Rain follows the forest:

Land use policy, climate change, and adaptation*

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Abstract

Human actions can alter the local and regional climate, particularly via land use. We assess the impact of the Great Plains Shelterbelt, a large-scale forestation program in the 1930s across six US Midwestern states that is comparable to contemporary tree-planting efforts. This program led to a regional increase in precipitation and decrease in temperature, with impacts persisting for several decades. The change in climate extended to adjacent unforested land up to 200km away—inducing economic spillovers and enabling us to directly study climate adaptation. In downwind places now facing more favorable growing conditions, crop yields increased by 11-22%. Farmers adapted, switching to more water-intensive production. Due to adaptation, yield increases were up to 120% larger than predictions based on improved weather conditions only. This paper highlights the endogeneity risk in using spatial variation in climate trends in estimating climate damages, as well as the potential for tree planting to regionally mitigate climate change impacts. *JEL: Q1, Q5, N5, O13*

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1 Introduction

The popularity of large-scale tree planting has rapidly increased over the last two decades. Prominent examples include the Great Green Wall, a pan-African initiative from 2007 to grow trees across the entire continent along the Sahel, and the One Trillion Trees Initiative launched by the World Economic Forum in 2020. In lower-income countries, such as China, Pakistan, and Mexico, the goal of these programs is to stabilize soils and reduce erosion, dust storms, and landslides. In higher-income settings, the focus is increasingly on carbon sequestration, bolstered by recent work arguing that afforestation[1] and forest restoration could sequester enough carbon to reduce atmospheric CO_2 levels by 25% (Bastin et al. 2019).[2]

As a natural and proven way to capture and store carbon, tree planting is popular among policy makers. Over 50% of the 193 countries in the Paris Agreement list land use and forestry as a priority area for achieving CO_2 mitigation targets (UNFCCC 2022).[3] A recent study on pathways to net zero emissions estimated that $900 billion must be invested by 2030 into afforestation, requiring 160 million hectares of new forest land globally (McKinsey Global Institute 2022)—an area larger than France, Spain, and Germany combined.

The natural science literature has debated another potential outcome of large-scale tree planting: local climate change. Such climate effects are driven by trees' impact on energy and water fluxes. Atmospheric models predict an increase in precipitation where trees are planted, as well as in downwind areas. For temperature, the direction of the local effect depends on land characteristics, but a decrease in temperature is predicted in downwind areas (Bonan 2008).

Such policy-induced climate change can, in turn, affect economic outcomes—both locally where the trees are planted and in locations downwind. The total effect will depend on the mechanical response to the change in climate (e.g., higher crop yields in response to more favorable growing conditions) as well as the extent to which agents adapt by adjusting their behavior in response to the new climate. Neighboring areas may also be influenced through general equilibrium effects.

In this paper, we examine the causal impact of a large-scale tree-planting program on both climate and economic outcomes. We empirically test the predictions from atmospheric models in response to afforestation and estimate the resulting magnitudes. We then leverage

[1] Afforestation involves tree planting to establish forests on land not previously forested.

[2] One provocative study argues that the Little Ice Age was partially driven by CO_2 declines from reforestation in the Americas following the mass death of indigenous peoples after European contact (Koch et al. 2019).

[3] All possible pathways identified by the IPCC to limit global warming at the 1.5° include the removal of CO_2 from the atmosphere (IPCC 2019).

this policy-induced change to identify the long-term effects of climate change on economic outcomes and assess the extent of adaptation.

We focus on the Great Plains Shelterbelt in the United States. Planned in response to the Dust Bowl, the government-funded program aimed to reduce soil erosion and dust storms in the US Midwest. Announced in 1932 and implemented from 1935 to 1942, the program led to the planting of 220 million trees. Trees were grown in windbreaks, which consisted of numerous strips of trees planted between fields and farms. The resulting 'belt' of trees bisected the US from north to south, spanning 1,700km and crossing six states from North Dakota to Texas.

The largest afforestation effort of its time, the Great Plains Shelterbelt is now rivaled in scope by multiple tree-planting projects around the world. We focus on this specific program to leverage its unique combination of characteristics. While it was implemented over 80 years ago, we note that the socioeconomic conditions of the US Midwest in the 1940s are comparable to the many lower and middle-income countries where similar programs are being designed and implemented today. The historical context provides the long timeframe required for a direct study of the drivers and consequences of climate change, i.e., changes in the *distribution* of weather events over the medium to long term. Historical data for the United States from the onset of the 20^{th} century allows us to empirically consider a rich set of outcomes over a long period (for our main sample, 1930-1965) and precisely characterize the adaptation to climate change. This data availability, combined with the short and delimited implementation period, enables us to use simple and clean identification strategies.

We implement a difference-in-differences identification strategy that exploits prevailing wind patterns. Prevailing winds are the primary physical mechanism by which trees planted in a given location influence climate in nearby areas where the program is not implemented. We compare the evolution in outcomes between the pre-planting and the post-planting periods across four groups: (i) 'Shelterbelt' counties, which see tree planting under the Shelterbelt project, (ii) 'downwind neighbor' counties, which neighbor the treated counties and are most exposed to summer winds from the treated areas, (iii) 'other neighbor' non-downwind counties, and (iv) 'pure control' counties located 200 to 300km from the nearest treated county.

In a first step, we estimate the effects of large-scale tree planting on the climate. Comparing the temporal change in outcomes in the treated group (i) relative to the control group (iv) identifies the direct climate effect, while comparing the temporal change in the spillover group (ii) relative to control group (iv) identifies the spillover climate effects on downwind areas where trees are not planted. Comparing the changes in the other neighbor group (iii) relative to the control group (iv) provides a placebo test for our identification strategy since the climate in non-downwind neighboring counties should *a priori* be unaffected by the tree planting.

In a second step, we turn to the effects of climate change on the economy. Identification comes from comparing the temporal change in the spillover group (ii) to the control group (iv).[4] It uses the change in climate induced by tree planting but occurring in areas where trees have not been planted. We focus on agriculture, the sector highly exposed to climate and representing a large share of the economy of the post-war US Midwest. We test for effects on crop yields, as well as for adaptation. We complement these direct tests by estimating the relative role of direct climate effects and adaptation in driving the overall yields results.

We find that large-scale tree planting substantially changes the climate. Precipitation increased by 2.7%, or 2.3mm per month, during the summer months in the treated counties (p=0.010), and by 3.3%, or 2.9mm, in the downwind neighbor counties (p=0.003). In line with these effects, maximum temperature decreased in both treated (-0.10°C, $p = 0.001$) and downwind neighbor (-0.13°C, $p < 0.001$) counties. Extreme heat, which has a strong negative impact on yields, decreased even more dramatically, with degree days above 29°C falling 7.4% (p<0.001) and 6.4% (p<0.001) in afforested and downwind neighboring areas, respectively. Similar effects are estimated on the Palmer Drought Severity Index (PDSI), a measure of crop water availability jointly determined by temperature and precipitation anomalies. The direction of these effects is consistent with the qualitative predictions from atmospheric models. In contrast to these economically and statistically significant results, the point estimates for the non-downwind 'neighboring control' counties (iii), which serve as a placebo test, are an order of magnitude smaller, and statistically indistinguishable from zero.

We also perform sensitivity tests to address endogeneity concerns and the potential for mean reversion following the Dust Bowl. Results are similar using a synthetic difference-in-differences method to account for potential differential pre-trends (including potential differential exposure to the Dust Bowl); a long differences method to account for uncertainty about the specific timing of treatment; controlling for the severity of exposure to the Dust Bowl; using a continuous wind exposure measure instead of the downwind and other neighbor

[4] Changing the climate in a given area can have spatial spillover effects through the reallocation of labor (Albert et al. 2021; McGuirk and Nunn 2020). If the spatial spillovers are strongest on neighboring areas, comparing (ii) to (iv) will isolate the combined effect of the climate change in (ii) plus of the spatial economic spillovers from climate change in (i). Our design still allows us to identify the economic effect of climate change in (ii), by comparing (ii) to (iii).

groups; and an instrumental variable approach that accounts for the potential strategic selection of farmers into the Shelterbelt project. These tests, along with other robustness checks, indicate that these potential concerns are unlikely to be confounding our estimates.

Having established that the Shelterbelt project induces climate change, we next estimate the effects of this climate change on the economy and test for any follow-on adaptation. We find that corn yields increased by 11% in response to the policy-induced changing climate in the treated spillover counties (p=0.006). We implement the same robustness checks as we do for the climate effects, and find estimates ranging from 19 to 22%. Part of this effect may be attributable to reduced dust exposure—another co-benefit of tree planting—but since this effect diminishes with distance, it would be less apparent in these neighboring spillover counties. We also address this issue in our long difference analysis by controlling for initial levels of soil erosion.

The estimated effect on agricultural productivity combines the mechanical effect of improved weather conditions with the adaptation effect of farmers' responses. Adaptation is non-negligible: the area of corn planted increased by 21% (p=0.069) as farmers reallocated production from pasture to cropland and switched from less water-sensitive crops (e.g., wheat) to more water-sensitive crops (e.g., corn). Overall, the estimated total yield effect, which is inclusive of adaptation, is up to 2.2 times larger than the yield increase predicted by the weather improvements only.

Our study advances our understanding of the interactions between climate and the economy both substantively and methodologically. First, we contribute to an emerging literature on the endogeneity of local climate to land use. Economists generally assume local climate to be exogenous to local socioeconomic activities. We provide novel evidence that this is not the case.[5] Other recent work in this vein includes Braun and Schlenker (2023), who find that the historical expansion of irrigation in the US affected temperature, both locally and in downwind areas. In the Amazonian context, Araujo (2023) finds a downwind precipitation response to changes in forest cover. Taken together, these two recent working papers confirm the external validity of our first set of results, the endogeneity of climate to land use changes, in a range of settings.

[5] This idea has long been explored in the natural science literature. Atmospheric models are used to describe the response of local and regional climate to changes in land use (Devaraju et al. 2015). Other studies estimate the reduced-form climate effect of various land use changes, including irrigation (e.g., Lobell et al. 2008; DeAngelis et al. 2010; Mueller et al. 2016; Braun and Schlenker 2023), crop choice (Loarie et al. 2011; Georgescu et al. 2011), and forestation (Smith et al. 2023; Alkama and Cescatti 2016; Peng et al. 2014). Many of these studies are either observational or compare trends in areas with land use change to adjacent unchanged areas, and, therefore, cannot identify spillover effects.

Our findings have implications for our understanding of place-based policies, as well as localized changes in productivity. Such changes are known to induce economic spillovers to other regions through the spatial reallocation of capital and labor (Kline and Moretti 2014; Bustos et al. 2016; Bustos et al. 2020; Asher et al. 2022; Hornbeck and Moretti, n.d.). Our study, which shows that land use policy can induce climate change across an area far beyond where the policy is implemented, demonstrates economic spillovers through a third potential channel involving climate change.

We next describe the methodological implications that extend from our findings on climate endogeneity. The elasticity of agricultural productivity with respect to climate is a key parameter to assessing the economic consequences of climate change, including agricultural outcomes, food security, structural transformation, and specialization and trade flows. As detailed below, we propose a novel method to identify this elasticity and estimate it with a reduced-form empirical strategy. This elasticity derives from the direct, mechanical effect of weather shocks drawn from a different distribution (i.e., climate change), combined with the effects of adaptation. This paper provides evidence on both of these components.

In terms of the direct impact of climate change, our findings have implications for the vast body of work using climate as a source of identifying variation. While debates on the economic effects of climate can be traced back centuries (Montesquieu 1750), the credibility revolution in economics and growing concerns about anthropogenic climate change have spurred a revival of studies focusing on climate impacts. A wide range of outcomes are affected by annual weather shocks (see Dell et al. 2012 for a seminal paper, and for reviews Dell et al. 2014 and Carleton and Hsiang 2016). However, identifying the effects of climate (i.e., the distribution of weather events over time) based on observed variations in the realizations of that distribution (i.e., weather shocks) presents challenges (Hsiang 2016; Kolstad and Moore 2020; Lemoine 2021).[6]

One common way to circumvent this problem is through a long differences approach: estimating the correlation between long-term changes in climate and outcomes of interest (Burke and Emerick 2016). Identification then relies on the assumption that long-term trends in climate are exogenously determined across spatial units. Our results showcase the potential for reverse causality-driven bias when using spatial variation in climate trends to assess impacts on economic outcomes—given that these climate trends themselves may be driven by endogenously-determined policies—and thereby invite increased caution when using climate

[6] The effect of weather shocks can be larger than climate change if adaptation is less costly over the long run than over the short run (e.g., if fixed cost investments are required). The converse is possible if short-run adaptation strategies like irrigation become more costly over time (Hornbeck and Keskin 2014).

trends as source of identifying variation.

By demonstrating that local climate change can be policy induced, our study provides a natural direction to advance this literature. We can indeed use standard tools developed in modern applied microeconomics, such as difference-in-differences or regression discontinuity design, to assess whether policies have the potential to affect the climate and to subsequently study the consequences of this policy-induced climate change. Importantly, exploiting such policy changes can then enable researchers to argue more convincingly for causal identification of climate effects.

In terms of climate change adaptation, existing research provides valuable insights on how economic agents respond to a shock to agricultural productivity, including soil erosion from the US Dust Bowl (Hornbeck 2012) and permanent reductions in groundwater in India (Blakeslee et al. 2020). Economic agents, however, may respond differently to climate change—that we conceptualize, following Hsiang (2016), as a permanent change in the distribution of transitory productivity shocks—than to single, either permanent or transitory, productivity shocks. Unfortunately, appropriate data and identification strategies are often lacking to study adaptation. A robust body of work in recent decades has focused on testing whether the response of crop yields in the US to weather shocks vary depending on variables such as time, space, and climate trends, with mixed results.[7] Most of our current knowledge of mechanisms for climate adaptation comes from observational studies.[8]

Notable exceptions include studies focusing on adaptation to medium-to-long-term fluctuations in the monsoon regime and temperature in India (Kala 2017; Taraz 2017; Liu et al., forthcoming), which combine agricultural and economic data over several decades with five to ten year changes in the timing and intensity of monsoons, as well as temperature and precipitation, to provide causal evidence on crop and labor adaptation. Our study advances this literature by providing direct causal evidence of significant farmer adaptation to a long-term change in continental climate across a range of dimensions, and estimates how these responses moderate the overall impact of climate change (relative to no adaptation).

