shot game of permanent grassland conversion supports multiple equilibria among neighbors when strategic complementarities are present. Whether a unique or multiple equilibria will emerge is characterized by a threshold,* $T = \max_i(n_i)$, *and the landowner's private incentives from conversion. The threshold that characterizes the game's equilibria depends on an agent's degree of interconnectedness or the number of neighbors.* That is, if

(i) $\left|\frac{\Delta\pi^{a_i,-a_i}}{J}\right| > T\ \forall i$, then there exists a unique equilibrium with $a_i^* = 1\ \forall i$ if $T > 0$ or $a_i^* = -1\ \forall i$ if $T < 0$.

(ii) $\left|\frac{\Delta\pi^{a_i,-a_i}}{J}\right| < T\ \forall i$, there exist multiple equilibria with $a_i^* = 1\ \forall i$, $a_i^* = -1\ \forall i$, and combinations of $a_i^* = 1$ for some agents and $a_i^* = -1$ for others. However, $a_i^* = 1(-1)\ \forall i$ is Pareto-superior or payoff-dominant for $\Delta\pi^{1,-1} > (<) 0$.

Example: We now turn to illustrating the analytical results **R1** and **R2** by simulating the N.E. for a specialized case where we fix *I* = 6, $n_i = 3\ \forall i$, *J* = 1 and vary $\Delta\pi^{1,-1}$. The simulation results are presented in tables 1-7. Tables 1-6 present the cases when the game of strategic complementarity with binary choices generate multiple N.E. This is in line with our result **R2 (ii)** that $\Delta\pi^{1,-1}/J \le 2n_i$ (= 6 here) generates multiple equilibria. Further, as soon as $\Delta\pi^{1,-1}/J > 2n_i (=6)$ is satisfied there is a unique N.E. such that all players convert, as we assert in **R2 (i).** Upon comparing tables 4 and 5 we find equilibrium choices to be identical given $\Delta\pi^{1,-1}/J$ remains the same, as asserted in **R1**. Although we present only one case where **R1** holds we find this true for all other cases (results not shown to save space).

We further observe that when $\Delta\pi^{1,-1}/J \le 2$ the game generates more than two N.E. In particular, when $\Delta\pi^{1,-1}/J < 2$ the game generates four N.E.: all players convert, none convert, and players on the upper (lower) ring convert and players on the lower (upper) ring do not convert. For $\Delta\pi^{1,-1}/J = 2$ the game generates three additional N.E., i.e. total seven N.E., where two out of three players on each ring convert and the remaining stays in grass. This observation of more than two N.E. for lower levels of $\Delta\pi^{1,-1}/J$ can be explained by the increased opportunity to stay in grass as private payoffs from conversion decrease while the extent of social spillovers remains fixed with constant *J* and n_i. These intermediate equilibria also exist due to the structure of a torus and the players' placement on the upper/lower rings. In addition, for all the cases with multiple equilibria we find the equilibrium where all players convert to crop to be Pareto superior as each player earns a higher payoff relative to the other equilibria.

Equilibrium Selection

Milgrom and Shannon (1994) showed for the games with strategic complementarities that pure strategy N.E are supremum and infimum of the set of equilibria obtained from the method of iterated elimination of strictly dominated strategies (Kultti and Salonen, 1997). Kultti and

Salonen (1997) built upon this work and showed that these extremal equilibria are 'undominated' to other pure and mixed strategy N.E. The authors defined undominated equilibrium as one where no player's strategy is weakly dominated by another pure strategy. For our study the undominated extremal equilibria are $a_i^* = 1\ \forall i$ and $a_i^* = -1\ \forall i$. We now seek to understand whether the deductive equilibrium selection principles of payoff-dominance (PD) and risk-dominance (RD) would allow us to select the solution of this game.[41]

The PD criterion selects the equilibrium where each player's payoff is strictly higher. That is, among the undominated equilibrium strategies $\{a_i^{*,pd}\}_{i=1}^{I}$ is payoff-dominant if

$$\pi_i(a_i^{*,pd}, a_{-i}^{*,pd}) > \pi_i(-a_i^{*,pd}, -a_i^{*,pd})\ \forall i \tag{4}$$

Clearly, $a_i^{*,pd} = 1$ if $\Delta\pi^{1,-1}/J > 0$ and $a_i^{*,pd} = -1$ if $\Delta\pi^{1,-1}/J = 0$.

However, a payoff-dominant best response offers strategic risk as a player's expectation about neighbors' choices may not be accurate. The RD criterion searches for an equilibrium that offers the highest payoff while exhibiting the least strategic risk. Harsanyi (1995) provided a theoretical basis for selecting among multiple equilibria and found that when PD and RD diverge on equilibrium selection, the selection criteria should be RD (or the N.E. with highest probability of emergence considering the strategic risk).

We now formally present the idea of a risk-dominance in the context of this study and evaluate the scenarios when RD and PD diverge. For each player *i*, there are $M = 2^{n_i}$ possible

41 In our illustrative example we find more than two N.E. when $\Delta\pi^{1,-1}/J \le 2$. Although additional N.E. exist other than $a_i^* = 1$ or $-1\ \forall i$ when $\Delta\pi^{1,-1}/J = 2$ but both strategies provide equal payoff on these additional equilibria. That is not the case when $\Delta\pi^{1,-1}/J < 2$ but we find extremal equilibria to be strictly Pareto superior here. Moreover, these additional equilibria emerge due to the structure imposed by the torus and number of neighbors assigned to each player. These factors are subjective to the analyst and so we will consider only the two extremal equilibria for our analysis.

distinct strategy vectors for i's neighbors $((a_{j,m})_{j\in N(i)})_{m=1}^{M}$. Let $m=1$ be the case when $a_j=-1$ $\forall j\in N_i$, and $m=M$ when $a_j=+1\ \forall j\in N_i$. Further, let $p_{i,m}$ be the subjective probability that i places on the neighbors' strategy vector m. We say a_i is risk-dominant strategy if $E_i\pi_i(a_i,a_j)>$ $E_i\pi_i(-a_i,a_j)$. That is,

$$\frac{\Delta\pi_i^{a_i,-a_i}}{J}>-2a_i\sum_m\sum_j a_{j,m}p_{i,m};\ j\in N_i, m=1,2,...,M \tag{5}$$

The strategy set that satisfies equation (5) for all i is the risk-dominant equilibrium. Now each player would assign $p_{i,m}>0$ only for set m that generates either of the game's undominated extremal N.E. So, we know that $p_{i,m}=0$ for $m = 2, 3,\ldots, m-1$ and $p_{i,1}+p_{i,M}=1$ with $(p_{i,1},p_{i,M})\geq(0,0)$. Hence, $a_i^*=1$ is i's risk-dominant strategy if

$$\frac{\Delta\pi_i^{1,-1}}{J}>-2n_i(2p_{i,M}-1);\ j\in N_i \tag{6}$$

Equations (4) and (6) suggest that among risk-neutral players, i.e. when $p_{i,1}=p_{i,M}=0.5$ for all i, $\Delta\pi_i^{1,-1}/J>0$ (<0) will imply $a_i^*=1\ \forall i$ $(a_i^*=-1)$ to be the game's N.E. based on the PD and RD criterion.

Heterogeneous Agents

We posit agent heterogeneity as allowing for different payoffs for players from similar decisions. Specifically, we allow variable private payoffs from conversion while keeping the strategic complementarity parameter J constant with cross-sectional invariance. Such a framework for analyzing heterogeneity is dual to varying parameter J while keeping the private payoffs same across players (as noted earlier in **R1**). We evaluate the impact of heterogeneous private payoffs on each player's profit maximization problem by examining its implications for equilibrium characterizing equation (3). For example, we know that $a_i = 1$ is *i*'s unique payoff maximizing strategy if $\Delta\pi_i^{1,-1} / J > -2\sum_j a_j$. Clearly, the condition for the strength of private conversion incentives towards 'convert to crop' uniquely maximizing *i*'s total payoff is less stringent when more number of players in his/her neighborhood 'convert to crop', i.e. $a_j = 1$. We now examine the implications of this intuition formally.

Consider a scenario where a fraction of player *i*'s neighbors 'convert to crop'. That means that these neighbors have $\Delta\pi_j^{1,-1} / J > T; j \in N_i$ satisfied, see **R2 (i)**. Such strong incentives to crop in a neighborhood may arise due to better soils, strong commodity basis and better access to demand-terminals, or due to idiosyncratic reasons like ability or willingness to crop. For the purpose of exposition we let N_i be the set of *i*'s neighbors who convert such that $\# N_i = n_i \in (0, n_i)$. Under this scenario, *i* will choose action $a_i = 1$ if

$$\frac{\Delta\pi_i^{1,-1}}{J} > -2\left(\sum_j a_j + n_i\right); \; j \in N_i \setminus N_i \tag{7}$$

Now, the R.H.S. in equation (7) is bounded in the range $[-2n_i, 2(n_i - 2n_i)]$. Therefore, when n_i of *i*'s neighbors are certain to choose to 'convert to crop', the threshold on $\Delta\pi_i^{1,-1} / J$ that ensures $a_i = 1$ is the payoff maximizing strategy is $4n_i$ units lesser than when $n_i = 0$. In other words, for every extra neighbor *j* who converts to crop with certainty, the threshold that $\Delta\pi_i^{1,-1} / J$ asserts conversion is payoff-maximizing is reduced by 4 units. An implication for the Dakotas is that the social spillovers from the pre-existing croplands would increase the propensity to convert on existing grasslands. Our model specification exhibits social spillovers favorable towards cropping to compensate for low private payoffs from conversion potentially leading to conversion on lands with moderate soil quality. The inference is symmetrically opposite for evaluating the 'stay in grass' option implying that higher grass density inhibits conversion on as the social payoffs lower the incentive towards conversion.

See that in our static framework landowners who are projected to 'convert to crop' or 'stay in grass' due to strong private incentives are similar to existing croplands or grasslands prior to those deciding upon conversion in a time-varying framework. This suggests that our analytical model in line with our earlier observation that recent permanent grassland conversions were 'islands' within large contiguous croplands in North Dakota. Hence, our next result.