In summary, we find that the Great Plains Shelterbelt—in part inspired by a climate shock itself—induced a significant change in regional climate. This policy-driven climate change, in turn, affected economic outcomes for decades. We also find strong evidence of climate adaptation by farmers. The geographic scale of these effects are large, encompassing an area

[7] See, for instance, Schlenker and Roberts 2009; Annan and Schlenker 2015; Burke and Emerick 2016; Malikov et al. 2020; Yu et al. 2021.

[8] Agricultural adaptation to climate change can occur through channels including crop choice (Kurukulasuriya and Mendelsohn 2008; Sloat et al. 2020; Cui 2020; Burlig et al. 2021), ecological practices (Schulte et al. 2017), and irrigation (Taylor 2022).

the size of California.

Recent global enthusiasm for tree planting for climate change mitigation raises many questions about how to best design tree planting projects.[9] We believe our study of the Great Plains Shelterbelt, which entailed a unique ecological design that we describe later, is relevant to the many countries considering large-scale tree planting projects as a way to meet their national climate mitigation targets and maximize societal benefits. This is especially true among countries still highly dependent on agriculture (like the US Midwest in the 1940s) as well as global breadbasket regions with similar soil and climate characteristics to the US Great Plains.

2 Background

The Great Plains Shelterbelt project, also known as the Prairie States Forestry Project, was a Great Depression-era effort to plant forest buffers and windbreaks in the US Midwest. It was the largest afforestation program to date, with over 220 million trees planted between 1935 and 1942. Unlike other regions historically covered by forests in which the expansion of farming came through extensive deforestation, most of the Midwest was covered in grasslands. In 1800, less than 1% of the area of future Shelterbelt counties was forested. While the problems of drought and soil erosion were not new in the prairies of the Great Plains, the destructive Dust Bowl of the 1930s led to a renewed interest in making the Great Plains states more habitable and suitable for agriculture.

Franklin D. Roosevelt conceived of the shelterbelt idea while running for President (Droze 1977). FDR had a long-running interest in forestry and experience with reforestation projects as Governor of New York and believed that an investment in forestry might improve the climate and agriculture of the Great Plains. As president, Roosevelt commissioned a report recommending the planting of trees in 100-foot strips or "shelterbelts" that protect homes, crops, and livestock from the wind and destructive dust storms. FDR's plan, which was controversial among foresters at the time (Munns and Stoeckeler 1946), called for a Shelterbelt 100 miles across and 1,300 miles long, bisecting the continental US from North Dakota to Texas along the the country's 18-inch rainfall line. Figure A1 shows both the planned and actual zone of Shelterbelt planting.

FDR signed an executive order in 1934, and the first tree was planted in 1935 in Oklahoma.

[9] There are many valid concerns around large-scale tree planting, including the scale of the land required, the timing and permanence of the CO_2 reductions, and its potential ecological impacts.

For the most part, seedlings from nurseries were planted instead of seeds to increase survival rates, and irrigation was not used. In total, over 30 species of trees and shrubs were selected—tall and short trees, fast and slow growing trees, hardwoods and conifers—most of which were native and thus locally adapted (Read 1958) to ensure species diversity and ecological resilience in a way that mimicked naturally-occurring forests.

At first, the government leased the land for tree planting but soon transitioned to cost-sharing programs with landowners. The Great Plains project was later part of the Works Progress Administration, which required 90% of the workers hired for the Shelterbelt project were hired from relief rolls. The program stopped in 1942 due to funding cuts that resulted from the US's World War II efforts (Droze 1977).

It is worth noting the focus of the Shelterbelt project on local and regional climate at the time of its inception. The *New York Times* described the project as an "experiment in climate control to combat the ravages of drought" when it first reported on the program ("Tree Belt in West to Fight Droughts" 1934). Indeed, Snow (2019) describes the controversy around the program as a battle between 'ecological foresters' who believed that policy decisions impact local climate and environmental conditions and 'determinist geographers' and foresters who saw climate as static.

3 Data

Our main analysis is based on a county-by-year dataset, constructed from four types of data: digitized historical maps of Shelterbelt plantings to define treatment status, wind data to construct our Shelterbelt wind exposure metric, temperature and precipitation data for our climate outcomes, and agricultural census data for our economic outcomes. We focus in our main analysis on the period 1930-1965.[10] Our results are robust to using different start and end years.

Shelterbelt definition: We digitize maps of the Shelterbelt locations from Read (1958) for our measure of treatment assignment under the Shelterbelt project. Though we do not have an exact measure of trees or windbreaks planted in each county, Read (1958) maps the areas with intensive afforestation. We therefore take the percentage of each county covered by "areas of concentrated Shelterbelt planting", and define counties with over 5% of this measure (corresponding to the 20th percentile of counties with non-zero tree planting area) as Shelter-

[10] We start in 1930 due to concerns about data quality and availability before that date. We end in 1965 to limit the overlap with other agricultural changes, including the expansion of irrigation and urbanization, could be influenced by tree planting and influence the climate themselves.

belt counties. Throughout the paper, we use "Shelterbelt counties" and "treated counties" interchangeably. Figure 1 shows the location of the concentrated Shelterbelt planting areas.

We validate our Shelterbelt measure with an alternative source of data. Snow (2019) digitized actual Shelterbelt plantings surviving during the post-treatment period from the United States Geological Survey (USGS) Topographic Map Quadrangles.[11] We calculate each county's area covered by the Shelterbelts from her digitized shapefiles, and compare with our main measure. Appendix Figure A2 plots the two measures side-by-side to show the similar geographic coverage of the two measures (correlation is 0.80).

Wind data: Wind is an essential driver of regional climate change in relation to afforestation. Trees usually increase the amount of water being released into the atmosphere through evapotranspiration. This atmospheric water vapor then travels with wind, increasing precipitation in areas downwind from the tree planting. We therefore construct a measure of counties' exposure to winds from the Shelterbelt, to determine which neighbor counties are most likely to have their climate influenced by the Shelterbelt project.

For our primary analyses, we use the North American Land Assimilation System (NLDAS-2) gridded wind data available from NASA. The NLDAS-2 combines multiple sources of observations such as precipitation gauge data, satellite data, and radar precipitation measurements to produce climatological estimates with a 1/8th-degree spatial resolution.[12] Specifically, we use their hourly u-wind (east-west dimension) and v-wind (north-south dimension) measures, 10 meters above the surface level.

Using the NLDAS-2 data, we create a time-invariant approximate measure of how exposed each neighboring county is to winds from the shelterbelts in the summer (w_i). To do so, we project an imaginary particle at a given speed and direction, and record all counties that it crosses over the course of 24 hours. We project these particles from each vertex of each Shelterbelt county, and repeat it from each summer hour (June through August) of each year between 1981 and 2010.[13] For each particle, we use the speed and direction of the wind from NLDAS-2 for that specific origin vertex and time. To avoid Shelterbelt counties'

[11] USGS undertook the detailed mapping of the conterminous US through the production, by hand, of over 55,000 quadrangle maps covering about 64 square miles each from 1947 to 1992. Snow 2019 identifies in each map the vegetative areas with the characteristic shape and scale of Shelterbelt plantings (e.g., linear features that run east/west or north/south) and extracts the corresponding polygons. She validates this procedure by comparing the final digitized Shelterbelt acreage totals by state to official project totals.

[12] NCEP North American Regional Reanalysis (NARR) data, used widely in environmental economics (e.g., Deryugina et al. 2019), is the main input for NLDAS-2 but available only 8-times a day and at a 32km grid. We use NLDAS-2 for its hourly temporal frequency and 14km spatial resolution.

[13] High-resolution wind data is only available starting in 1979. Section 5.4 addresses the potential bias that might arise from using post-treatment period wind data when classifying counties by downwind extent.

shape to affect their weight in our wind exposure measure, we assign each particle a weight, inversely proportional to the number of vertices from their origin Shelterbelt county. We then count, for each neighbor county, how many (weighted) particles originating from any Shelterbelt county crossed it during the simulation. Finally, we rescale the metric by dividing it by its maximum value. The resulting wind exposure metric $w_i \in [0, 1]$ is a time-invariant approximate measure of how exposed a neighbor county i is to winds from *all* Shelterbelt counties. Figure 2 illustrates the construction of the wind metric and the resulting downwind exposure for all spillover counties. Further details are provided in Appendix A.1.

Temperature and precipitation data: We construct a county-by-year panel of precipitation and temperature based on daily weather stations data, using a methodology inspired by Schlenker and Roberts (2006). We start from the Global Historical Climatology Network daily (GHCNd) dataset provided by the US National Oceanographic and Atmospheric Administration (NOAA). We clean this dataset and create a balanced panel of stations reporting between 1930 and 1965 in order to ensure that changes in the measured climate are not driven by changes in the underlying set of measuring stations. We spatially interpolate the station data to obtain a gridded dataset at a 0.1 degree resolution, and average the resulting measures at the county-by-day level. Finally, we compute for each month the average daily precipitation, average maximum temperature, maximum temperature, and total number of daily degree days at various thresholds. To move from this county-by-month dataset to county-by-year, our main analysis focus on the average of these measures over the summer months (June through August). Details on the construction of this dataset are available in Appendix A.3.

Degree days have been shown to be a relevant measure of temperature when studying impacts on crops or physiology, performing better than maximum or mean temperature, and have become widely used in economics following work by Schlenker and Roberts (2006; 2009). Yield growth increases gradually up to but decreases sharply above critical temperature thresholds. For corn, our main crop of interest, the critical threshold is 29°C, so we include 29°C degree days as one of our primary climate dependent variables.

Standard gridded weather datasets (applying complex improvements and interpolation algorithms to the raw station data) with historical coverage, such as NOAA's NClimDiv and PRISM, do not include degree days and are at the monthly level, not allowing their computations. This motivated our choice to construct our main weather dataset directly from the daily station data. Still, we verify the robustness of our results on precipitation and mean and maximum temperature to using the standard NClimDiv dataset.

Economic data: We use crop yields, production, and area harvested data from USDA agricultural censuses and surveys. The National Agricultural Statistics Survey (NASS) has conducted agricultural surveys and censuses at the county level annually and every five years, respectively. For our primary specification investigating the effects of tree planting and changing climate on corn yields, we use the annual agricultural surveys conducted by NASS. While survey data before the 1940s is available only for a subset of states and counties, its temporal resolution is an advantage over the agricultural censuses. For yield robustness checks and to study possible adaptation to changing climates, we also use the digitized versions of the 1930 - 1964 censuses provided by Haines et al. (2018). The main outcomes of interest from the censuses are county-level corn yields, corn and wheat acreage, and farm, harvest, and pasture acreages. While the agricultural census covers almost all counties of interest, the temporal resolution is low. Appendix Figure A7 shows the coverage of the census and surveys in our study.

4 Empirical approach

Our main empirical analyses exploit prevailing wind patterns in a difference-in-differences framework. We study changes in climate and economic outcomes not only in counties with afforestation, but also in spillover areas near Shelterbelt counties. Tree planting may lead to precipitation in nearby *downwind* areas through the transport of the increased moisture produced from higher evapotranspiration. We classify counties into the following groups based on the specific location of tree planting and the prevailing winds:

i) Shelterbelt counties, with concentrated windbreak planting covering at least 5% of county area

ii) Downwind neighbor counties, with centroids within 200km of Shelterbelt counties and above median wind exposure from afforested areas[14]

iii) Other neighbor counties, with centroids within 200km of Shelterbelt counties and below median wind exposure from afforested areas

iv) Pure control counties, with centroids 200-300km away from Shelterbelt counties

We compare climate and economic outcomes across these four groups of counties, which can be visualized in the map in Figure 3. We start by comparing counties affected by the Shelterbelt (Shelterbelt and Downwind neighbor counties) to counties that are not affected

[14] See Appendix Figure A8 for the distribution of wind exposure measures for neighbor counties.

(Other neighbor and Pure control counties). We estimate the following equation

$$y_{it} = \alpha(T_i \times P_t) + \delta_{st} + \zeta_i + \eta_{it} \tag{1}$$

where y_{it} is the outcome of interest at the county-year level (e.g., summer temperature, precipitation, yields), T_i is an indicator for affected counties. P_t is a dummy variable equal to one for years after 1942.[15] We also include state-by-year (δ_{st}) and county (ζ_i) fixed effects.

We then separate the local and regional effects of the Shelterbelt tree-planting. We define the local effects of tree planting as the impacts on the Shelterbelt counties themselves, while the regional effects are the impacts on the neighboring downwind counties. We expect little to no effect on the climate of the other (non-downwind) counties. We therefore use them as a placebo test when considering climate outcomes. Economic outcomes, however, can be affected in the non-downwind counties, in the presence of spatially concentrated general equilibrium effects. For instance, a local change in productivity induced by tree planting can lead to the spatial reallocation of labor and capital.

We estimate the following equation

$$y_{it} = \beta_1(S_i \times P_t) + \beta_2(D_i \times P_t) + \beta_3(U_i \times P_t) + \gamma_{st} + \nu_i + \epsilon_{it} \tag{2}$$

which has the same structure as Equation (1), but where S_i is an indicator for Shelterbelt counties, D_i is an indicator for downwind neighbor counties, and U_i is an indicator for other neighbor counties.