R3: *Localized spillovers from existing or projected* (*with certainty*) *croplands or grasslands in a neighborhood encourage remaining decision-makers to ether* '*convert to crop*' *or* '*stay in grass*' *respectively by compensating for potentially moderate private payoffs. That is, agent i with has higher incentives towards choosing* $a_i = 1$ *than* $a_i = -1$ *when* $\sum_{j \in N_i} a_j > 0$, *and vice versa, irrespective of the relative private payoffs from two actions,* $\Delta\pi_i^{1,-1}$.

Example: We present three specialized cases to understand the implications of agent heterogeneity on individual land use decisions and the game's N.E.

(i) Set $\Delta\pi_i^{1,-1} = 6.1$ for $i = \{1, 4\}$. Our earlier analysis suggests that $a_1^* = a_4^* = 1$ irrespective of their neighbors' actions. Based on their pre-assigned positions all other players, say $k \in \{2, 3, 5, 6\}$, have exactly one neighbor who is projected to 'convert to crop' with certainty (see figure 3). We find that whenever $\Delta\pi_k^{1,-1} > 2$ the remaining players support a unique N.E.

where all players 'convert to crop'. This is consistent with our analytical finding that for every neighbor who converts to crop the threshold for private payoffs that sustains conversion as the unique optimal strategy is reduced by 4 units.

(ii) An alternative structure of agent heterogeneity is achieved by setting $\Delta\pi_i^{1,-1} = 6.1$ for $i = \{1,6\}$. Now, each of the remaining players have two neighbors each who will convert with certainty. We find that $\Delta\pi_k^{1,-1} > -2$ for $k \in \{2,3,4,5\}$ would sustain a unique equilibria where all players 'convert to crop', which is also consistent with our analytical exercise above.

(iii) Conversion cascades: A specialized and more interesting example emerges from our simulations where heterogeneous payoffs generate conversion 'cascades', which are parallel to the concept of information cascades introduced by Bikhchandani et al. (1992). Information cascades occur as limited information from predecessors transcends to the successive generations as social norms leading to uniformity in social behavior. For our study, cross-sectional interdependence among players can generate similar results through spatial lags as shown by Bikhchandani et al. (1992) in presence of temporal interdependence.

To visualize a conversion cascade for our illustrative example in figure 3, we divide the six player on the torus in four cohorts: $s \in \{1,3\}$, $t \in \{2\}$, $u \in \{4,6\}$, and $v \in \{5\}$. We set $\Delta\pi_s^{1,-1} > 6$ so that $a_s^* = 1 \forall s$. Hence, player 2 with two neighbors projected to convert to crop with certainty will convert as well if $\Delta\pi_t^{1,-1} > -2$. Next the system in figure 3 with $\Delta\pi_s^{1,-1} > 6$ and $\Delta\pi_t^{1,-1} > -2$ will $a_u^* = 1 \forall u$ if $\Delta\pi_u^{1,-1} > -2$, which in turn would mean $a_v^* = 1$ as long as $\Delta\pi_t^{1,-1} > -6$. So, this conversion cascade portrays a situation where two agents with very strong private incentives to crop lead cropping into the regions where grass-based land use was relatively more profitable. Although this case is only an interesting theoretical possibility, it is relevant for our region of study where more cropland is added on relatively poor quality soils along the western fringes of the WCB characterizing its westward expansion in the past decade.

Easement Allocations

As discussed earlier, easements are perpetual contracts that landowners may enter voluntarily permanently giving up their right to cultivate in lieu of a payment and related tax incentives. Although it is the landowners who decide upon enrolling their lands to conservation easement contracts in the first place, the available grassland acreage from willing landowners is in excess of the budgetary capacity of concerned conservation agencies. Therefore, it is critical to analyze the efficiency of past allocations and seek to inform the future allocations to obtain higher cost effectiveness and ecological output. In this study, we evaluate the social welfare from easement acquisitions when strategic complementarities exist among landowners.

Easements generate ecological benefits from conserved mixed-prairie in return of a cost of acquisition. The ecologists recommend conserving large, contiguous tracts to support higher biodiversity and the economists have proposed agglomeration bonuses for efficient voluntary conservation of contiguous lands. Here, we evaluate total social welfare derived from of acquiring easements. We set per-acre ecological benefits derived to be constant and focus on the per-acre cost of acquiring easements to emphasize strategic complementarities in private returns from landowners who enter the contract. It would be interesting to incorporate variable benefits from acquiring contiguous and isolated easements if the acquisition costs offered a trade-off. Instead, we find that similar to the benefits per-acre cost of easements are reduced when acquired in contiguity with other easements. By ignoring variable benefits from the structure of acquisition the level of social welfare generated may be under- or over-estimated but the underlying recommendations towards future easement acquisitions will hold.

Consider a scenario where all agents in a neighborhood have strong private incentives to crop such that $a_i^* = 1\ \forall i$ in absence of any government intervention. Define the social welfare function as $W^e = Be - C^e$, where W^e is social welfare from acquiring *e* easements, *B* is the ecological benefit per acquired easement and C^e is the total cost of easement acquisition such that the each eased agent *i* can no longer cultivate crops or $a_i = -1$. The easement acquisition costs have two components: (i) cost to FWS, which is *i*'s minimum willingness to accept (WTA) upon ceding the right to cultivate, denote C_i, (ii) spillover cost to the neighbors who would still crop and defecting from the eased player *i*, denote $C_{j \in N_i}$. That is,

$$\begin{aligned} &\text{(i)}\ \ C_i = \Delta\pi_i^{1,-1} + 2Jn_i \\ &\text{(ii)}\ C_{j\in N_i} = \sum\nolimits_j 2J = 2Jn_i \end{aligned} \tag{8}$$

Hence, the total cost of acquiring *i* is $C^1 = \Delta\pi_i^{1,-1} + 4Jn_i$ and $W^1 = B - (\Delta\pi_i^{1,-1} + 4Jn_i)$. Equation (8) also reveals that acquiring easements is less costly when the relative private incentives to crop are low. Now consider a case when players *i* and *k* are eased such that $a_i^* = a_k^* = 1$ and $k \in N_i$, $i \in N_k$. These easements accrue benefits 2*B* and the two components of total costs are

$$\begin{aligned} &\text{(i)}\ \ C_l = \Delta\pi_l^{1,-1} + 2Jn_l - J;\ l \in \{i,k\} \\ &\text{(ii)}\ C_{j\in N_l} = 2J(n_l - 1);\ l \in \{i,k\} \end{aligned} \tag{9}$$

Equation (9 (i)) reveals that the players' WTA when eased alongside an immediate neighbors is lower by *J* units. That is because *i* and *k* conform to each other gaining extra payoff from the localized spillovers. Also, there is now one neighbor less whose payoffs are lower when *i* and *k* are eased. Therefore, the social cost is lower by *J* units from easing each neighbor, see equation (9 (ii)). So, $W^2 = 2B - C^2$ and $C^2 = \Delta\pi_i^{1,-1} + \Delta\pi_k^{1,-1} + 4(n_i + n_k) - 6J$. Clearly, the per-unit cost of easing i and k as immediate neighbors is lower when eased in isolation. Hence, our next result.

R4: *The per-unit cost of acquiring multiple easements in contiguity is lower than acquiring those easements in isolation. Consequently, the overall social welfare from easements providing equal ecological benefits is maximized under a contiguous arrangement rather than in isolation.*

<u>Role of transfer payments: Federal tax deductions on easement payments</u>

Notice that our welfare analysis has ignored any transfer payments from enrolling under easement contracts. Federal tax deductions are offered on payments received by landowners to encourage higher enrolment under these easement contracts. We show in an appendix that transfer payments do not change the inference of efficient of easement allocations. However, ignoring transfer payments will lead to miscalculated value of overall social welfare.

Can easement acquisitions trigger non-conversion in their neighborhood?

We now evaluate whether easements can trigger non-conversion in their neighborhood and analyze the social welfare implications of such a scenario. Easements lock lands in grass thereby taking away the option to crop. An uneased player will only forgo conversion if the relative private payoffs from cropping are less than the penalty generated by defecting from his/her eased neighbors. Formally, if e_i denotes the number of i's eased neighbors in set $N_i^e \subseteq N_i$ then $a_i^* = -1$ is optimal when

$$\pi_i^1 + J\left(\sum_j a_j - e_i\right) < \pi_i^{-1} + J\left(e_i - \sum_j a_j\right);\ j \in N_i \setminus N_i^e$$
or
$$e_i > \frac{\Delta\pi_i^{1,-1}}{2J} + \sum_j a_j;\ j \in N_i \setminus N_i^e \qquad (10)$$

Since $\max \sum_{j \in N_i \setminus N_i^e} a_j = n_i - e_i$, e_i easements lead to non-conversion by player *i* only if

$$e_i > \frac{1}{2}\left(\frac{\Delta\pi_i^{1,-1}}{2J} + n_i\right) \tag{11}$$

Equation (11) suggests that the number of easements that would lead to non-conversion is specific to each player's private incentive to crop and the degree of interconnectedness. So easements may trigger non-conversion when placed strategically such that in a population of *I* players each player has at least $\max_{i \in I} 0.5\left(\Delta\pi_i^{1,-1} / 2J + n_i\right)$ neighbors who are eased.

We now evaluate the total social welfare when easements indeed trigger non-conversion. Since all players are eased as grasslands the total benefit equals *IB*, which is obviously the highest achievable ecological benefit. Among the components of acquisition costs, only the loss of private payoff from staying in grass are relevant as social costs are equal to zero since all players conform to each other. Hence, the total acquisition cost equals the total WTA for all individuals, i.e. $\sum_i \Delta\pi_i^{1,-1}$. When easements do not trigger non-conversion at least one player converts to crop, say player *j* converts, and so the cost of acquiring *j* is greater than $\Delta\pi_j^{1,-1}$ due to social spillover effects. Therefore, the cost of acquisition is minimum when easements are strategically allocated to trigger non-conversion, also maximizing the social welfare. Hence, our next result.