Our main coefficients of interest are β_1 and β_2, which measure the change in post-1942 outcomes relative to control counties for Shelterbelt and downwind counties, respectively. β_1 is the local effect of tree planting among Shelterbelt counties, while β_2 is the spillover effect of tree planting among downwind neighbors. The effect on other neighboring counties is β_3. When examining climate outcomes as the dependent variables in our model, β_1 and β_2 are the local and spillover effects of tree planting on rainfall and temperature. β_3 is expected to be zero, and serves as a placebo test. For economic outcomes such as corn yields and agricultural practices, β_1 represents the combined effects of tree planting (e.g., reduction in erosion) and climate change, while β_2 are the effects of climate change only. The latter is

[15] The Shelterbelt project was conducted from 1935 to 1942. Implementation started slowly, with most trees planted in the final years of the project. (See Appendix Figure A3 for the timing.) We can further expect the impact of tree planting to increase over time, as trees grow. We therefore make the conservative choice of using 1942 as the start of the treatment period. (If treatment effects happened earlier, our estimation would underestimate the true effect.) We also implement a long differences strategy to side-step this uncertainty about the exact start of the treatment.

due to the fact that no trees were planted in downwind neighbor areas and we can assume the local soil and wind impacts are limited to the afforested areas. If β_3 is different from zero, tree-planting leads to spatially concentrated general equilibrium effects. In this case, under the assumptions that this reallocation affects all neighboring counties similarly, we can isolate the effect of climate change only as $\beta_2 - \beta_3$.

The effects we identify are equilibrium outcomes. For instance, it is possible that planting trees affects the downwind climate, which in turn induces people to change their land use in these downwind areas. This land use change, itself, can have a local effect on the climate. This does not threaten the internal validity of our approach: we only need to interpret the estimated coefficients as the resulting equilibrium effects of large-scale tree planting in a given area.

Our identification strategy relies on the assumptions that in the absence of tree planting, all groups of counties would have experienced the same changes in outcomes and that the group compositions do not vary over time. Assuming that group composition is not changing over time is reasonable. Indeed, as the Shelterbelt project was cut short in 1942, the tree planting did not materially continue in the region after the project's conclusion—thereby keeping the treated groups unchanged. The parallel trends assumption is not testable. Nonetheless, we provide evidence that the pre-treatment trends are parallel across the groups.

We also supplement our main empirical approach with several alternative methodologies described in Section 5.3. Using these analyses, we address the potential endogeneity of which counties are selected for the Shelterbelt project and the potential for reversion to the mean following the Dust Bowl. We repeat our analyses using synthetic difference-in-differences to account for possible concerns regarding the parallel trends assumption, including potential differential exposure to the Dust Bowl. We also utilize a long differences approach to account for uncertainties regarding the specific timing of treatment effects. In this specification, we also include controls for the severity of exposure to the Dust Bowl, which helps address potential dust-related confounders. Finally, we use an instrumental variables approach to address potential endogeneity concerns regarding the selection into taking-up tree planting under the Shelterbelt project.

5 Results

We now present our main results on the impact of Shelterbelt tree planting on local and regional climate, and the resulting economic consequences. We first discuss results from our difference-in-differences approach that exploits wind patterns, on climate outcomes (5.1). We then present the economic effects of this policy-induced climate change, and discuss the role of adaptation (5.2). We then show that our results are robust to a range of alternative empirical strategies (5.3), and address potential threats to the internal validity of our main results (5.4).

5.1 Climate impacts

Overall effects: We begin with a graph showing average climate outcomes over time (Figure 4). For improved visibility, given the high variability of rainfall and temperature, we average 2-year precipitation and temperature measures across all areas affected by the Shelterbelt project (pooling directly treated areas and downwind neighbors) and control counties. This figure allows us to visually check for the existence of pre-exposure trends, which helps argue for the validity of the parallel trends assumptions required for identification of the difference-in-differences model. The two groups exhibit parallel trends before the treatment for the measures of precipitation and temperature. For precipitation, there might be a widening gap between treated and control counties in the few years immediately before treatment starts—which we address by using synthetic difference-in-differences and long differences methods.

Our regression results from our coarser empirical model (Equation 1) show that summer precipitation increased while summer temperature decreased in areas affected by the Shelterbelt. Table 1 shows the climate effect of afforestation for all regions the program affected decades after its implementation. Summer rainfall post-treatment increased by 2.6% relative to control areas. We also find summer temperatures decreased: average and maximum temperatures fell by 0.4% in impacted areas. Exposure to extreme temperatures harmful for corn yields also decreased significantly in afforested and downwind neighboring areas. Average monthly degree days above 29°C decreased by 1.7 in treated areas, equivalent to a 5.6% decrease. Overall, these results show that tree planting resulted in more favorable growing conditions.

Direct vs. spillover effects: We next examine climate effects separately for afforested and neighboring areas. We estimate Equation (2). Table 2 shows the impact of Shelterbelt afforestation on local and regional climates. We find that summer precipitation increased while summer temperature decreased relative to control counties both in Shelterbelt and downwind neighboring counties. Reassuringly, rainfall and temperature are not affected in other non-downwind neighboring counties. Local summer rainfall post-treatment increases by 2.6% relative to control counties. The regional impacts are even more prominent, as afforestation increases regional precipitation by 3.3% in downwind spillover counties compared to control counties. We find similar decreases in local and regional summer temperatures: average temperatures fall by 0.4% and 0.5% in Shelterbelt and spillover counties, respectively. Similarly, reductions occur in maximum temperatures and degree days above 29°C. These results are consistent with increased evapotranspiration from the Shelterbelt trees. Evaporative demand is greatest during high temperatures, which means that the cooling influence of evapotranspiration is expected to be most pronounced for periods of high temperatures (Mueller et al. 2016). This is exactly what we find, as the decreases in maximum temperatures and degree days above 29°C are greater than the decrease in average temperatures.

Temperature and precipitation jointly determine crop water availability, the variable that ultimately drives crop yields. Therefore, we also test the impact of the Shelterbelt program on an alternative proxy of crop water availability: the Palmer Drought Severity Index (PDSI).[16] We observe an increase in PDSI, which represents a lower likelihood of drought conditions, in both Shelterbelt and downwind neighboring counties (Appendix Table A1). We also run our main spillover analysis using a continuous wind exposure measure (w_i) instead of the downwind and other neighbor dummies. Appendix Table A2 shows that precipitation is higher and temperatures are lower for counties more exposed to summer winds from the Shelterbelt; summer precipitation is 3.7mm higher and summer mean temperature is 0.2°C lower in counties in the 90th percentile of wind exposure compared to counties in the 10th percentile of wind exposure.

As a robustness check, we rerun our climate results with only year – instead of state-by-year – fixed effects (Figure A4). Next, we rerun our analyses separately dropping the project implementation years (1936 to 1942) and peak Dust Bowl years (1934, 1936, 1939) from our baseline period. Appendix Tables A3 and A4 show the results are generally consistent with our main findings. We then repeat the analysis separately for the northern and southern portions of the US. While Shelterbelt tree planting was well distributed across Midwestern latitudes, overall the South was more affected by the Dust Bowl, the epicenter of which took place in northern Texas and the Oklahoma panhandle. We rerun our analysis for both regions separately to address concerns that impacts from the Dust Bowl—rather than Shelterbelt tree planting—may drive our results. We define the North as north of 43°N latitude, which is the border of Nebraska and Kansas. Appendix Table A5 shows that the

[16] PDSI measures the departure from the local average of atmospheric moisture. The index ranges from -10 to +10, with lower values signifying stronger drought conditions.

results generally hold for both the North and South, though the effects on precipitation are larger in the South. Finally, to address concerns about spatial correlation, we implement Conley standard errors in Appendix Table A6. We show that even using a conservative, large distance cutoff (1000km), most of our main estimates remain statistically significant despite slightly less precise estimation.

5.2 Economic impacts

Our results so far show that Shelterbelt tree planting affected the climate in both directly afforested areas and downwind neighbors, via increased summer rainfall and reduced summer temperatures. We now turn to the economic effects of this engineered change in the climate, which became more favorable to agriculture. While tree planting can have local economic consequences due to both the direct effect of afforestation and the induced change in climate, we can focus on areas *downwind* from the policy-induced tree planting, who haven't been directly affected themselves, to identify the economic consequences of a change in climate. We first estimate the effects of this changing climate on corn yields, using our difference-in-differences empirical strategy. We then test for a range of possible agricultural adaptation strategies, and quantify the relative importance of adaptation responses and direct climate effects in driving the estimated change in agricultural output.

Crop yields: As before, we begin with a graph showing crop yields over time. Note we focus on corn, a crop grown across the Midwest and for which there is extensive historical data. Figure 6 shows annual corn yields for all areas affected by the Shelterbelt (pooling afforested counties and their downwind neighbors) as well as control counties. There does not appear to be differential pre-trends in corn yields in the 1930s, despite substantial year-to-year variability. The trends start to differ following the Shelterbelt implementation, with corn yields increasing 14% in these treated counties relative to control counties. See regression results in Appendix Table A7.

We next separately examine changes in yields for afforested and neighboring areas in Table 3. The term in the first row, 'Shelterbelt:Post 1942' (β_1 in equation 2), represents the combined effects in Shelterbelt counties of improved soil conditions due to tree planting and changes in climate (as documented in the previous section). The next term, 'Downwind Neighbor:Post 1942', captures the yield impact in downwind neighboring counties (β_2 in equation 2). This is our main object of interest as it identifies changes due to improved climate conditions alone.[17]

[17] We also repeat our analysis using a continuous wind exposure measure, w_i. These results are shown in

While all counties may be affected in general equilibrium, effects are likely to be stronger closer to the Shelterbelt. To account for this possible mechanism, we include non-downwind neighboring counties, represented by the third term, 'Other Neighbor:Post 1942' (β_3 in equation 2). Stronger local general equilibrium effects are likely the only mechanism that can account for changes in yields in these areas, where no trees were planted and the climate did not change due to afforestation (as shown in Table 2). By estimating the additional effect for downwind counties, our empirical strategy enables us to identify the effect of climate change on yields separate from other mechanisms. In other words, the difference between downwind and other neighbors—the second and third terms in Table 3—is the effect of climate on yields accounting for the possibility of stronger local general equilibrium effects.

In terms of results, Column (1) of Table 3 shows the impact of the Shelterbelt on corn yields, utilizing the annual agricultural survey results, which is our preferred source of crop yield data due to its temporal frequency. In Column (2), we verify our results with the agricultural census which encompasses more counties but which is only available every five years. Both show an increase in corn yields in Shelterbelt as well as downwind counties. Corn yields increased 11% - 22% in Shelterbelt counties and 11% - 14% in downwind neighboring counties relative to control counties. Notably, the difference between downwind and other neighbor effects is positive and statistically significant, meaning that improved climate conditions alone—without other mechanisms such as direct soil benefits of tree planting or general equilibrium effects—lead to higher yields in areas downwind of afforestation.[18]

While the yield increases we find are very large by today's standards, they occurred in the post-war period when agricultural productivity was very high and yields were rapidly increasing across the United States (Jorgenson and Gollop 1992). In our context, corn yields in control areas surrounding the Shelterbelt increased by 160% between 1930 and 1965, making our yield results more reasonable relative to this background level of change.

Adaptation: Next, we ask whether farmers adapt to the changing climate by altering their agricultural input decisions. In other words, are farmers re-optimizing their planting decisions when the return to one output—corn, in the case of our study—increases due to the geoengineered climate change?

A first test for adaptation comes from investigating the yields results. Specifically, a change in yields can be driven by a change in output, in area planted, or both. In the absence of

Appendix Table A8. Corn yields increased 19-29% in counties in the 90th percentile of summer Shelterbelt wind exposure relative to counties in the 10th percentile of wind exposure.

[18] A 1955 survey in South Dakota estimated direct local effects, reporting corn yields of 8 bushels per acre higher in fields next to shelterbelts compared to non-shelterbelt fields, or about 30% of average yields in South Dakota during that period (Ferber et al. 1955).

climate adaptation, the effect of climate on yields should be entirely driven by a change in output, while the area planted should not vary. We directly test this hypothesis, with results presented in Table 3, Column (4). We can reject the hypothesis that area planted does not vary, and thereby provide evidence that farmers do adapt to the changing climate.

Next, we seek to refine our understanding of farmers' land use choice. We therefore estimate the effect of climate change on a range of potential land use choices, including cropland vs. pastureland, and planting corn vs. wheat. When crop yields increase because of more favorable growing conditions, the returns to cropland increase. If the substitution effect dominates the income effect, cropland should increase. That increase can either come by an increase in total farmland (at the cost of acquiring new land) or a decrease in pastureland (at the cost of foregoing returns from pasture). A priori, the choice will depend on the relative costs of the two options. Empirically, we find that cropland area did increase in both Shelterbelt and downwind neighboring counties relative to control counties (Column (1), Table 4), albeit the estimate is imprecise in Shelterbelt counties. Importantly, that increase in cropland came at the expense of pastureland (Column (2), Table 4).

Corn and wheat were two of the major crops grown in the region at the time. Importantly, precipitation has historically been a major determinant of crop choice in the US. As such, dryland wheat is the main crop grown in areas with annual rainfall under 18 inches (Horner et al. 1957), while dryland corn generally requires over 25 inches annually (Neild and Newman 1987). We can therefore expect the share of cropland devoted to more water-intensive crops to increase when precipitation increase. Empirically, we see a 5.2 percentage point increase in Shelterbelt areas and a 2.4 percentage point increase in downwind spillover areas (Column (4), Table 4). At the same time, wheat's share of cropland decreased by 3.5 and 1.6 percentage points in Shelterbelt and downwind counties, respectively (Column (5), Table 4). In line with theory, we therefore find an increase in the share of cropland used for corn production, at the expense of wheat production.

At first, our findings could appear at odds with prior work. Li (2021) studies the local effect of the Shelterbelt project on agricultural outcomes, and finds a shift in production towards pasture. However, the author includes annual weather variables such as rainfall and precipitation as controls, which we show are actually outcomes of the Shelterbelt.

Direct climate effects vs. adaptation: How much of the observed changes in yields are due to the direct effect of more favorable climate conditions, relative to the consequences of adaptation behaviors?