***R*5**: *When localized spillovers exist among landowners deciding between 'convert to crop' and 'stay in grass' strategically placed easements can trigger non-conversion. Further, overall social welfare is maximized when easements trigger non-conversion.*

Empirical Analysis

The analytical results of this study are conditional on the fact that strategic complementarities exist among Dakotas landowners. To test this conjecture we employ an empirical strategy that utilizes a duration model to estimate the risk of permanent grassland conversion. Specifically, we track the dynamics of parcels that were classified as grass in 1997 for eastern North Dakota and record the 'duration-to-convert' as number of years from 1997 each parcel stayed in grass before it was permanently converted to crop. We model this 'duration-to-convert' as a function of the neighborhood grassland density. Notice that our empirical strategy is appropriate due to the availability of spatially-delineated land use data and an extensive application of remote-sensing techniques that provided us the G and GC sequences of land use conversions. We next provide the data used to estimate a duration model followed by a discussion on the workings of a duration model and our identification strategy. We then present estimation results.

Data

As mentioned above, our dependent variable is the duration to permanent conversion or years to conversion for parcels that were classified as grass in 1997. We designate 0.5 km, 1 km and 2 km outer rings that correspond to each parcel's designated neighborhood, i.e. n_i. We attribute percent grass from the CDL and percent easements from the National Conservation Easement database for the outer rings as spatial lags to capture the localized spillovers among landowners, see figure 5 for spatial schematics. We obtain parcel level and neighborhood soil quality data from the Web Soil Systems portal of USDA-National Resource Conservation Service (NRCS). We calculate weighted Land Capability Classification (WLCC) and slope (WSLP) as control variables for soil quality. Briefly, LCC groups soils into eight categories each representing the degree of impediments towards cropping with higher categories meaning greater impediments. We also control for access to infrastructure for each parcel as its Euclidean distance to the nearest principal highway and town center, for which the data were acquired from U.S. Census Bureau's TIGER portal. The variable summaries are listed in table 8 and will be discussed hereafter.

Modelling Strategy

We model the duration to convert T, which is assumed to be distributed with a differentiable c.d.f. $F(T)$ and p.d.f. $f(T) = F'(T)$. In this study $F(T)$ represents the probability that a representative grassland parcel is permanently converted to crop in T years post-1997, or $T = 0$ in 1997. Further, the probability of surviving conversion until T years is defined as survival probability or $S(T) \triangleq 1 - F(T)$. The instantaneous risk of conversion at T, also known as the hazard rate, is defined as $\lambda_{GC}(T) = f(T)/S(T)$, where GC signifies permanent conversions. We estimate this hazard rate or the risk of conversion as a function of neighborhood characteristics (and other controls) to identify localized spillover effects.

We utilize a semi-parametric Cox-proportional hazard model to estimate the risk of permanent conversions due to a covariate vector Z. That is

$$\lambda_{GC}(T \mid Z; \beta) = \lambda_o \exp(Z'\beta) \tag{12}$$

Here, λ_o is defined as the baseline hazard from cross-sectional heterogeneity among parcels (Greene, 2003, p. 799). The parameter coefficient, β, translates into a $100(\exp(\beta) - 1)\%$ change in hazard rate due to unit increase in the corresponding explanatory variable. Notice that we have a panel dataset of the dependent and explanatory variables but the regression framework is still static because we only record these variables at the time of each parcel's conversion. A regression framework is achieved by specifying an indicator variable of whether or not each parcel converted every period, i.e. $I_{i,t=T} = 1$ if the parcel was convert at *t* (or after duration *T*) or 0 otherwise. So our dependent variable is specified as $T \times I_{i,t=T}$ leading to the following regression equation[42]

$$T \times I_{i,t=T} = \beta_o + \beta_1 X_{i,T} + \beta_2 Y_{n_i,T} + \beta_3 \omega_{n_i,T} + \varepsilon_{i,T} \tag{13}$$

In equation (13), $\beta_o, \beta_1, \beta_2$ and β_3 are regression parameters. $\beta_3 = J$ in the conceptual model above. Vector $X_{i,T}$ contains explanatory variables for parcel *i*, $Y_{n_i,T}$ contains explanatory variables in the neighborhood of *i*, and we define $\omega_{n_i,T}$ as the average neighborhood choice level. In other words, $\omega_{n_i,T} = 1$ if neighborhood grassland density at *T* is 0% (or cropping density is 100%) and $\omega_{n_i,T} = -1$ if neighborhood grassland density at *T* is 100%.

Our duration model and our game-theoretic conceptual model for conversions may be linked by assuming T to be linearly dependent but inversely proportional to the difference between total payoffs from the game's choices: 'covert to crop' and 'stay in grass'. This makes sense because the higher the returns from conversion the earlier the farmers are expected to 'convert to crop'. Based on this assumption the parameter β_3 in equation (13) directly corresponds to the strength complementarities parameter *J*. Hence, estimating β_3 is the primary interest of our empirical exercise. However, the neighborhood decision level, $\omega_{n_i,T}$, is likely

[42] Under the Cox-proportional specification the log-likelihood function is specified as $L(\beta) = \prod_{i:I_{i,t}=1} \frac{\exp(Z'_{i,T}\beta)}{\sum_{t \geq T} \exp(Z'_{i,t}\beta)}$ where *T* is the duration of the event (time to convert here).

endogenous to variables in vector $Y_{n_i,T}$ leaving β_3 unidentified. This is the classic reflection problem introduced by Manski (1993) and addressed by Brock and Durlauf (2007) for the discrete choice problems. We briefly discuss this identification strategy in the context of our study below.

Identification Strategy

Manski (1993) pointed out that the social interactions parameter β_3 is difficult to identify because $\omega_{n_i,T}$ is likely functionally dependent upon $Y_{n_i,T}$. To see this, let us consider the following reduced form framework that models individual decision level to social interactions below.

$$a_{i,T} = \beta_o + \beta_1 X_{i,T} + \beta_2 Y_{n_i,T} + \beta_3 \omega_{n_i,T} + \varepsilon_{i,T} \tag{14}$$

Under rational expectations we can write $\omega_{n_i,T} = E(a_{i,T} \mid X, Y)$ (Brock and Durlauf, 2001 pp. 240). Hence, $\omega_{n_i,T} = (1-J)^{-1}(\beta_o + \beta_1 X_{i,T} + \beta_2 Y_{n_i,T})$ implies a linear dependence of $\omega_{n_i,T}$ on $X_{i,T}$ and $Y_{n_i,T}$ leaving β_3 unidentified. However, in this study we estimate equation (13) and not equation (14), which implies

$$E(a_{i,T}) = \Pr(t = T \cap I_{i,T} = 1) - (1 - \Pr(t = T \cap I_{i,T} = 1)) \tag{15}$$

For a duration model with Cox-propositional hazard specification we have

$$\Pr(t = T \cap I_{i,T} = 1) = \frac{\exp(Z_T'\beta)}{\sum_{t \geq T} \exp(Z_t'\beta)} \tag{16}$$

which implies under rational expectations that

$$\begin{aligned} &E(a_{i,T}) = 2\frac{\exp(Z_T'\beta)}{\sum_{t \geq T} \exp(Z_t'\beta)} - 1 \text{ and} \\ &\omega_{n_i,T} = 2\int \frac{\exp(Z_T'\beta)}{\sum_{t \geq T} \exp(Z_t'\beta)} dF_{X,Y} - 1 \end{aligned} \tag{17}$$

Clearly in equation (17), $\omega_{n_i,T}$ is not linearly dependent on $X_{i,T}$ and $Y_{n_i,T}$ and hence the identification issue proposed by Manski (1993) does not hold here. Note that the fact that the coefficients in model (13) will be identified is hinged upon the fact that $\omega_{n_i,T}$ is restricted between 1 and –1 whereas the explanatory variables in $X_{i,T}$ and $Y_{n_i,T}$ are distributed over a relatively large space (Brock and Durlauf, 2007).

Even though we use duration as dependent variable, which induces non-linearity between $\omega_{n_i,T}$ and the parcel-level characteristics, neighborhood decisions may still be co-determined. In order to ensure that the coefficient to neighborhood-level variables, i.e., $\omega_{n_i,T}$, is identified we follow the instrumental variable regression approach. We require the instrumental variables to be correlated with the dependent variable, i.e. *duration*, but uncorrelated with the residuals in equation (13). Therefore, soil quality and access to infrastructure are valid instruments, in that they would determine the relative profitability towards crop-based and grass-based land uses for neighboring land parcels. In addition, we know that the FWS's strategy for past easement acquisitions is likely to be determined by an area's duck-pair density (Walker et al. 2013). Since wetlands are critical to sustain breeding of ducks, we introduce neighborhood-level wetlands density to instrument the presence of easements. Furthermore, wetlands also generate marketable ecosystem services, and so would serve as an appropriate instrument for the grasslands. Specifically, we instrument the neighborhood-level variables (grassland and easement density here) on (i) wetland density, (ii) soil quality, and (iii) distance to the nearest city/highway.

Estimation Results

We estimate equation (13) and denote our dependent variable $T \times I_{i,t=T}$ as 'duration'. Table 8 summarizes the dependent and explanatory variables for the full sample containing land parcels under GC and G sequences. Table 8 reveals that the unconverted parcels (sequence G) during 1997-2015 had higher slopes, poorer soils for cropping (or higher LCC), and were more distant to the highways and city centers as compared the ones that did convert during this period (sequence GC). Further, the neighborhood grass density of unconverted parcels is much higher than the ones that underwent permanent conversion. Notice that the standard deviation of soil quality variables is high, so we utilize a t-test to find the mean the soil quality is statistically different across sequences G and GC, see table 9.

Next, we find parcel-level soil quality regressors to be highly correlated with neighborhood-level regressors, especially for the neighborhood designations as 0.5 km and 1 km outer-rings, see table 10. High correlation exists despite increasing the size of the outer-ring to 2 km. A typical U.S. farm of 160 acres roughly translates into a square shaped plot with 0.8 km sides. This means that our designation of 0.5 km (1 km, 2km) outer ring roughly accounts for the average neighborhood decision level of one (two, three) adjoining farms on each side of the parcel. Since soil quality is highly correlated even to the extent of thirst-order neighbors, include parcel-level land quality for an amenable interpretation towards conversion decisions.

It is a standard practice in case of duration analyses to present the estimated survival probabilities, $S(T)$, in each period of the study. We estimate the non-parametric Kaplan-Meier survival probabilities based on the recorded duration to permanent conversion in our sample, see figure 6. We find that a large proportions of the regression sample (more than 90%) contains parcels in the sequence G. Among the ones that did convert, i.e. the GC sequence, more than 85% converted in just one year. Table 8 shows that among the converted parcels average duration was about 2.6 years. A highly skewed sample is a caveat of this analysis and warrants more work to reconcile this issue. Since the number of observations in sequence G is much greater than that in GC, we estimate two separate regressions for the full sample and only the GC category in order to document any relevant differences in estimation results.

The hazard regression estimates for the ‘full’ sample are listed in Table 11 and the corresponding hazard rates are listed in Table 12. We find that a unit increase in the proportion of grasses within a representative parcel’s 0.5 km neighborhood would decreases the conversion risk by 99%. Correspondingly, higher grass density within larger neighborhoods of 1 km and 2 km decrease the hazard rate by 97% and 94% respectively. This suggests a non-increasing strategic response to larger neighborhood. We find that the easements reduce hazard rates by a 100% meaning that the advent of an easement completely halts conversion. These results are driven by the fact that permanent conversions are concentrated in areas that were historically cropped and past easements were allocated away from the converted parcels. Further, higher slopes, and more distant cities and highways also reduced the conversion risks. Finally, a higher percentage of land under LCC categories I and II reduced conversion risk while we had expected otherwise. For robustness we estimate hazard rates for only the GC sequence, results are presented in tables 13 and 14. Briefly, higher grass density as well as more eased acres are related to lower hazard rates, although the impact of easements is insignificant.

In order to ensure that the coefficients to spatial lags are identified we first instrument grass density and easement density variables for the pre-designated outer rings on their proximity to near-by wetlands, their soil quality and access to infrastructure, see tables 15 and 16. Here, we find higher grass density as well as more eased acres are related to hazard rates. This means that easements were strategic complements to higher grass density towards inhibiting permanent conversions. However, it is interesting that the impact of an extra easement acre is stronger than that of a grass acre in reducing conversion risk. This result potentially suggests an educational impact on the environmental conscience in neighborhoods with near-by easements.

Long-term grasses: Filter for one-time permanent grassland conversions

A concern with pooling the G and GC categories for our hazard model estimation is that the mean duration to convert is only 2.6 years, which is indicative of the fact that 'grass' in 1997 could have been converted earlier and these parcels were possibly switching between grass and crop prior to 1997. This is problematic since GC parcels that were out of grass before 1997 do not represent one-time permanent grass conversions as currently incorporated in our hazard rate estimation framework.

To ensure estimating the hazard rates for one-time conversions we utilize our findings from Chapter 3 to characterize long-term grasses. Specifically, we utilize the Landsat5 sensor data for North Dakota (path 31, rows 27-28, ch.3 p.202) for years 1984 and 1987 as 'filters' for determining parcels that were grass historically. We then exclude parcels that were grass in 1997 but not grass in 1984/87 from our dataset, thereby designating the remaining parcels as long-term grasses. Rest of the components of the regression analysis are kept the same as earlier, including the IV regressions for the spatial lags. One issue with this strategy of characterizing long-term grasses is that since we only generate historical data for only a portion of eastern North Dakota (figure1-ch.3 p.202) this new filtered parcel-level data is truncated in an arbitrary manner.

Upon filtering the original dataset, we are left with only 60 GC category parcels (out of 972) and only 734 G category parcels (out of 12,420 compared to the original dataset). Consequently, the resulting mean duration is now double at 5.2 years, see figure 7. The coefficient estimates of the resulting hazard regressions for the three outer-rings are significant in only some cases indicating lost estimation power due to truncation. Higher density grasses are still found to inhibit conversions in all cases, whereas easements reduce conversion risk for 0.5

km and 1 km and not in case of the 2 km neighborhood. We caution the reader of the discrepancies in these results compared to the ones obtained from using the unfiltered dataset earlier. The loss of parameter significance may be associated with the noise introduced due to filtering, and so we designate these results preliminary. To that extent, this section warrants further investigation.

Concluding Remarks

We evaluate the role of localized spillovers on permanent grassland conversions and on the efficiency of past allocations of grassland conservation easements. We focus on the recent land use dynamics in the Prairie Pothole Region where extensive grassland losses have been reported in the literature. The grasslands are considered critical to the native and migratory birds habitat in North America, and so the FWS actively engages in buying perpetual easements to conserve these habitats. Past studies have investigated conservation targeting, including conservation easements, by contrasting scenarios that determine conversion probability as a function of the tract-level benefits and costs. We evaluate conservation targeting by incorporating network effects into the private landowners decision problem. We conjecture that strategic complementarities exist on land use decisions such that higher crop density encourages more cultivation in the neighborhood through better access to agricultural services, supporting infrastructure and demand terminals.

We first present a game-theoretic binary choice model of strategic complementarities based on our conjecture that grassland owners derive a positive social payoff by conforming to their neighbors' actions. We specify pairwise strategic interactions among players to incorporate agent heterogeneity, neighborhood-level interactions, and to evaluate easement allocations. We find that multiple equilibria are supported where all players 'convert to crop' or 'stay in grass'.

Positive social spillovers can encourage landowners with weak cropping incentives to convert to crop following their neighbors' choice. We evaluate easement allocations by calculating overall social welfare that accounts for spatial spillovers among neighbors. We find that easements can inhibit conversion more efficiently when the private incentives to convert are weak (poor soils) and when easements are acquired on neighboring plots of land.

We support our conceptual model by empirically testing whether or not localized spillovers exist in permanent grassland conversion in the Dakotas. Our analysis suggests that localized spillovers do exist such that higher density grassland inhibits conversion in its neighborhood. We find easements to be strategic complements to existing grasses as they too inhibit conversion. Our empirical analysis has major caveats that warrant future work. We need to reconcile a highly skewed distribution as our sample has more than 90% parcels in permanent grassland category and that most parcels were converted in the first year. In order to evaluate long-term grasses we need to incorporate historical grass acreage that will be accomplished through a separate exercise of processing raw satellite imagery in future.

Overall, our analysis is based on the fact that croplands and grasslands exist as large, nearly-contiguous tracts in the eastern North Dakota where permanent conversions have occurred as islands within the crop-intensive areas. Easements, on the other hand, were allocated near permanent grasslands as contagious tracts in proximity to the grasslands that did not convert anyway. However, the fact that existing easements are contiguous tracts on relatively poor soils is in agreement with our conceptual model's recommendation for efficient easement allocations when network effects are present among private landowners. In that respect, past easement allocations were cost-effective.

TABLES

Table 7. Simulated N.E. for the illustrative example. $\Delta\pi^{1,-1} = 0$, $J = 1$.

a_1^*	a_2^*	a_3^*	a_4^*	a_5^*	a_6^*	π_1^*	π_2^*	π_3^*	π_4^*	π_5^*	π_6^*
-1	-1	-1	-1	-1	-1	3	3	3	3	3	3
-1	-1	-1	1	1	1	1	1	1	1	1	1
1	1	1	-1	-1	-1	1	1	1	1	1	1
1	1	1	1	1	1	3	3	3	3	3	3

Table 2. Simulated N.E. for the illustrative example. $\Delta\pi^{1,-1} = 1$, J = 1.

a_1^*	a_2^*	a_3^*	a_4^*	a_5^*	a_6^*	π_1^*	π_2^*	π_3^*	π_4^*	π_5^*	π_6^*
-1	-1	-1	-1	-1	-1	3	3	3	3	3	3
-1	-1	-1	1	1	1	1	1	1	2	2	2
1	1	1	-1	-1	-1	2	2	2	1	1	1
1	1	1	1	1	1	4	4	4	4	4	4

Table 3. Simulated N.E. for the illustrative example. $\Delta\pi^{1,-1} = 2$, J = 1.

a_1^*	a_2^*	a_3^*	a_4^*	a_5^*	a_6^*	π_1^*	π_2^*	π_3^*	π_4^*	π_5^*	π_6^*
-1	-1	-1	-1	-1	-1	3	3	3	3	3	3
-1	-1	-1	1	1	1	1	1	1	3	3	3
-1	-1	1	-1	-1	1	1	1	1	1	1	1
-1	1	-1	-1	1	-1	1	1	1	1	1	1
1	-1	-1	1	-1	-1	1	1	1	1	1	1
1	1	1	-1	-1	-1	3	3	3	1	1	1
1	1	1	1	1	1	5	5	5	5	5	5

Table 4. Simulated N.E. for the illustrative example. $\Delta\pi^{1,-1} = 3$, $J = 1$.

a_1^*	a_2^*	a_3^*	a_4^*	a_5^*	a_6^*	π_1^*	π_2^*	π_3^*	π_4^*	π_5^*	π_6^*
-1	-1	-1	-1	-1	-1	3	3	3	3	3	3
1	1	1	1	1	1	6	6	6	6	6	6

Table 5. Simulated N.E. for the illustrative example. $\Delta\pi^{1,-1} = 9$, $J = 3$.

a_1^*	a_2^*	a_3^*	a_4^*	a_5^*	a_6^*	π_1^*	π_2^*	π_3^*	π_4^*	π_5^*	π_6^*
-1	-1	-1	-1	-1	-1	9	9	9	9	9	9
1	1	1	1	1	1	18	18	18	18	18	18

Table 6. Simulated N.E. for the illustrative example. $\Delta\pi^{1,-1} = 6$, $J = 1$.

a_1^*	a_2^*	a_3^*	a_4^*	a_5^*	a_6^*	π_1^*	π_2^*	π_3^*	π_4^*	π_5^*	π_6^*
-1	-1	-1	-1	-1	-1	3	3	3	3	3	3
1	1	1	1	1	1	9	9	9	9	9	9

Table 7. Simulated N.E. for the illustrative example. $\Delta\pi^{1,-1} = 6.1$, $J = 1$.

a_1^*	a_2^*	a_3^*	a_4^*	a_5^*	a_6^*	π_1^*	π_2^*	π_3^*	π_4^*	π_5^*	π_6^*
1	1	1	1	1	1	9.1	9.1	9.1	9.1	9.1	9.1