To answer this question, we estimate the direct (mechanical) effect of the Shelterbelt-induced climate change on yields, in the downwind neighbor counties. We do so in three steps. First, we estimate the direct relationship, absent adaptation, between climate and yields. We use the canonical piece-wise linear model from Schlenker and Roberts (2009), which includes year and county fixed effects. Since identification stems from weather variations across years and counties, it does not capture farmers' response to a long-term change in the climate. We can therefore use it to compare yields under different climates in the absence of adaptation. Second, we estimate the causal effect of the Shelterbelt project on each climate variable entering the Schlenker and Roberts 2009 model, for downwind neighbor counties. We use these estimates to predict, for each county, the climate that they would have experienced absent the Shelterbelt project. Third, we use the estimated climate-yield relationship absent adaptation to predict yields both (i) under the actual realized climate and (ii) under the climate that would have existed absent the Shelterbelt project. The average difference in values from (i) and (ii) gives us the direct, mechanical, effect of the Shelterbelt-induced climate change on yields.[19]

We estimate that corn yields in downwind neighbor counties increased 10% from the direct (without adaptation) climate effect of the Shelterbelt tree planting. By comparison, the overall yield effect in downwind neighboring counties is a 11-22% increase (Figure 5). The total estimated effect of climate on yield is therefore 1.1 to 2.2 times larger than the direct, mechanical effect.

Ex-ante, the influence of adaptation on average yields is ambiguous. For instance, the change in climate could have induced new entrants with lower productivity, dampening the mechanical effect on overall average productivity. We find that the adaptation response did not come at the expense of average productivity. On the contrary: average productivity increases were up to the double of what would have been expected based on a mechanical response to improved weather conditions only. This suggests that the marginal cropland newly devoted to corn had high potential corn productivity, or that additional adaptation behaviors were implemented that amplified the direct productivity gains. For instance, initial yield increases might have alleviated liquidity constraints and enabled the adoption of new profitable technologies.

Overall, these results point to the key role of adaptation for climate effects—and indicate that extrapolating estimates from short-term weather variations to predict climate impacts, thus omitting the potential for adaptation responses, can lead to severe bias.

[19] More details are provided in Appendix A.4.

5.3 Alternative specifications

In this section, we show that our results are robust to several alternative methodologies that address possible concerns with our difference-in-differences methods. These alternate results are summarized in coefficient plots in Figures 5 and 7 for climate and economic outcomes, respectively. We next describe each of the alternative methods and corresponding results in more detail.

Synthetic difference-in-differences: To address possible concerns with the parallel trends assumption, we repeat our empirical analyses using a synthetic difference-in-differences approach. Since the synthetic difference-in-differences creates parallel pre-trends across treated and control units by design, the method also addresses concerns regarding differential exposure to the Dust Bowl.

The synthetic difference-in-differences method, described by Arkhangelsky et al. (2021), combines features of the synthetic control and difference-in-differences methods. The synthetic difference-in-differences method weakens reliance on parallel trends by reweighing and matching pre-exposure trends. The method then uses the resulting weights in a two-way fixed effects regressions to estimate the average causal effect of exposure to the treatment. We use the synthetic difference-in-differences method to compare treated Shelterbelt counties to a synthetic control and to compare downwind and other neighbor counties to separate synthetic controls. Possible contributors to the synthetic controls are counties from the pure control group and from outside our study sample. They all come from areas in the Northern and Southern Great Plains. Specifically, we use counties with centroids between 108°West and 88°West.

Formally, consider a balanced panel with N total counties (e.g., Shelterbelt and pool of untreated counties, or spillover and pool of untreated counties) indexed by i and U periods indexed by t. Like before, treatment exposure is denoted by $(T_i \times P_t) \in \{0, 1\}$, where T_i indicates treatment status and P_t treatment timing. The synthetic differences method finds weights $\hat{\omega}^{sdid}$ and $\hat{\lambda}^{sdid}$ to align pre-exposure trends in treated and unexposed counties as well as to balance pre-exposure periods with post-exposure ones. These weights are used in the following two-way fixed effects regression

$$(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \arg\min \{ \sum_{i=1}^{N} \sum_{t=1}^{U} (y_{it} - \mu - \alpha_i - \beta_t - (T_i \times P_t)\tau)^2 \hat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid} \}. \tag{3}$$

The difference between equation 3 and the standard two-way fixed effects regression described in equation 2 is only the addition of the unit and time weights ($\hat{\omega}^{sdid}$ and $\hat{\lambda}^{sdid}$) (Arkhangelsky et al. 2021).

Appendix Table A10 shows the results for climate outcomes. The results for rainfall are slightly higher in magnitude, while the results for the various temperature measures are slightly lower in magnitude. Nonetheless the overall results are consistent with our main difference-in-differences estimates. Appendix Table A11 presents results for corn yields, which are slightly lower in magnitude, but generally in line with our main results. Appendix Figures A9 and A10 shows the trends in outcomes and corresponding treatment effects for Shelterbelt and downwind neighbor counties compared to the synthetic controls for climate and economic outcomes.

Long differences: We can use a long differences approach to model changes in outcomes over time as a function of group membership (Shelterbelt, downwind neighbor, other neighbor). An advantage of utilizing a long differences method is that it is not sensitive to treatment timing. While tree-planting began in 1935 and lasted throughout 1942, trees take time to grow and realize their full potential, and it is, therefore, unclear exactly when the benefits of the windbreaks began. In our difference-in-differences model, we treat years after 1942 as our post-treatment period, but we do not have to make such an assumption in our long differences setup.

Furthermore time-invariant county-level unobservable factors drop out due to taking a difference in county-level outcomes. Unbiased estimates require that Shelterbelt treatment status is not correlated with time-varying unobservables that also affect outcomes of interest. We estimate the following long differences model:

$$\Delta y_i = \beta_{LD1} S_i + \beta_{LD2} D_i + \beta_{LD3} U_i + \Delta\epsilon_i \tag{4}$$

where Δy_i is the change in some outcome y in county i between two periods. We take averages of each outcome y over 1930-1935 and 1960-1965 and difference these averages to arrive at Δy_i. As before, S_i, D_i, and U_i are dummy variables for Shelterbelt, downwind neighbor, and other neighbor counties. We also include state fixed effects, α_s, to control for unobserved state-level trends, as well as various county-level controls in some specifications.

Appendix Tables A12 and A13 present our long differences results without and with additional county-level controls. The long differences design also allows us to control for Dust Bowl intensity, which helps address potential confounders related to dust exposure. Appendix Table A23 shows the results from estimating equation 4 with controls for erosion and temperature and precipitation anomalies during the 1930s.

All of our long differences estimates are generally consistent with our difference-in-differences estimates: we find an increase in rainfall in both Shelterbelt and downwind neighboring counties and a decrease in mean and maximum temperatures. The results are robust regardless of including controls such as latitude and longitude and changes in irrigated area. While we see a statistically significant increase in rainfall in other neighboring counties (Table A12, Column (1) and Table A23, Column (1)), the increase is much lower in magnitude than for Shelterbelt or downwind neighbor counties. We note that since we split neighboring counties into downwind and other groups based on our wind exposure measure, there are still some counties with non-zero wind exposure from afforested areas.

Appendix Tables A14 and A15 show our long differences results for corn yields, using both survey and census data, though our preferred data source is the survey due to its annual availability. Our main difference-in-differences results using the survey data are robust to using long differences with and without controls.

Instrumental variables: Finally, we address the concern that the decision to plant trees as part of the Shelterbelt project might be endogenous to changes in climate or agricultural outcomes. For instance, Howlader (2020) studies how market factors influenced participation in the Project. She finds that areas growing crops whose prices increased were less likely to take up tree planting. If farmers responded to these price changes by also changing other agricultural decisions that had an effect on local yields or the local climate, then our difference-in-differences estimates would be biased. For this reason, we instrument the presence of actual windbreaks with a variable related to where windbreaks were planted but unrelated to changes in climate and socioeconomic outcomes.

We use as an instrument each county's share of ustoll soils. A suborder of the 'black earth' breadbasket soil called mollisols, ustolls are a type of Great Plains soil that is quite fertile but has a high erosion risk and can thus especially benefit from tree planting—making it a target for the Shelterbelt project.[20] Soils are classified through on-the-ground surveys based on their physical characteristics (e.g., texture, structure, depth) which are a product of geological, climactic, and biological processes over millennia. The first nationwide soil map was created in 1909, well before the Dust Bowl and the Shelterbelt project.

We first estimate the relationship between tree planting under the Shelterbelt project and

[20] Soil data derived from USDA NRCS's Global Soil Regions product (so2015v2.tif). For an overview of ustolls, see https://www.nrcs.usda.gov/conservation-basics/natural-resource-concerns/soils/mollisols.

our instrument using the following equation:

$$S_i = \phi_1 Soil_i + \varepsilon_i \tag{5}$$

where S_i is the dummy variable for Shelterbelt counties and $Soil_i$ is the instrumental variable discussed above. We then predict the likelihood of Shelterbelt planting for each county and construct a dummy variable predicted Shelterbelt measure (SP_i). We then repeat the wind exposure measure construction steps described in Section 3, except replace Shelterbelt county indicators with the predicted SP_i. We construct predicted downwind neighbor (DP_i) and other neighbor (UP_i) indicators based on the predicted downwind exposure measure. We pool predicted Shelterbelt counties and predicted downwind neighbor counties and set TP_i to one if a county is either a predicted Shelterbelt county or a predicted downwind neighbor. We then use this binary variable as an instrument in a two-stage least squares (2SLS) regression, where the first stage is the following:

$$T_i = \xi_1 TP_i + \varepsilon_i \tag{6}$$

where T_i is the dummy variable for Shelterbelt and downwind neighbor counties. In some specifications, we include other controls. The model for the second-stage estimation is then:

$$\Delta y_i = \beta_{IV1} T_i + \Delta\epsilon_i \tag{7}$$

where T_i, the dummy variable for Shelterbelt counties, is instrumented by TP_i. This model is equivalent to equation 4, pooling Shelterbelt and downwind neighbor counties and instrumenting for treatment.[21]

First, we show that the share of county area covered by ustolls is a strong predictor for Shelterbelt planting (equation 5, Table A16). Counties with a higher share of ustolls soils are more likely to be afforested under the Shelterbelt project. We then use this estimated equation to predict our Shelterbelt dummy variable and select the top 139 counties with the highest predicted measure to be predicted Shelterbelt counties.[22] We rerun our wind exposure estimation based on the new predicted Shelterbelt counties and define predicted downwind neighbor counties. We then pool predicted Shelterbelt and downwind counties together into predicted treated areas. We use the predicted treated areas dummy variable

[21] Note that since our instrument is non-time varying, we employ this empirical approach using our cross-sectional long differences model rather than our panel model difference-in-difference model.

[22] Our main analysis has 139 counties classified as Shelterbelt counties, so we construct the same number of predicted counties.

as an instrument for actual treated areas.

Appendix Tables A17 and A18 show the results of our estimation using the instrumental variables approach. Column (5) of these tables shows the first stage estimation results from using the predicted treated area dummy as an instrument for actual treated areas (equation 6). The first stage is strong. Columns (1)-(4) of these tables show the instrumental variables estimates according to equation 7. Our estimate for rainfall and the various temperature measures are all similar in magnitude to the long differences results in Appendix Tables A12 and A13. Finally, we repeat the analyses for corn yields. Appendix Tables A19 and A20 show the results for pooled Shelterbelt and downwind neighbor counties. Using the survey data, our preferred source, our main estimates are robust to the long differences with instrumental variables method—both with and without additional controls.

5.4 Internal validity

We now consider factors other than the Shelterbelt that could threaten the internal validity of our results, by potentially explaining the climate and economic effects we find.

Wind: Spatially consistent wind data are only available beginning 1979. As such, our classification of counties into "downwind neighbors" and "other neighbors" cannot be based on baseline data. Instead, we derive it from long-term prevailing wind patterns computed over 1981-2010. We test whether our results could partly be driven by this classification using ex-post data.

Direct empirical evidence suggests that prevailing winds have remained stable throughout our study period. Our classification of counties would thus have likely been similar, had baseline data been available. First, we construct an alternative measure of wind exposure, based on 1938-1942 data from the available weather stations in our study area that monitored wind.[23] We find a correlation of 0.89 between the two measures—indicating that wind exposure from the Shelterbelt has been stable throughout the period. Going one step further and implementing a long differences empirical strategy on this subsample of observations, we do not find evidence that Shelterbelt tree planting affects this wind measure.

Beyond this direct evidence, the pattern of our main results is inconsistent with a bias induced by a misclassification of counties from the use of post-intervention wind data. Assume indeed that the Shelterbelt tree planting changes wind patterns in a way that affects climate in

[23] The construction procedure is described in Appendix A.2. This exercise cannot be meaningfully conducted before 1938, due to the sparsity of weather station data in the Great Plains region then.

neighboring counties. Then, a bias would occur if we classify as downwind neighbor areas that now receive precipitation from the new wind regime but didn't before. However, this new precipitation would be reallocated towards the downwind neighbors from counties that we classify as other non-downwind neighbors: they used to receive precipitation from the wind, but do not anymore due to the new wind pattern. Then, if the Shelterbelt tree planting were affecting wind patterns in a way that reallocates precipitation, we should observe an effect of the intervention on the downwind neighbor counties of the same magnitude and opposite direction than the effect on the other non-downwind neighbor counties. But since we do not find a negative treatment effect on other non-downwind neighbor counties, it is unlikely that there was any material reallocation of precipitation.

Taken together, these results suggest that classifying neighboring counties based on wind data from the post-intervention period is unlikely to be biasing our estimates.

Irrigation: If irrigation is correlated with tree planting, it may be that our results are in fact driven by changes in local climate from irrigation as opposed to afforestation. Like trees, irrigation can increase local evapotranspiration and thus influence the local climate (e.g., Lobell et al. 2008; DeAngelis et al. 2010; Mueller et al. 2016; Braun and Schlenker 2023). There are two concerns: first, that the trees planted as part of the Shelterbelt may have been directly irrigated, and second, that afforested and downwind neighboring lands were more likely to be irrigated, but not the Shelterbelt trees themselves. When discussing cultivation of Shelterbelt windbreaks, Barton (1936) describes preparation of the ground to store precipitation as well as clean cultivation in years after planting (i.e., getting rid of grass and weeds under seedlings), but there is no mention of irrigation. The contemporaneous account shows windbreaks were very unlikely to be irrigated, as water was scarce and irrigation did not expand in earnest until the post-war period.