Table 8. Variable Summaries

Variable	**Mean**	**Median**	**Std Dev**	**Minimum**	**Maximum**
PERMANENT CONVERSIONS (i.e. sequence GC, N = 972)					
Parcel Characteristics					
Duration	2.59	1.00	3.99	0.00	18.00
Acres	12.76	8.23	13.08	5.12	142.55
WSLP	3.25	2.80	1.87	1.00	11.30
WLCC	2.41	2.00	0.77	2.00	7.00
%LCC ≤ 2	72	100	44	0.00	100
Highway (km)	4.49	3.87	3.49	0.00	16.60
City (km)	7.57	7.11	3.70	0.52	21.09
Neighborhood-level Characteristics					
%Eased (0.5 km)	0.00	0.00	0.90	0.00	20.00
%Eased (1 km)	0.10	0.00	2.30	0.00	46.00
%Eased (2 km)	0.20	0.00	1.60	0.00	30.00
%Grass (0.5 km)	31.00	28.00	17.00	0.00	94.00
%Grass (1 km)	26.00	23.00	15.00	0.00	95.00
%Grass (2 km)	24.00	21.00	14.00	0.00	97.00
NEVER CONVERT (i.e. sequence G, N= 12,420)					
Parcel Characteristics					
Duration	19.00	19.00	0.00	19.00	19.00
Acres	16.98	9.34	21.98	5.12	199.49
WSLP	7.68	7.00	3.60	1.10	29.00
WLCC	3.07	2.00	1.69	1.82	7.00
%LCC ≤ 2	65	100	47	0.00	100
Highway (km)	6.22	5.63	4.37	0.00	27.14
City (km)	10.15	9.67	4.60	0.26	25.21
Neighborhood-level Characteristics					
%Eased (0.5 km)	1.50	0.00	0.082	0.00	100
%Eased (1 km)	1.40	0.00	0.063	0.00	87.30
%Eased (2 km)	1.40	0.00	0.046	0.00	71.80
%Grass (0.5 km)	67.00	69.00	24.00	0.00	100.00
%Grass (1 km)	56.00	57.00	26.00	0.00	100.00
%Grass (2 km)	49.00	48.00	26.00	0.00	100.00

Table 9. A t-test with unequal variance to compare mean of land quality variables among G- and GC-sequences. Null hypothesis is that this difference is zero.

Variable	Difference ($M_{GC} – M_{G}$)	t-value	p-value
WSLP	-4.43	-64.87	<0.0001
WLCC	-0.66	-22.63	<0.0001
%LCC ≤ 2	7.61	5.12	<0.0001

Table 10. Person's Correlation Coefficient among parcel-level land quality variables and their respective neighborhoods characterized as outer-rings.

Variable	0.5km Outer Ring	1km Outer Ring	2km Outer Ring
WSLP	0.97	0.93	0.86
WLCC	0.97	0.93	0.86
%LCC ≤ 2	0.97	0.94	0.88

Table 11. Cox-Proportional Hazard Regression Estimates. Dependent Variable: **Duration**.

Variable	0.5km Outer Ring	1km Outer Ring	2km Outer Ring
Grass Proportion	-4.31***	-3.56***	-2.83***
Eased Proportion	-14.53***	-11.74***	-19.08***
WSLP	-0.53***	-0.60***	-0.63***
%LCC ≤ 2	-0.37***	-0.38***	-0.33***
Highway (km)	-0.03***	-0.04***	-0.05***
City (km)	-0.02**	-0.02**	-0.02**
-2LogL	15230.30	15538.45	15691.51
AIC	15242.30	15550.45	15703.51

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

Table 12. Cox-proportional hazard rates.

Variable	0.5km Outer Ring	1km Outer Ring	2km Outer Ring
Grass Proportion (0.5km)	0.01	0.03	0.06
Eased Proportion (0.5km)	0.00	0.00	0.00
WSLP	0.53	0.55	0.53
%LCC ≤ 2	0.69	0.68	0.72
Highway (km)	0.97	0.96	0.96
City (km)	0.98	0.98	0.98

Table 13. Cox-Proportional Hazard Regression Estimates for the GC sequence. Dependent Variable: **Duration**

Variable	0.5km Outer Ring	1km Outer Ring	2km Outer Ring
Grass Proportion	-1.33***	-1.27***	-1.34***
Eased Proportion	-0.30	-0.81	-0.54
WSLP	-0.10***	-0.11***	-0.09***
%LCC ≤ 2	-0.13*	-0.12	-0.12
Highway (km)	-0.000	-0.003	-0.004
City (km)	-0.01	-0.004	-0.005
-2LogL	12113.13	12126.56	12128.10
AIC	12125.13	12138.56	12140.10

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

Table 14. Cox-proportional hazard rates for the GC sequence.

Variable	0.5km Outer Ring	1km Outer Ring	2km Outer Ring
Grass Proportion	0.26	0.28	0.26
Eased Proportion	1.35	0.44	0.59
WSLP	0.90	0.90	0.92
%LCC ≤ 2	0.88	0.89	0.89
Highway (km)	1.00	1.00	0.97
City (km)	0.99	1.00	0.99

Table 15. Cox-Proportional Hazard Regression Estimates using instrumental variable approach for 'Grass proportion' and 'Eased Proportion' variables. Dependent Variable: **Duration**

Variable	**0.5km Outer Ring**	**1km Outer Ring**	**2km Outer Ring**
Grass Proportion	-7.74***	-12.91***	-14.77***
Eased Proportion	-67.12***	-62.68***	-29.10***
WSLP	-0.51***	-0.33***	-0.30***
%LCC ≤ 2	-0.08	-0.38***	-0.30***
Highway (km)	-0.0004	0.02	-0.03***
City (km)	0.01	0.04**	0.01
-2LogL	15,814.13	15,735.96	15,657.73
AIC	15,826.13	15,747.96	15,669.73

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

Table 16. Cox-proportional hazard rates using instrumental variable approach for 'Grass proportion' and 'Eased Proportion' variables.

Variable	**0.5km Outer Ring**	**1km Outer Ring**	**2km Outer Ring**
Grass Proportion	0.00	0.00	0.00
Eased Proportion	0.00	0.00	0.00
WSLP	0.60	0.72	0.70
%LCC ≤ 2	0.92	0.68	0.70
Highway (km)	1.00	1.02	1.00
City (km)	1.01	1.04	1.00

Table 17. Variable Summaries for the truncated sample that represents long-term grass.

Variable	Mean	Median	Std Dev	Minimum	Maximum
PERMANENT CONVERSIONS (i.e. sequence GC, N = 60)					
Parcel Characteristics					
Duration	5.15	1.50	6.03	1.00	18.00
Acres	11.58	8.45	9.50	5.12	55.15
WSLP	3.91	3.60	1.90	1.70	10.94
WLCC	2.40	2.00	0.95	2.00	6.00
%LCC $\leq$ 2	0.80	1.00	0.39	0.00	1.00
Highway (km)	5.63	4.92	4.33	0.00	15.29
City (km)	8.35	8.23	4.14	1.74	17.35
Neighborhood-level Characteristics					
%Eased (0.5 km)	0.00	0.00	0.00	0.00	0.00
%Eased (1 km)	0.00002	0.00	0.0001	0.00	0.001
%Eased (2 km)	0.001	0.000	0.01	0.00	0.04
%Grass (0.5 km)	0.43	0.38	0.23	0.13	1.19
%Grass (1 km)	0.36	0.34	0.19	0.11	1.12
%Grass (2 km)	0.34	0.31	0.18	0.10	1.08
NEVER CONVERT (i.e. sequence G, N= 674)					
Parcel Characteristics					
Duration	19.00	19.00	0.00	19.00	19.00
Acres	13.23	8.45	13.82	5.12	119.43
WSLP	7.10	7.00	2.90	2.30	11.30
WLCC	3.03	2.00	1.58	2.00	7.00
%LCC $\leq$ 2	0.64	1.00	0.47	0.00	1.00
Highway (km)	6.70	6.40	4.18	0.00	19.10
City (km)	9.98	9.28	4.49	0.86	22.63
Neighborhood-level Characteristics					
%Eased (0.5 km)	0.01	0.00	0.04	0.00	0.34
%Eased (1 km)	0.02	0.00	0.06	0.00	0.61
%Eased (2 km)	0.03	0.00	0.07	0.00	0.38
%Grass (0.5 km)	0.67	0.69	0.23	0.04	1.60
%Grass (1 km)	0.57	0.56	0.25	0.00	1.59
%Grass (2 km)	0.49	0.45	0.25	0.00	1.40

Table 18. Cox-Proportional Hazard Regression Estimates using instrumental variable approach for 'Grass proportion' and 'Eased Proportion' variables. Dependent Variable: **Duration**

Variable	**0.5km Outer Ring**	**1km Outer Ring**	**2km Outer Ring**
Grass Proportion	-9.06	-8.70**	-6.12*
Eased Proportion	-21.44	-10.39	60.04
WSLP	-0.25*	-0.25*	-0.39***
%LCC ≤ 2	0.20	0.06	-0.10
Highway (km)	0.05	0.05	0.04
City (km)	0.02	0.02	-0.08
-2LogL	702.86	706.71	706.85
AIC	714.86	718.71	718.85

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

Table 19. Cox-proportional hazard rates using instrumental variable approach for 'Grass proportion' and 'Eased Proportion' variables.