To address the second concern, we plot concentrated Shelterbelt planting and wind exposure measure against share of area irrigated pre- and post-planting at the county level (Figure A11). Areas that become irrigated are orthogonal to both the areas planted under the Shelterbelt program, and the areas downwind from the Shelterbelt. As a further test, we also replicate our long differences analyses (equation 4) with change in irrigated share of land between 1935 and 1959 as a dependent variable. The results of this analysis are shown in Appendix Table A21. Even though irrigated areas and Shelterbelt planting are orthogonal at the county level, treated and neighboring areas as a whole see an increase in irrigated share of land over this time period. We therefore include the change in irrigated share of land as a control variable in various specifications (Appendix Tables A15 and A20). We still find an increase in yields, showing that while irrigation may have some role in the changing climate in the region, our results are not driven by it. As such, even though irrigation has the potential to influence the local climate, it is unlikely to confound our results.

Dust Bowl and medium-term climate fluctuations: Finally, we consider a potential threat to the identifying assumption of parallel trends: that the groups of counties considered were exposed to different weather shocks or medium-term climate patterns. The Shelterbelt project was indeed conceived and implemented in reaction to the Dust Bowl—a major climatic episode that spanned much of the 1930s.[24] One might wonder, consequently, whether a reversion to non-shock conditions might have occurred around the time of the tree planting. More broadly, it is well established that oceanic oscillations influence regional climate over the course of years and decades. The most prominent is the El Niño-Southern Oscillation (ENSO) in which warming in the Pacific Ocean produces periodic climate shifts that differentially affect regions across the globe (Zebiak and Cane 1987). These fluctuations might then differentially affect the counties in our sample.

Reassuringly, the counties affected and non-affected by the Shelterbelt project exhibit parallel trends in the baseline period. Nonetheless, the counties affected appear to be drier and hotter than control counties, on average (Figure 4). Despite the observed parallel trends, there remains a concern that differential exposure to a decennial weather shock during the baseline period could induce this level difference across the affected and control counties. We address this concern in several ways.

First, we expand the time span of our analysis further back in time, and replicate our main analysis by comparing affected and control counties facing the same medium-term climate fluctuations. Our main analysis starts in 1930, a choice driven by concerns about the availability and quality of pre-1930 climate and agricultural data (Knappenberger et al. 2001; Kunkel et al. 2007). With that caveat, we use the available climate data from 1910 onward for this exercise.[25] There appear to be different pre-exposure trends between Shelterbelt and control counties in the 1910s and 1920s, leading up to the differential levels observed in the 1930s (Appendix Figure A14). We note that replicating our main difference-in-differences analysis for 1910 through 1965 produces similar results to our main analysis, though somewhat less precise and lower in magnitude. But given these divergent early-period pre-trends, we further focus on counties experiencing similar climate patterns from 1910

[24] Interestingly, climate scientists argue that the Dust Bowl of the 1930s was caused by a combination of oceanic anomalies (which are exogenous to human activities in the US Midwest) and of local human-induced land degradation (Cook et al. 2009).

[25] In order to replicate our analysis for 1910 through 1965, we repeat the construction of a county-by-year precipitation and temperature panel based on daily weather stations, except using a balanced panel of stations reporting between 1910 and 1965 instead of 1930 and 1965.

to 1942 (our pre-exposure period)—and since they do not experience differential patterns, concerns about medium-term climate reversion are alleviated.

To this end, we provide evidence from two methods: first, we repeat the synthetic difference-in-differences approach for this longer time period and second, we control for the magnitude of the 1930s climate shock in our long differences approach. By construction, the synthetic difference-in-differences control region experiences the same climate trends throughout the pre-treatment period as the treated counties.[26] Appendix Table A22 contains the results of the synthetic difference-in-differences analysis for the periods from 1910 to 1965 and 1919 to 1965. Despite our concerns about data quality in the early period, our main precipitation results in downwind counties are remain robust in this version of the analysis. Temperature results are lower in magnitude but directionally consistent with our headline results.

Second, we also rerun our long differences analysis but add additional controls for the intensity of the 1930s Dust Bowl climate shock.[27] By controlling for the intensity of the shock, we are comparing counties experiencing similar medium-term climate patterns. Our main long differences results are robust to these additional controls (Appendix Table A23).

Next, we take a completely different approach in addressing concerns about medium-term climate reversions. We repeat our analysis at a hyperlocal level, using individual weather station data and the shapefile of the exact location and area of surviving Shelterbelt plantings (Snow 2019) to calculate afforested area in the vicinity of each station. Variations in tree planting intensity at this very local level are uncorrelated or only weakly correlated with measures of Dust Bowl intensity. The hyperlocal comparison essentially allows us to control for climate patterns at broader spatial and temporal scales. We find that stations with more nearby afforestation recorded higher precipitation and lower temperatures in the decades after the Shelterbelt project (Appendix Table A24). These results, though likely partially mitigated by spillover effects that we document, show that the change in climate due to tree planting holds at the local level—and not just at spatial scales that could reflect multi-decadal climate phenomena like oceanic oscillations. Further discussion of the station-level results is provided in Appendix A.5.

[26] More precisely, the weighted pre-exposure climate trend will be the same for the treated units and the synthetic control units. The synthetic difference-in-differences graphs show that most pre-treatment periods receive non-zero weights.

[27] For measures of Dust Bowl intensity, we use the share of county area with high erosion from Hornbeck (2012). We also calculate separate precipitation and temperature anomalies in the 1930s as our other two measures of Dust Bowl intensity. To do this, we regress each climate measure on a county-specific time trend over the time period before the Dust Bowl (1910 to 1929), then predict precipitation and temperature given the baseline trend. Finally, we compute the difference between predicted and realized climate measures.

6 Conclusion and discussion

While tree planting is often positioned as an important tool in mitigating global climate change, the impacts of massive tree-planting programs on local and regional climate—and resulting economic effects—are less often examined and discussed. In this paper, we study the Great Plains Shelterbelt project, which planted over 220 million trees in the US Midwest between 1935 and 1942, representing what is likely the largest afforestation initiative in history up to that date.

We digitize historical maps of the Shelterbelt project to study the effects of tree planting on precipitation and temperature and economic outcomes like yields. We use a difference-in-differences approach that exploits wind patterns. We compare counties in the Shelterbelt and in downwind unforested 'spillover' counties with further away control counties. We find that rainfall increased and temperature decreased in both the forested and the spillover counties. Our results are robust to various alternate empirical methods, including synthetic difference-in-differences, long differences, and instrumental variables approaches.

Are these climate effects realistic given the scale of the tree-planting effort? One way to test this is to compare the precipitation effect we find in Table 1 to the theoretical transpiration rate of trees. Our estimated precipitation coefficient is 0.22 cm per month. Summing this over the three summer months that we analyze from June to August (0.66 cm), and multiplying by the total Shelterbelt and downwind areas (812,200 km^2), results in an increase of 1 cm of water per year spread across 538,500 km^2, which is equivalent to 4.4 million acre-feet of water (1.42 trillion gallons). In terms of theoretical transpiration, the Shelterbelt program planted 220 million trees with an estimated survival rate of 61% (Read 1958). USGS estimates that a large oak tree can transpire 40,000 gallons per year.[28] Proportionally allocating across the three summer months equates to 10,000 gallons per tree per year. Thus the surviving 134 million trees could produce 1.34 trillion gallons of water via transpiration—which is remarkably consistent with the 1.42 trillion gallons attributable to increased precipitation. While this exercise is coarse and simplistic[29]—the general alignment between the program's estimated and physical potential is reassuring.

After establishing the climate effects of the Shelterbelt project, we turn to study the economic impacts of this engineered climate change. Our strategy enables us to disentangle the effect of a changing climate on economic outcomes from other mechanisms. We find that corn

[28] See https://www.usgs.gov/special-topics/water-science-school/science/evapotranspiration-and-water-cycle

[29] This back-of-the-envelope calculation omits many important factors, including direct evaporation from the soil, interactions with cropland, and differential transpiration rates across tree species, baseline climate, and temporally across the growing season.

yields increase by 11-22% in Shelterbelt and downwind spillover areas. We also observe adaptation to more favorable climate conditions as farmers reallocate pastureland to cropland in afforested counties and downwind neighboring areas. Furthermore, farmers switch from less water-sensitive crops like wheat to more water-sensitive crops like corn.

Our findings are especially timely given the global enthusiasm for large-scale tree planting as a means of mitigating climate change in light of estimates that such activities could potentially could reduce atmospheric CO_2 levels by 25% (Bastin et al. 2019). Tree planting is a major part of nearly all proposed pathways to 'net zero' emissions, with estimated capital requirements on the scale of hundreds of billions of dollars. The excitement around tree planting is further evidenced by the increasing number of national forestry initiatives used by countries to meet their mitigation targets under the Paris Agreement.[30]

There are good reasons for this enthusiasm. Tree planting is a 'simple technology' enjoying high levels of public approval. And prior to concerns about climate change, afforestation initiatives like the Great Plains Shelterbelt and China's Three-North Shelterbelt Program were implemented to stabilize soils and reduce erosion and dust storms. Our paper adds another co-benefit to this list. The increased precipitation and decreased extreme heat that we find during the growing season provides a major benefit to most types of agricultural production—particularly in the major cropland regions of the world that face hot summers and limited rainfall—conditions that are worsening under climate change. So in this sense, tree planting can be both a tool for mitigation (by sequestering carbon), as well as adaptation (by reducing the negative impact of global warming on agriculture).[31]

However, large-scale afforestation is not without controversy, particularly regarding the enormous amount of land required to reduce CO_2 levels at a meaningful scale.[32] Some critics worry that massive afforestation efforts could come at the expense of cropland and thus food security, while others are concerned that about the dispossession of land from pastoralists

[30] Recently national initiatives include Pakistan's 10 Billion Trees Tsunami (2018), India's Tree-planting pledges (2017), Mexico's Sowing Life Program (2019), Kazakhstan's Two Billion Tree Project (2020), Turkey's Breath for the Future (2021), Mongolia's One Billion Tree Project (2021), and WEF's One Trillion Trees (2020).

[31] An active literature in economics focuses on the drivers and consequences of deforestation, especially in the tropics (Burgess et al. 2012; Jayachandran et al. 2017; Burgess et al. 2019; Balboni et al. 2021; Araujo et al. 2022). A forthcoming review is provided by Balboni et al., n.d. Our study focuses on tree planting, but the benefits we identify can also represent costs from deforestation. By illustrating the challenges to maintain the current tree cover, this evidence base can help guide the design of afforestation programs.

[32] One estimate of the land required for afforestation to achieve a 'net zero' transition is 160 million hectares by 2030, larger than France, Spain, and Germany combined (McKinsey Global Institute 2022); another report estimated an even larger figure of 1.2 *billion* hectares to achieve the carbon sequestration from national climate pledges under the Paris Agreement—an area equivalent to all current global cropland (Dooley et al. 2022).

and other traditional groups. Another major concern relates to the timing of the CO_2 reductions, given that emission reductions are immediate while trees take decades to grow, as well as their permanence in light of the potential for large-scale tree mortality from drought, invasive species (e.g., mountain pine beetle), cyclones, and wildfires (Leverkus et al. 2022).

Many of these very real concerns can be addressed through the careful design of afforestation programs. It is important to note that not all tree planting initiatives are equal and that their outcomes and their co-benefits will be a function of the land selected, the tree species included, their ongoing management over time, and community engagement. In China, there is evidence of farmers cutting down native trees and replacing them with monocultural plantations (Hua et al. 2018). The program we study, the Great Plains Shelterbelt, was unique in that tree planting occurred in concentrated areas and windbreaks. Over 30 species of trees and shrubs were selected—tall and short trees, fast and slow growing trees, hardwoods and conifers—most of which were native and thus locally adapted (Read 1958) to ensure species diversity and ecological resilience in a way that mimicked naturally-occurring forests. Clearly, a tree planting program involving monocultures or non-native species could produce outcomes different than what we find—as well as different capital costs.

Relatedly, another valid question concerns the external validity of our results and the extent that the Great Plains is similar to other potential tree planting regions of the world. In terms of economic status, we first note that many countries today are still highly dependent on agriculture like the US Midwest was in the 1940s.[33] In terms of agronomic conditions, the Great Plains Shelterbelt occurred on mollisol soils, which are common throughout rainfall-limited regions that were historically grasslands. As shown in Appendix Figure A13, these soils are also present in the major crop growing regions of China, Russia, Kazakhstan, Ukraine, Turkey, Argentina, Uruguay, Mexico, and Canada—many of the same countries which have proposed large-scale tree planting programs. Thus it is reasonable to think that similar climate and yield effects from tree planting could occur outside the Great Plains context.