Variable	**0.5km Outer Ring**	**1km Outer Ring**	**2km Outer Ring**
Grass Proportion	0.00	0.00	0.002
Eased Proportion	0.00	0.00	1.2E+26
WSLP	0.78	0.78	0.68
%LCC ≤ 2	1.22	1.06	0.90
Highway (km)	1.06	1.05	1.04
City (km)	1.02	1.02	0.92

FIGURES

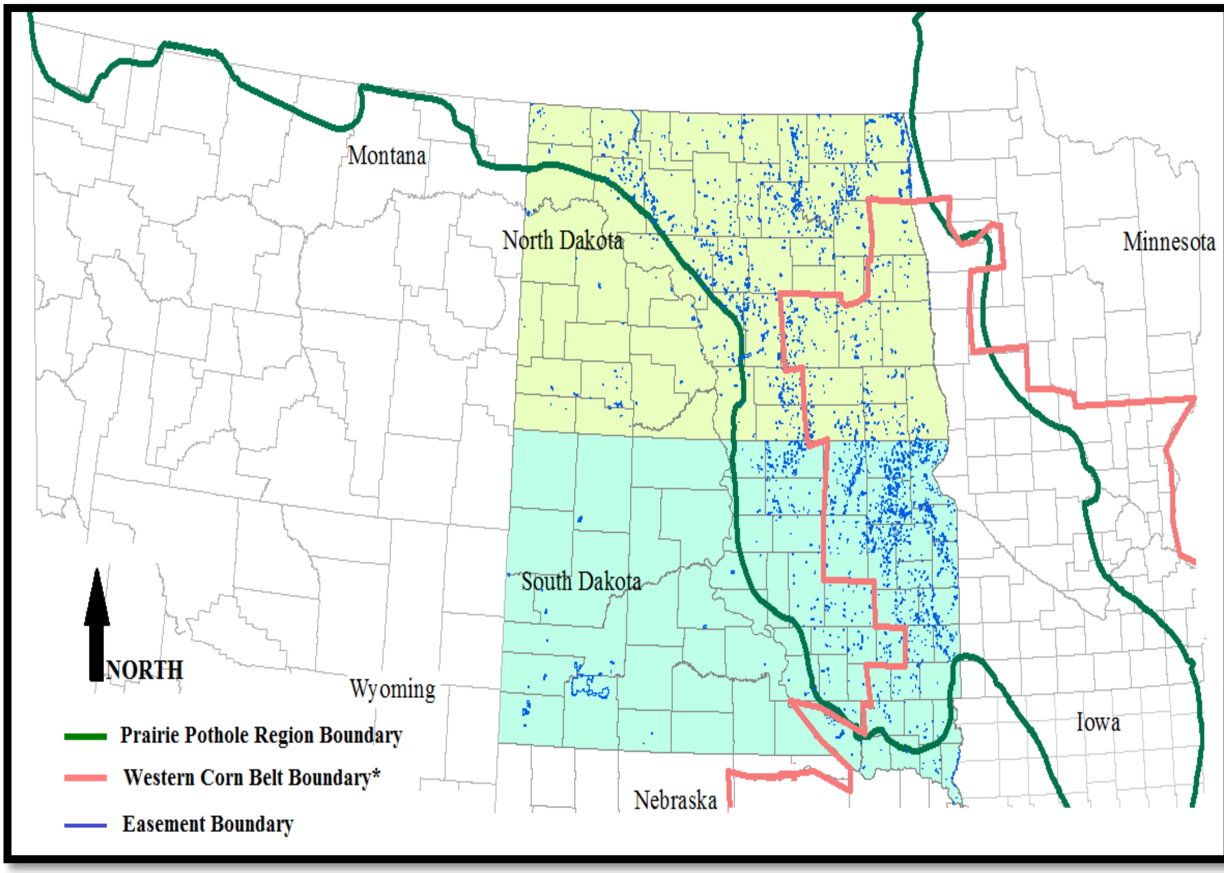


Figure 6. The U.S. Prairie Pothole Region, Western Corn Belt frontier and easement allocations in North and South Dakota. Not to scale.
*Notes: The representation of the Western Corn Belt frontier is approximate and manually built with the 2010 county-level map of the United States Department of Agriculture-National Agricultural Statistics Service's as a reference. Downloadable from: https://www.nass.usda.gov/Charts_and_Maps/Crops_County/.

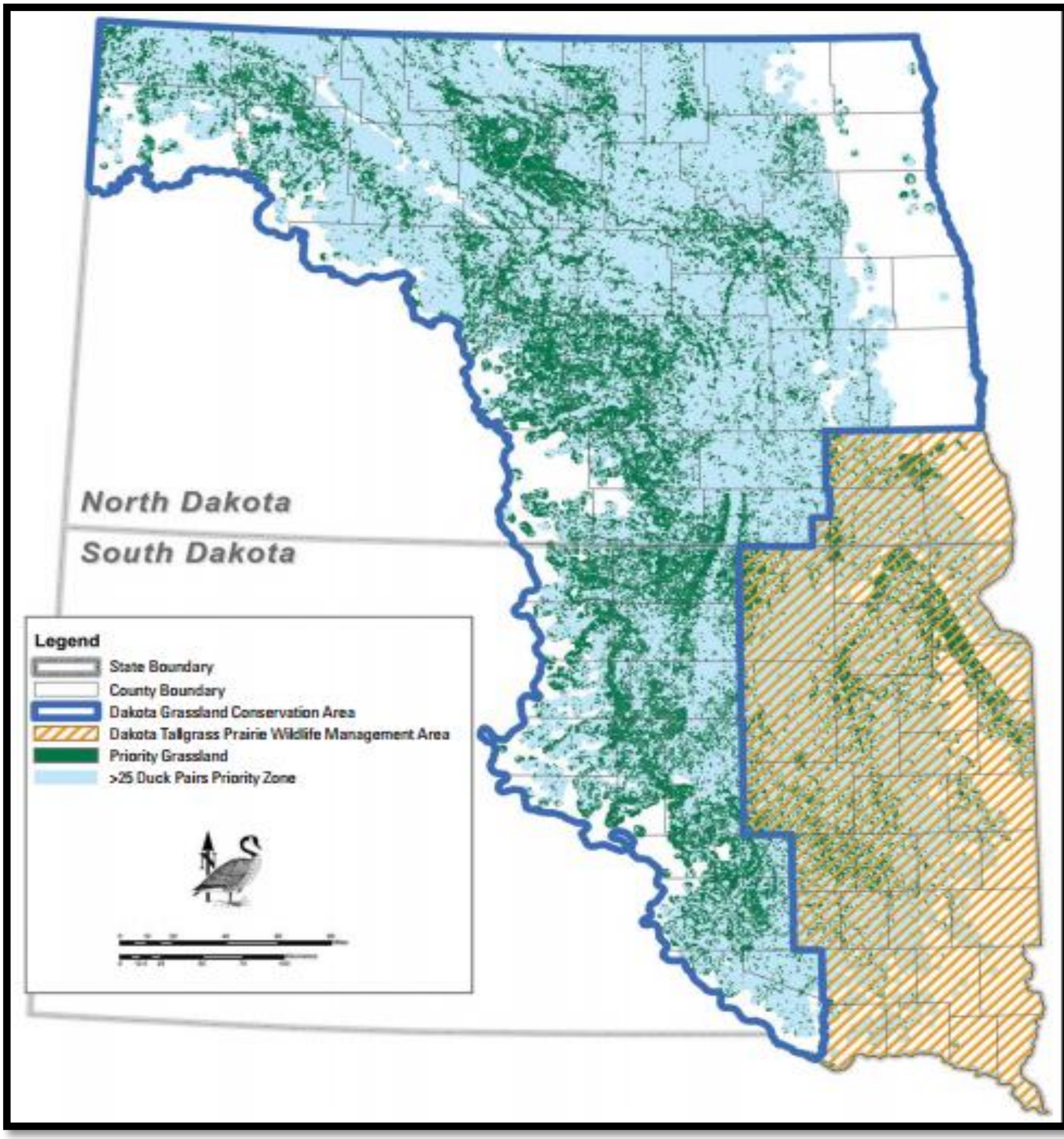


Figure 7. Waterfowl breeding density and USFWS Priority Conservation Acres. The figure has been taken from USFWS Land Protection Plan, 2011 pp. 4. Source: https://www.fws.gov/mountain-prairie/planning/lpp/nd/dkg/documents/dkg_lpp_final_all.pdf

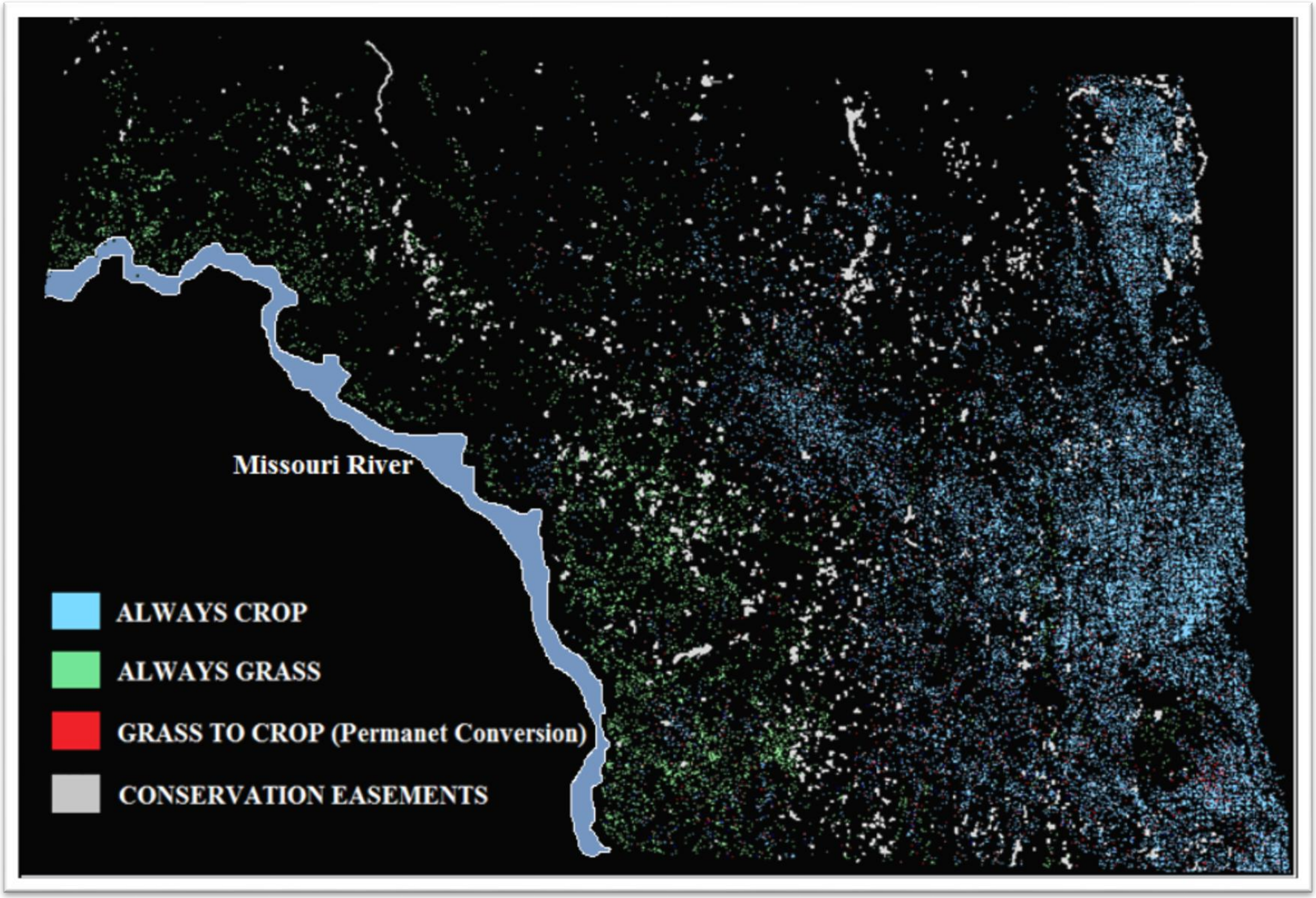


Figure 8. *Land use change combinations in eastern North Dakota and relative allocations of conservation easements.*