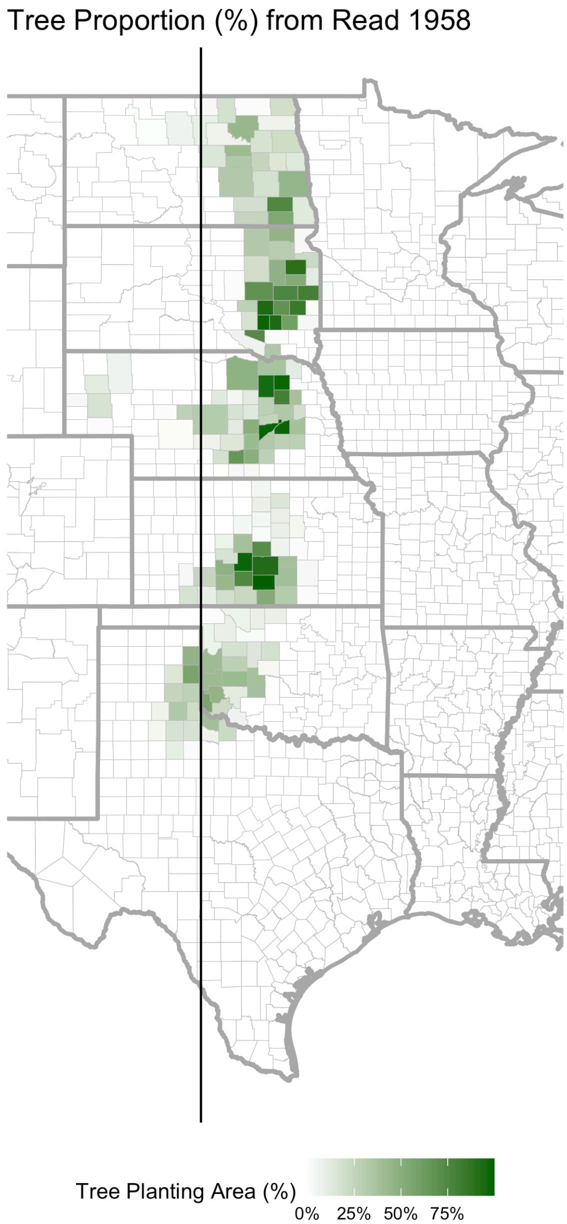
To conclude, we find that the Great Plains Shelterbelt altered the climate and growing conditions of a meaningfully large area—a region twice the size of California—over the course of several decades, producing important economic consequences. Our results show that human actions can alter local and regional climates through land use. In addition to the implications for tree planting initiatives and climate policy described above, our paper highlights the endogeneity risk in using spatial variation in climate trends to assess local climate change impacts and the potential bias it can imbue on climate change damage

[33] Both Mexico and China, for example, have a current GDP per capita and share of the population employed in agriculture similar to the US in 1940 (Appendix Figure A12).

estimates. Future work should investigate how drivers of climate spillovers can be used as instruments for identifying the effect of climate change on economic outcomes.

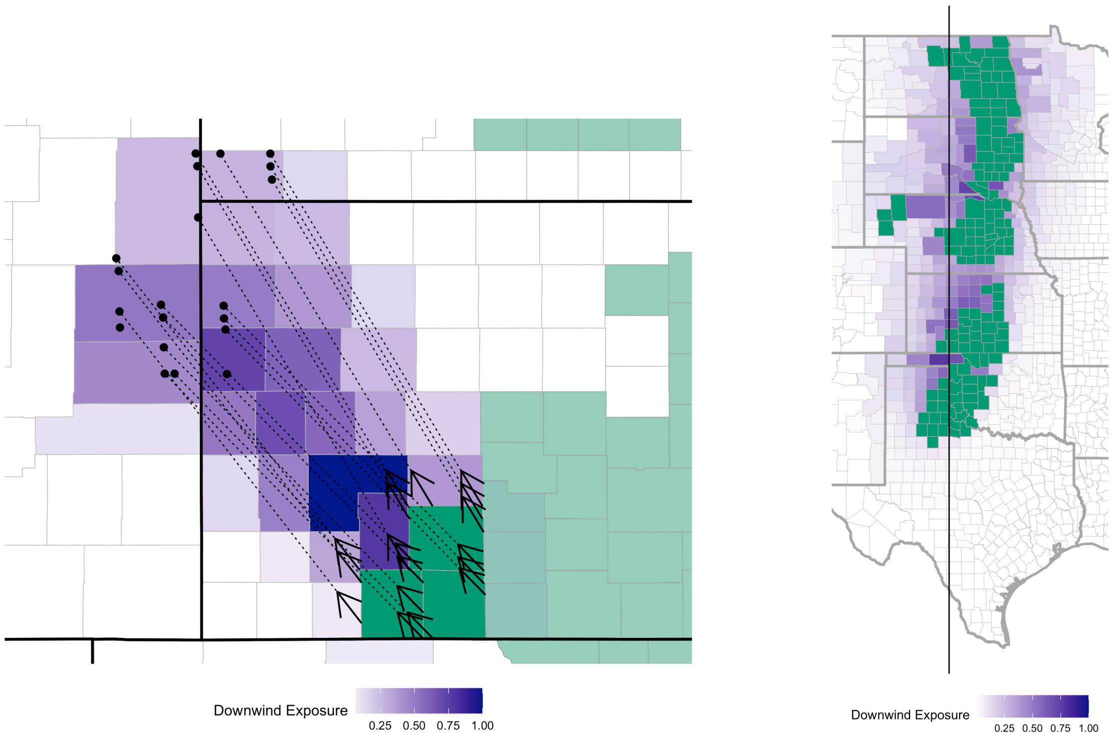
7 Figures

Figure 1: Shelterbelt Measure



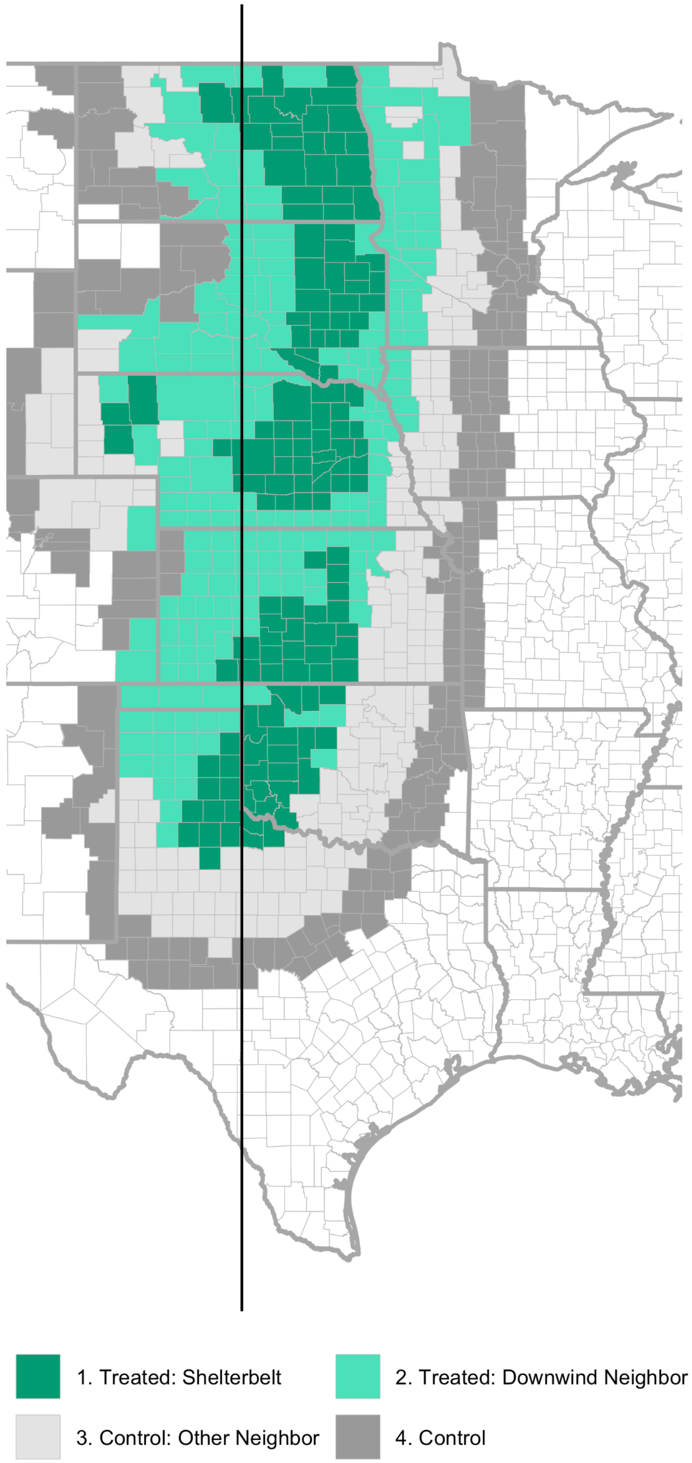
Notes: Figure shows intensive tree planting area (% of county area) based on digitized maps from Read (1958). We calculate the percentage of each county covered by "areas of concentrated Shelterbelt planting". Throughout the paper, we refer to counties with at least 5% tree proportion as Shelterbelt counties.

Figure 2: Shelterbelt Wind Exposure Measure



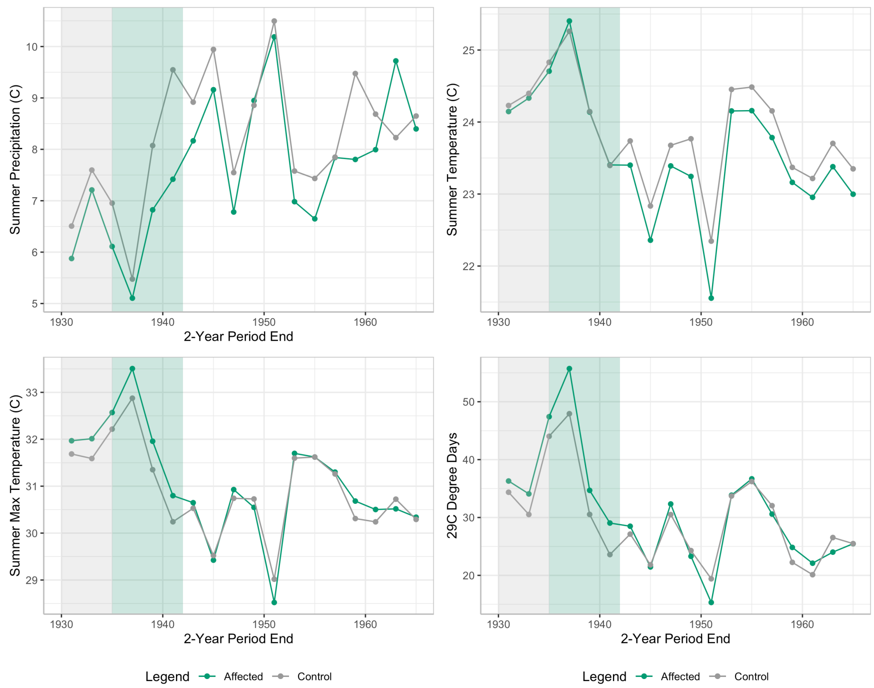
Notes: Figures illustrate the construction of our Shelterbelt wind exposure measure. Counties in green are treated Shelterbelt counties while purple shading shows continuous wind exposure measure. Left panel shows detail in Kansas for three Shelterbelt counties. Arrows represent direction and magnitude of prevailing winds for a given hour, while dotted lines show the path of imaginary particles projected from county vertices. Neighboring counties that intersect more paths are counties with higher exposure to winds that pass through Shelterbelt areas. Our final wind exposure measure is a weighted sum of wind exposure for all summer hours and from all Shelterbelt counties. Right panel shows the final continuous wind exposure measure for spillover counties.

Figure 3: Shelterbelt, Spillover, and Control Counties



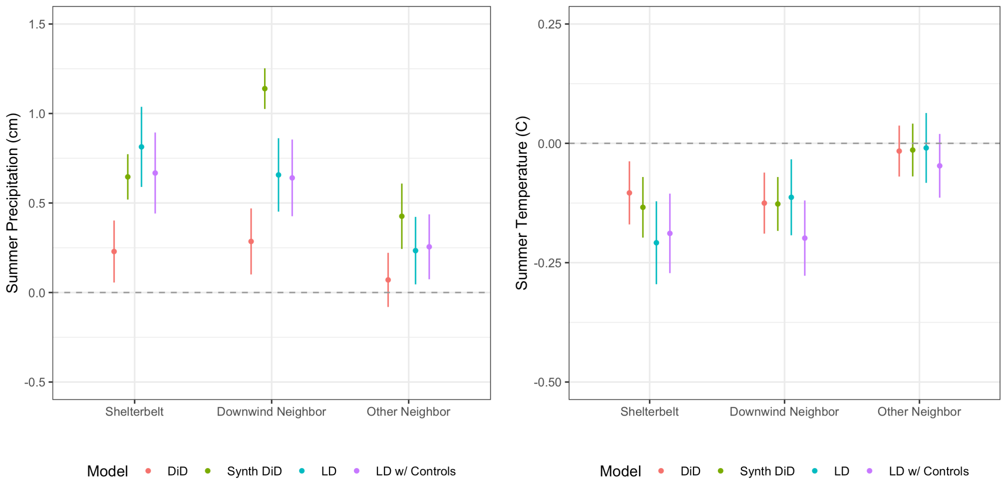
Notes: Map shows treated, downwind spillover, other spillover, and control counties used in main difference-in-differences analysis. Spillover counties are defined as counties with centroids within 200km of Shelterbelt counties, while control counties are counties with centroids 200-300km away from Shelterbelt counties.

Figure 4: Trends in Climate Outcomes for Affected and Control Counties



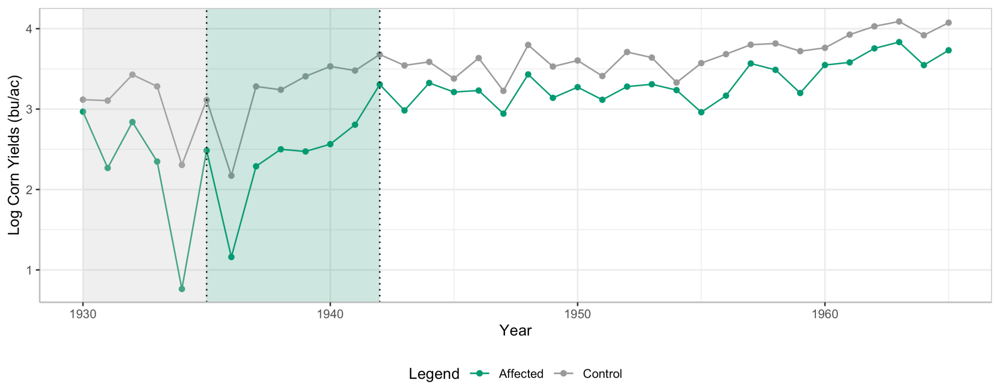
Notes: Figures plot mean summer precipitation, mean/maximum summer temperatures, and 29C degree days for all affected areas (Shelterbelt and downwind neighbors) and for pure control counties for 1930-1965. Climate outcomes are averaged for two year periods in order to smooth high year-to-year variation. Gray shaded area shows pure baseline period (without tree planting), green shaded area shows Shelterbelt project years.

Figure 5: Climate Results Summary



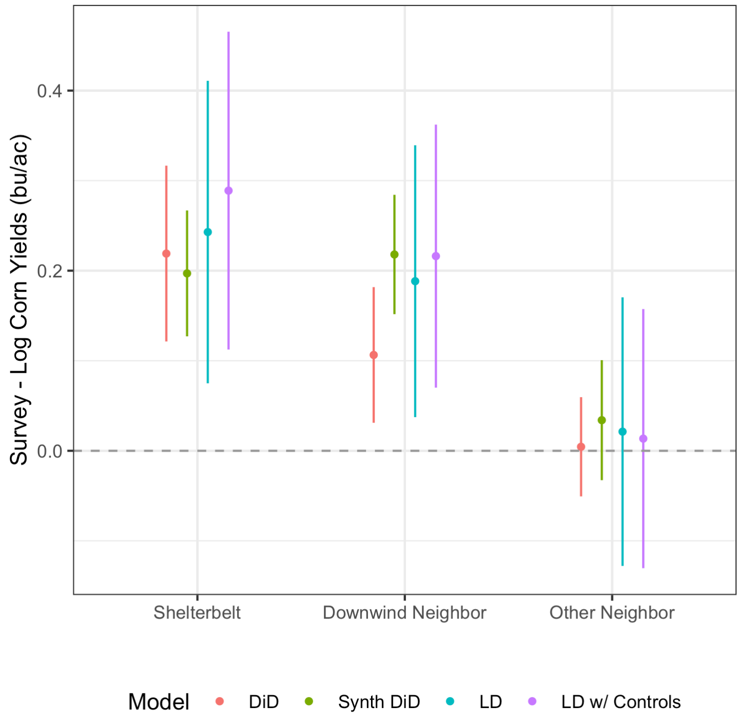
Notes: Figures plot coefficient estimates and 95% confidence intervals for mean summer precipitation and maximum summer temperatures across different models: difference-in-differences (equation 2), synthetic difference-in-differences (equation 3), long differences (equation 4) with and without controls.

Figure 6: Trends in Economic Outcomes for Affected and Control Counties



Notes: Figures plot (log) corn yields for all affected areas (Shelterbelt and downwind neighbors) and pure control counties for 1930-1965. Gray shaded area shows the pre-Shelterbelt period; green shaded area shows Shelterbelt project years.

Figure 7: Economic Results Summary



Notes: Figures plot coefficient estimates and 95% confidence intervals for corn yields using survey data across different models: difference-in-differences (equation 2), synthetic difference-in-differences (equation 3), long differences (equation 4) with and without controls.

8 Tables

Table 1: Impact of Great Plains Shelterbelt on Jun-Aug county climate, 1930 to 1965

	Dependent variable:			
	Precipitation (cm)	Temperature (C) Mean	Max	29C Degree Days
	(1)	(2)	(3)	(4)
All Impacted Areas:Post 1942	0.221***	−0.107***	−0.128***	−1.725***
	(0.074)	(0.022)	(0.031)	(0.314)
	[0.004]	[0.000]	[0.000]	[0.000]
Control:Post Mean	8.55	24.09	31.11	30.64
Control:Post Std.Dev.	3.97	3.27	3.33	24.45
Observations	24,408	24,408	24,408	24,408

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets. Table shows results for estimating equation 2. Dependent variables are June - August averages. County and state-by-year FE included.

Table 2: Impact of Great Plains Shelterbelt on Jun-Aug county climate, 1930 to 1965

	Dependent variable:			
	Precipitation (cm)	Temperature (C) Mean	Max	29C Degree Days
	(1)	(2)	(3)	(4)
Shelterbelt:Post 1942	0.229***	−0.104***	−0.160***	−1.986***
	(0.088)	(0.034)	(0.046)	(0.454)
	[0.010]	[0.003]	[0.001]	[0.000]
Downwind Neighbor:Post 1942	0.285***	−0.125***	−0.129***	−1.727***
	(0.094)	(0.033)	(0.043)	(0.410)
	[0.003]	[0.000]	[0.003]	[0.000]
Other Neighbor:Post 1942	0.071	−0.016	−0.022	−0.184
	(0.077)	(0.027)	(0.038)	(0.355)
	[0.361]	[0.552]	[0.551]	[0.606]
Shelterbelt=Neighbor	p = 0.422	p = 0.420	p = 0.435	p = 0.527
Downwind=Other	p = 0.020	p = 0.000	p = 0.005	p = 0.000
Control:Post Mean	8.60	23.61	30.59	26.91
Control:Post Std.Dev.	4.05	3.30	3.28	23.02
Observations	24,408	24,408	24,408	24,408

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets. Table shows results for estimating equation 2. Dependent variables are June - August averages. County and state-by-year FE included.

Table 3: Impact of Great Plains Shelterbelt on corn yields, 1930 to 1965

	Dependent variable:			
	Log Yield (bu/ac)		Log Production (bu)	Log Area (ac)
	(1)	(2)	(3)	(4)
Shelterbelt:Post 1942	0.219***	0.109***	0.396**	0.257*
	(0.050)	(0.036)	(0.157)	(0.145)
	[0.000]	[0.003]	[0.013]	[0.077]
Downwind Neighbor:Post 1942	0.106***	0.135***	0.374***	0.211*
	(0.038)	(0.035)	(0.125)	(0.116)
	[0.006]	[0.000]	[0.003]	[0.069]
Other Neighbor:Post 1942	0.004	0.048*	0.180*	0.113
	(0.028)	(0.029)	(0.098)	(0.091)
	[0.874]	[0.096]	[0.068]	[0.215]
Downwind=Other	p = 0.013	p = 0.012	p = 0.133	p = 0.411
Data Source	Survey	Census	Census	Census
Observations	11,088	5,344	4,736	4,736

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets. Table shows results for estimating equation 2, using both corn yields from agricultural surveys (annual, column 1) and censuses (every 5-years, columns 2 - 4). County and state-by-year FE included.

Table 4: Impact of Great Plains Shelterbelt on agricultural land use and adaptation, 1930 to 1965

	Dependent variable:				
	Cropland (1000ac)	Pastureland (1000ac)	Farmland (1000ac)	Corn Share (% of Cropland)	Wheat Share
	(1)	(2)	(3)	(4)	(5)
Shelterbelt:Post 1942	22.024^{***}	-108.036^{***}	-39.820^{***}	0.052^{***}	-0.035^{***}
	(5.743)	(25.516)	(11.963)	(0.006)	(0.009)
	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]
Downwind Neighbor:	38.512^{***}	-50.420^{**}	-16.550	0.024^{***}	-0.016^{**}
Post 1942	(6.352)	(23.692)	(11.852)	(0.006)	(0.007)
	[0.000]	[0.034]	[0.164]	[0.000]	[0.036]
Other Neighbor:	10.968^{**}	-43.369^{**}	-16.960^{**}	0.003	0.006
Post 1942	(5.415)	(17.390)	(8.469)	(0.006)	(0.005)
	[0.044]	[0.013]	[0.046]	[0.612]	[0.296]
Downwind=Other	p = 0.000	p = 0.671	p = 0.954	p = 0.000	p = 0.005
Control Post Mean	220.25	312.00	496.38	0.19	0.10
Control Post Std.Dev.	164.13	403.87	341.20	0.18	0.13
Δ Dep. Var. Control	49.28	36.37	-0.08	-0.03	156.06
Data Source	Census	Census	Census	Census	Census
Observations	4,904	4,904	4,904	4,899	4,678

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the county level are shown in parentheses; p-values shown in brackets. Table shows results for estimating equation 2 using data from agricultural censuses. County and state-by-year FE included.

Table 5: Implied changes in corn yields

	Dependent variable:				
		Degree Days		Precipitation	Log Yields
	10C	29C	39C	(cm)	Implied
	(1)	(2)	(3)	(4)	(5)
Downwind:Post 1942	-4.077^{***}	-1.727^{***}	-0.244^{***}	0.285^{***}	**0.104**
	(0.991)	(0.410)	(0.035)	(0.094)	-
	[0.000]	[0.000]	[0.000]	[0.003]	-
Observations	24,408	24,408	24,408	24,408	-

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets. Table shows results for estimating equation 2, for variables in the weather-yield relationship (equation 8) for Columns (1) - (4), including county and state-by-year FE. Column (5) shows the implied change in yields calculated using the steps described in Appendix A.4.

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A Appendix

A.1 Downwind county definition

In order to construct our time-invariant approximate measure of how exposed county i is to winds from all Shelterbelt counties ($w_i \in [0,1]$), we take the following steps. Let i index spillover counties, j index Shelterbelt counties and c index vertices of Shelterbelt counties. Finally, let h index the hours over the summer (June through August) for years 1981 - 2010 (e.g., $min(h)$ is on June 1st, 1981, while $max(h)$ is on August 31st, 2010). As discussed in the paper, we use hourly summer wind speed and direction for each Shelterbelt county for years 1981 - 2010 as spatially consistent hourly data are unavailable before the 1970s.

For each hour, we then repeat the following steps. From each vertex, v_{jc}, of each Shelterbelt county j (with total vertices V_j), we project where a particle would travel if it was blown by winds of the given direction and speed constantly for 1 day. For all unique outgoing-incoming county pairs, let $p_{ijch} = 1$ indicate if the particle from vertex v_{jc} of Shelterbelt country j intersects spillover county i for hour h. For each spillover county i, sum up all the particles originating from an outgoing county j and divide by the total number of vertices of the outgoing county.

$$p_{ijh} = \frac{\sum_c p_{ijch}}{V_j}$$

The resulting number, p_{ijh}, is the wind exposure from one county. Finally, sum up this measure from *all* Shelterbelt counties and all hours and normalize by dividing by the maximum value.

$$w_i = \frac{\sum_h \sum_j p_{ijh}}{\max \sum_h \sum_j p_{ijh}}$$

The resulting value $w_i \in [0,1]$ is the time-invariant approximate measure of exposure to winds from the shelterbelt.

A.2 1938-1942 Wind Interpolation

We construct an alternative measure of wind exposure, based on data for 1938-1942. We use NOAA's Integrated Surface Dataset for hourly data. We first collect hourly wind data from the weather stations with wind data. We then interpolate the hourly data to a 0.5 degree grid using nearest neighbor interpolation. Figure A5 shows what the data look like before and after interpolation. We then take the same steps, described in Section A.1, in constructing an alternate wind exposure metric as with the 1981-2010 gridded wind data.

Appendix Figure A6 compares the two resulting downwind exposure metrics. Reassuringly, the measures are very similar with a correlation of 0.89.

A.3 1930-1965 climate data construction

We build our main weather data from daily station data using methodology inspired by Schlenker and Roberts (2006). We use NOAA's Global Historical Climatology Network daily (GHCNd) data to create a balanced panel of stations with availability between 1930 and 1965. We take the following steps to construct our county-level daily data.

1. Start with precipitation and temperature stations from the GHCNd stations that are available for 1930 through 1965 (2,001 and 1,445 precipitation and temperature stations, respectively).
2. Select a constant set of stations based on availability. Keep stations with less than 5% missing observations between 1930 and 1965 (1,099 and 750 precipitation and temperature stations, respectively).
3. Fill in missing observations for this set of constant stations.
   a. For each station, S_i, find the 10 closest stations in the data.
   b. For each of the 10 nearby stations, calculate the percentile of the daily precipitation and maximum and minimum temperatures readings for each day, based on the entire available distribution of weather measures at the appropriate station.
   c. For each missing observation for station S_i, calculate the average percentile reading of the 10 closest stations (e.g., 71st percentile).
   d. Then, fill in the missing observation using the corresponding value from the distribution of S_i (e.g., if the 71st percentile corresponds to 20mm of precipitation at station S_i, the missing value will be filled in with 20mm).
4. Calculate degree days at each station.
5. Interpolate all variables to a 0.1 degree grid.
6. Average gridded values at the county level.

A.4 Decomposition of yield effects

We estimate the direct (mechanical) effect of the Shelterbelt-induced climate change on yields, in the downwind neighbor counties. We do so in three steps.

For the first step, we use the canonical Schlenker and Roberts (2009) piece-wise linear model to estimate the weather-yield relationship on counties non affected by the Shelterbelt project. Specifically, focusing on the non-downwind (other) neighboring and control counties, we use year-to-year variation in weather within counties and estimate the model for the period post-1942:

$$y_{it} = \mu + \delta_1 DD10_{it} + \delta_2 DD29_{it} + +\delta_1 DD39_{it} + \theta_1 precip_{it} + \theta_2 precip_{it}^2 + d_i + z_{it} + \nu_{it} \quad (8)$$

where y_{it} are annual log yields, DDX_{it} are average summer monthly degree days above $X°C$, $precip_{it}$ is average summer monthly precipitation, d_i are county fixed effects, and z_{it} are quadratic time trends for each state. Appendix Table A9 shows the results from this estimation. Consistent with the original results from Schlenker and Roberts 2009, 10°C degree days and precipitation have a positive impact on yields, while harmful degree days above 29°C and 39°C have negative effects on yields.

In the second step, we estimate treatment effects for each variable entering equation 8 above using our main difference-in-differences model. Table 5, Columns (1)-(5) show the results for each variable of interest. We then subtract the estimated treatment effects to obtain the weather absent Shelterbelt planting: $w_{1i} = w_{0i} - TE$.