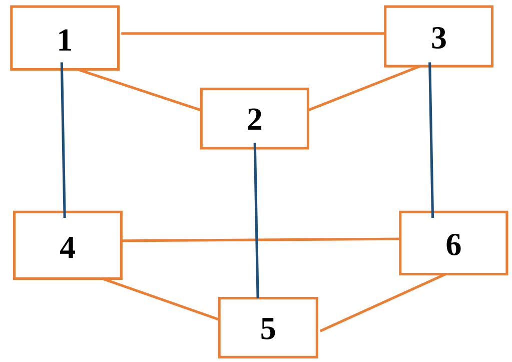


Figure 4. An example of inter-connected agents

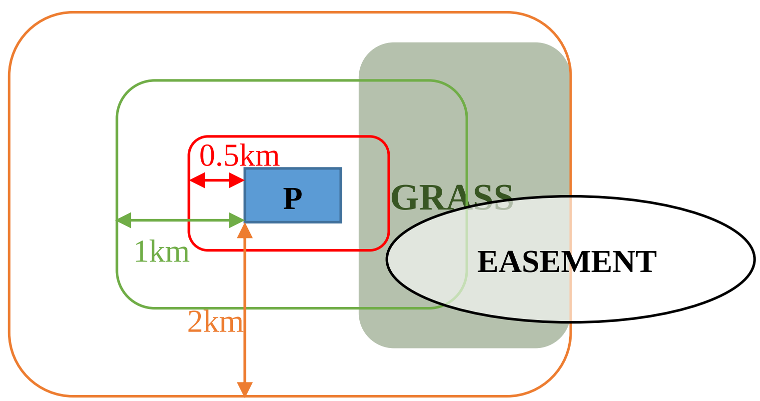
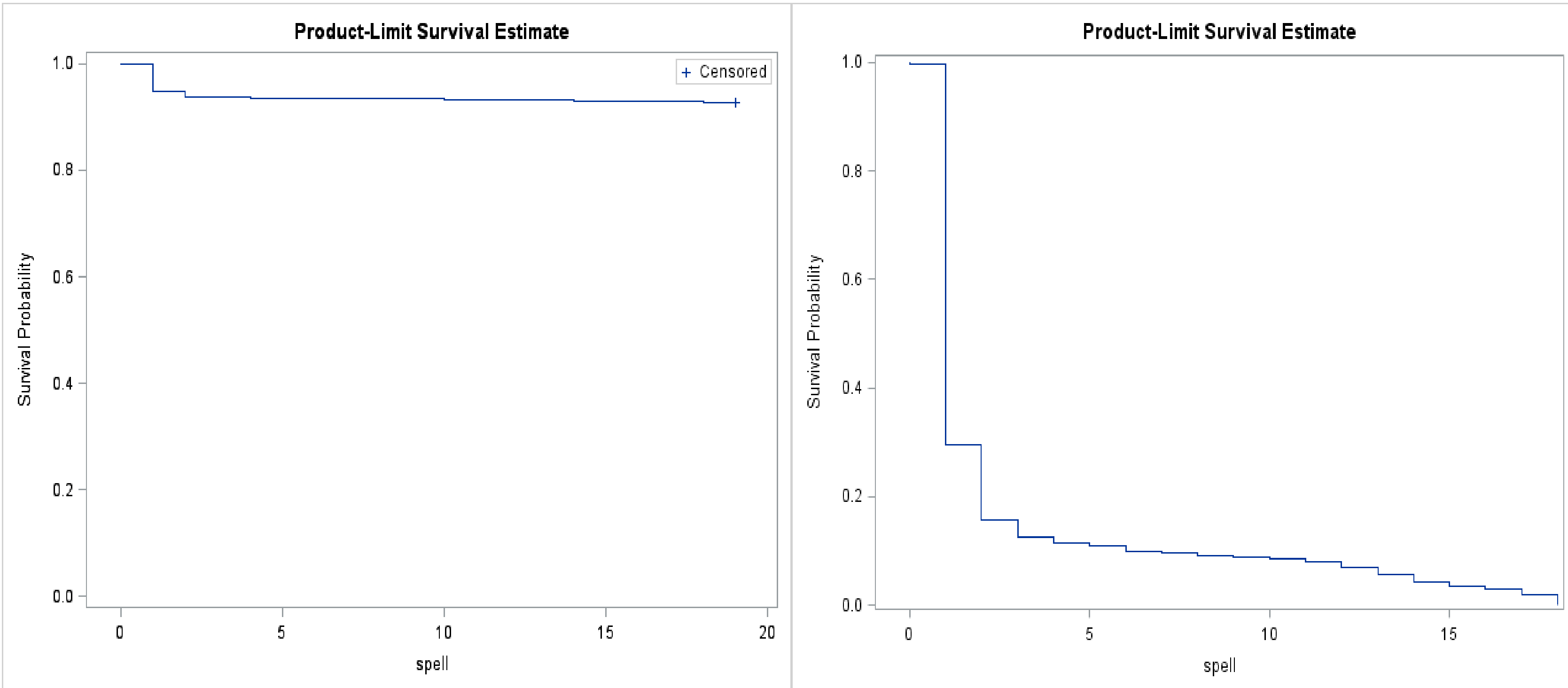
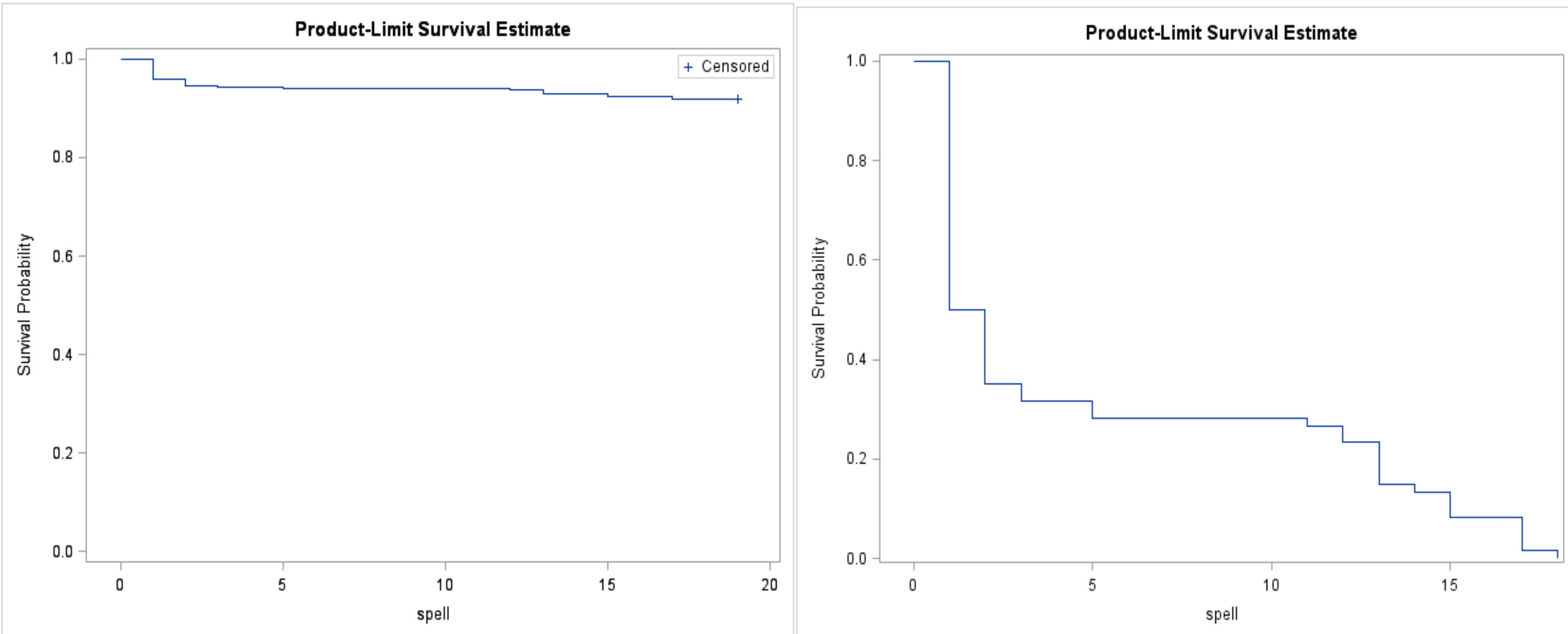


Figure 5. Spatial schematics of the neighborhood designations as outer-rings and easement allocations coverage for this study.



(a) (b)

Figure 6. Kaplan-Meijer Survival Probability Estimates. Panel (a) signifies that more than 90% of the sample is permanent grasslands. Panel (b) zooms into the converted parcels in our sample and presents corresponding estimates for survival probability.



(a) (b)

Figure 7. Kaplan-Meijer Survival Probability Estimates for ‘filtered’ parcels. Pane (a) is pooled data for G and GC categories; and Panel (b) zooms into the converted parcels or GC category in this filtered sample. The average mean survival time among the conversted parcels is now 5.2 years (almost double of what it was in the un-filtered sample in figure 6).

REFERENCES

Bikhchandani, S., Hirshleifer, D., Welch, I. 1992. " A theory of fads, fashions, custom and cultural change as informational cascade," *Journal of Political Economy*, 100(5): 992-1026.

Brock, W.A., Durlauf, S.N. 2001. "Discrete choice with social interactions," *Review of Economic Studies*, 68(2): 235-360.

Brock, W.A., Durlauf, S.N. 2007. "Identification of binary choice models with social interactions," *Journal of Econometrics*, 140(1): 52-75.

Drechsler, M., Watzold, F., Johst, K., Shogren, J.F. 2010. "An agglomeration payment for cost-effective biodiversity conservation in spatially structured landscapes," Resource and Energy Economics, 32(2): 261-275.

Durlauf, S.N. 1999. "How can statistical mechanics contribute to social science," *Proceedings of the National Academy of Sciences of the U.S.A.*, 96: 10582-10584.

Echenique, F. 2003. "Mixed equilibria in games of strategic complements," *Economic Theory*, 22(3): 33-44.

Edlin, A, Echenique, F. 2004. "Mixed equilibria are unstable in games of strategic complements," *Journal of Economic Theory*, 118(2004): 61-79.

Ellis, R. 1985. Entropy, large deviations and statistical mechanics, New York: Springer-Verlag, Ch. 4.

Greene W.H. 2003. Econometric analysis, 5th Ed., Ch. 22.5, pp. 791-801.

Harsanyi, J.C. 1995. "A new theory of equilibrium selection for games with complete information," *Games and Economic Behavior*, 10(2): 318-332.

Johnson, R.R., Granfors, D.A., Niemuth, N.D., Estey, M.E. Reynolds, R.E. 2010. "Delineating grassland bird conservation areas in the U.S. Prairie Pothole Region," *Journal of Fish & Wildlife Mgmt.*, 1(1): 38-42.

Kultti, K., Salonen, H. 1997. "Undominated equilibria in games with strategic complementarities," *Games and Economic Behavior*, 18(1): 98-115.

Manski, C.F. 1993. "Identification of endogenous social effects: the reflection problem," *Review of Economic Studies*, 60:531-42.

Mas-Collel, A., Whinston, M.D., Green, J. 1995. Microeconomic Theory. Oxford University Press, New York. Ch. 8.

Miao, R., Hennessy, D.A., Feng, H. 2016. "Grassland easement evaluation and acquisition: an integrated framework," *Selected Paper for the Agricultural and Applied Economics*

Association Annual Meetings, Boston, M.A. July 31-August 2, 2016.

Milgrom, P., Shannon, C. 1994. "Monotone comparative statics," Econometrica, 62(1): 157-180.

Parkhurst, G.M., Shogren, J.F., Bastian, C., Kivi, P., Donner, J., Smith, R.B.W. 2002. "Agglomeration bonus: an incentive mechanism to reunite fragmented habitat for biodiversity conservation," *Ecological Economics*, 41(2): 305-328.

Rashford B. S., Walker J. A., Bastian C. T. 2011. "Economics of grassland conversion to cropland in the Prairie Pothole Region," *Conservation Biology*, 25(2): 276-84.

Stephens, S.E., Walker, J.A., Blunck, D.R., Jayaraman, A., Naugle, D.E., Ringelman, J.K., Smith A.J. 2008. "Predicting risk of habitat conversion in native temperate grasslands," *Conservation Biology* 22(5):1320-30.

U.S. Fish and Wildlife Service. 2011. "Land Protection Plan-Dakota grassland conservation area, Lakewood, Colorado," *Department of Interior, Fish and Wildlife Service, Mountain-Prairie Region*, 169 p. Available at:https://www.fws.gov/mountain-prairie/planning/lpp/nd/dkg/documents/dkg_lpp_final_all.pdf

U.S. Government Accountability Office. 2007. "At current pace of acquisitions, U.S. Fish and Wildlife Service is unlikely to achieve its habitat protection goals for migratory birds," *Highlights of GAO-07-1093, a report to the Subcommittee on Interior, Environment, and Related Agencies, Committee on Appropriations, House of Representatives*.

Topkis, D.M. 1978. "Minimizing a submodular function on a lattice," *Operations Research*, 26(2): 305-321.

Van Nouhuys, S. 2009. "Metapopulation ecology," In Encyclopedia of Life Sciences, John Wiley & Sons.

Vives, X. 1990. "Nash equilibrium with strategic complementarities," *Journal of Mathematical Economics* 19(3): 305-321.

Walker J, Rotella JJ, Loesch CR, Renner RW, Ringleman JK, Lindberg MS, Dell R, Doherty KE. 2013. "An integrated strategy for grassland easement acquisition in the Prairie Pothole Region, U.S.A." *Journal of Fish & Wildlife Mgmt.*, 4(2): 267-279.

Wang, T., Luri, M., Janssen, L., Hennessy, D., Feng, H., Wimberly, M., Arora, G. 2016. "Farmers' rankings of the determinants of land use decisions at the margins of the Corn Belt," *Selected Paper for the Agricultural and Applied Economics Association Annual Meetings, Boston, M.A.* July 31-August 2, 2016.

Wright CK, Wimberly MC. 2013. "Recent land use change in the Western Corn Belt threatens grasslands and wetlands." *Proceedings of the National Academy of Sciences of the U.S.A.*, 110: 4134-4139.

APPENDIX

A simple algorithm to find all of the game's Nash Equilibria:

Define the one-shot simultaneous move game as follows

- $i \in I = \{1, 2, 3, 4, 5, 6\}$ players.
- Individual action set, $a_i \in \{-1,+1\}$ with $-1 \equiv$ 'stay in grass' and $+1 \equiv$ 'convert to crop'. Hence, the overall strategy set of the game is $a = (a_1 \times a_2 \times a_3 \times a_4 \times a_5 \times a_6)$.
- Game's payoff function: $\pi(a) = (\pi_i(a_i, a_{-i}))_{i=1}^{6}$, where the individual player's payoff function is defined as $\pi_i(a_i, a_{-i}) = \pi_i^{a_i} + J\sum_{j \in N(i), j \neq i} a_i a_j$.

Steps to find all Nash Equilibria of the game:

1. Collect all unique strategy sets and compute their corresponding payoffs with neighbors as in figure 1.
2. ID each strategy profile, $s = 1, 2, ..., 64$, and designate the strategy profile and corresponding payoffs with a superscript: $a^s = (a_i^s)_{i=1}^{6}$; $\pi(a^s) = (\pi_i(a_i^s, a_{-i}^s))_{i=1}^{6}$
3. Compare player 1's payoffs due to his/her strategy profile $a_1^s \in \{-1,+1\}$ conditional on each unique strategy combination of players other than 1. Collect the strategy ID's where player 1's payoffs are maximized conditional on each unique a_{-1}^s and store them in set $s(1)$.
4. Repeat Step 3 for all players.
5. Collect the set of unique strategy IDs, $s(I) = \bigcap_{i=\{1,...,6\}} s(i)$.

The strategy sets $a_i^{s(I)}$ have the property that $\pi_i(a_i^{s(I)}, a_{-i}^{s(I)}) \geq \pi_i(a_i, a_{-i}^{s(I)})\ \forall\ i \,\&\, a_i \in a \setminus a_i^{s(I)}$, which is the definition of N.E.

Welfare analysis of easement allocations with the federal tax incentives

Consider a scenario where all agents in a neighborhood have strong private incentives to crop such that $a_i^* = 1\ \forall i$ in absence of any government intervention. Given tax rate *t*, each player *i* earns a payoff that is net of taxes equal to $(1-t)(\pi_i^1 + Jn_i)$. We define a social welfare function as $W^e = Be - C^e$, where W^e is social welfare from acquiring *e* easements, *B* is the ecological benefit per acquired easement and C^e is the total cost of easement acquisition. Upon enrolling their lands as easements, the landowners are liable for a tax rate τ such that $\tau < t$. Now *i*'s net payoff after taxes upon eased is equal to $(1-\tau)(\pi_i^{-1} - Jn_i)$. Hence, *i*'s WTA or cost to FWS under federal tax incentives is equal to the difference between *i*'s net payoffs under no intervention and when eased. The social costs are still spillover cost to the neighbors who would still crop and defecting from the eased player *i*. We can express each cost component under the given taxes as

$$\begin{aligned}&\text{(i) } C_i = (1-t)(\Delta\pi_i^{1,-1} + 2Jn_i) - (t-\tau)(\pi_i^{-1} - Jn_i)\\&\text{(ii) } C_{j\in N_i} = 2(1-t)Jn_i\end{aligned} \tag{A1}$$

Hence, the total social cost of acquiring *i* under the given tax incentives is $C^1 = (1-t)(\Delta\pi_i^{1,-1} + 4Jn_i) - (t-\tau)(\pi_i^{-1} - Jn_i)$. Now consider a case when players *i* and *k* are eased such that $a_i^* = a_k^* = 1$ and $k \in N_i$, $i \in N_k$. These easements accrue benefits 2*B* and the two components of total costs are

$$\begin{aligned}&\text{(i) } C_l = (1-t)(\Delta\pi_l^{1,-1} + 2Jn_l) - (t-\tau)(\pi_l^{-1} - Jn_l) - (1-\tau)J;\ l \in \{i,k\}\\&\text{(ii) } C_{j\in N_l} = 2(1-t)Jn_l - 2(1-t)J;\ l \in \{i,k\}\end{aligned} \tag{A2}$$

Equation (A2 (i)) reveals that the players' WTA when eased alongside an immediate neighbors is lower by $(1-\tau)J$ units. That is because *i* and *k* conform to each other gaining extra payoff from the localized spillovers. Also, there is now one neighbor less whose payoffs are lower when *i* and *k* are eased. Furthermore, a loss in income for the eased players' neighbors also means slightly lower taxes because the taxable income is now lower. Therefore, the total social cost is lower by $(1-t)J$ units from easing each neighbor, see equation (A2 (ii)). Clearly, the per-unit cost of easing *i* and *k* as immediate neighbors is lower when eased in isolation. Hence, our result in the main text still holds that acquiring easements among in contiguity is more efficient than in isolation.