In the third step, we use the estimated equation from the first step and realized weather (w_{0i}) to predict yields for each county (y_{0i}). We average post-treatment (1942 to 1965) weather variables and predict average post-period log yields ($\hat{y}_{0i}$) for downwind neighbor counties. We then repeat these steps, except replacing average realized weather (w_{0i}) with average weather that would have taken place absent Shelterbelt planting (w_{1i}). We predict yields using w_{1i} to obtain counterfactual yields $\hat{y}_{1i}$. Finally, we compute the average treatment effects on log yields using

$$ATE_{mecha} = \frac{1}{N} \sum_{i=1}^{N} (\hat{y}_{1i} - \hat{y}_{0i})$$

The expected mechanical effect of climate change on yields is shown in Column (6) of Table 5.

A.5 Station-level analysis

We repeat our main analysis at a hyperlocal level, using individual weather station data along with the shapefile of the exact location and area of surviving Shelterbelt plantings (Snow 2019).

We start with weather station data from NOAA's Global Historical Climatology Network daily (GHCNd) data. We use the same procedure as for the construction of our main climate data described in Appendix Section A.3. However, we use 1910 - 1965 precipitation and temperature data and stop before interpolating to a grid. The procedure results in station-level daily data, which we average to monthly values as before. We keep GHCNd stations within the Shelterbelt (as defined by our Shelterbelt treatment dummy). This corresponds to 79 precipitation and 51 temperature stations.

Using the Shelterbelt shapefile from Snow (2019), we calculate the area of tree planting within a 25 km radius of each station. We then estimate a version of our main difference-in-differences equation (equation 1)

$$y_{st} = \beta_{LOC}(AA_s \times P_t) + \xi_t + \rho_s + \epsilon_{st} \tag{9}$$

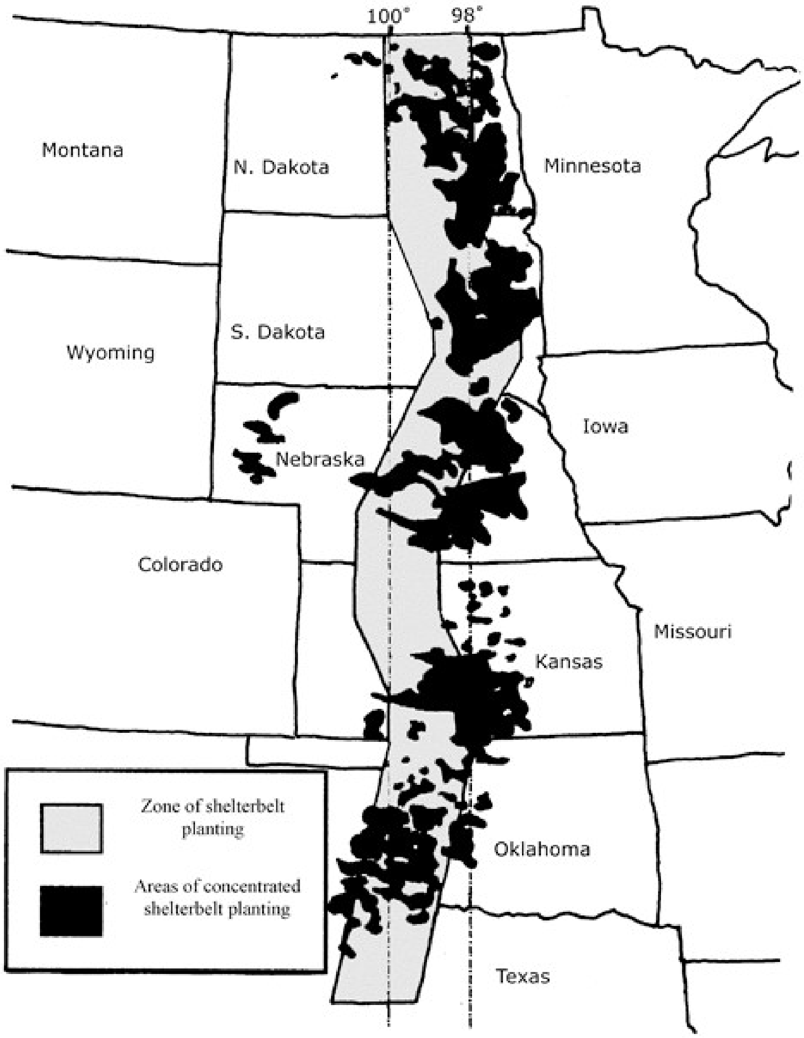
where y_{st} is the outcome of interest at the station-year level, AA_s is the area afforested within 25 km of the station (in 1000 acres), and P_t is a dummy variable equal to one for years after 1942. We include year (ξ_t) and station (ρ_s) fixed effects. β_{LOC} is the hyperlocal effect of planting an addition 1000 acres of trees for stations located in the Shelterbelt region.

Since we find significant spillover effects in our main analysis and these forces may impact our selected stations, we expect that the results from the hyperlocal analysis may be lower in magnitude than the true effect from local tree planting. Nevertheless, we find that stations with more nearby afforestation recorded higher precipitation and lower temperatures in the decades after the Shelterbelt project.

Appendix Table A24 shows the results. The results for precipitation are statistically significant and imply that planting 1000 additional acres of trees in the vicinity of a station lead to 1.2% more post-treatment summer precipitation. Average and extreme temperatures also decreased, though these estimates are less precise. These findings show that the change in climate due to tree planting holds at the local level.

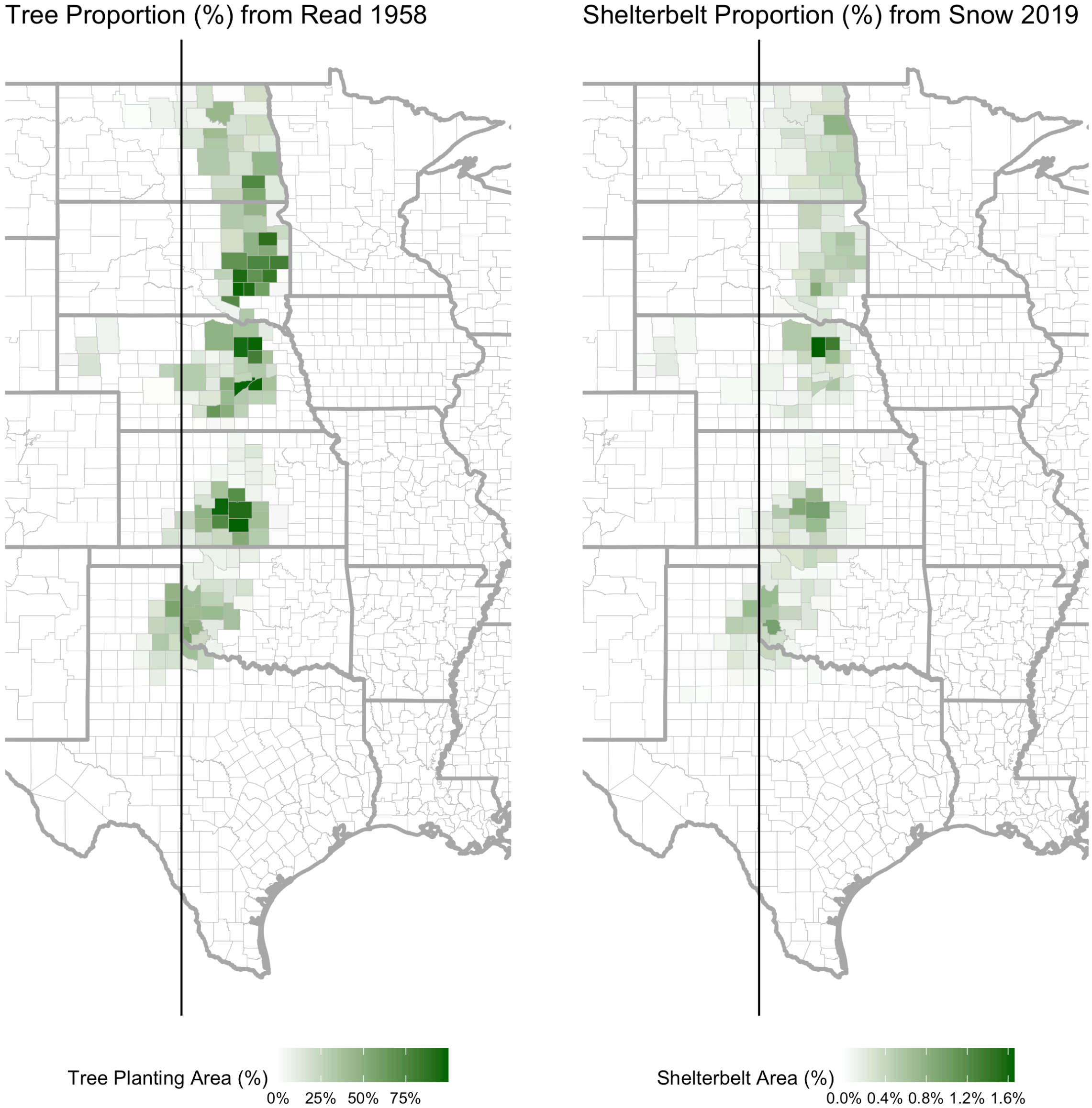
Appendix Figures

Figure A1: Shelterbelt Planned Area and Realized Concentrated Planning



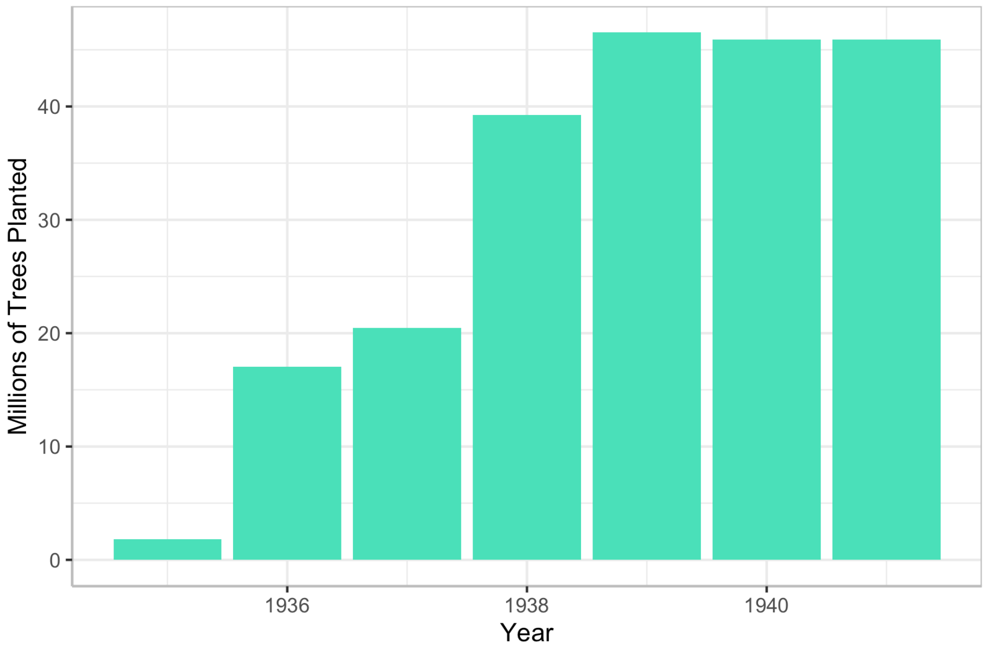
Notes: Map shows planned zone of Shelterbelt planning and areas of concentrated Shelterbelt planning accoring to Read 1958. Our Shelterbelt definition is based on county areas covered by the areas of concentrated tree planting.

Figure A2: Shelterbelt Measures



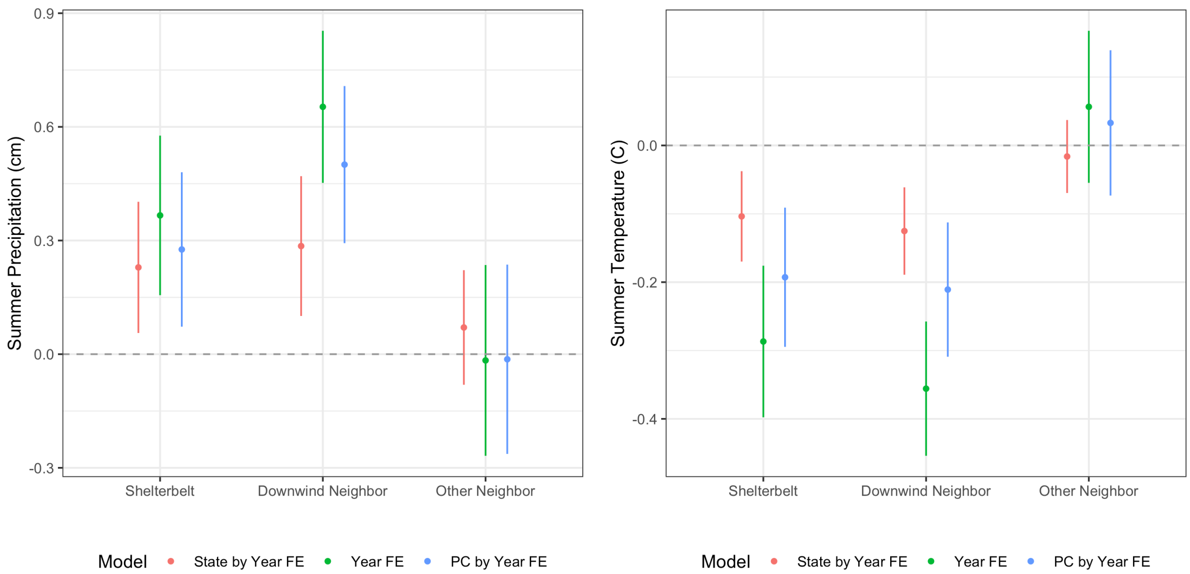
Notes: Figure compares our main measure of Shelterbelt treatment from Read (1958) and are alternate measure from Snow (2019) used for robustness checks. The two measures are similar (correlation 0.80).

Figure A3: Shelterbelt Tree Planting over Time



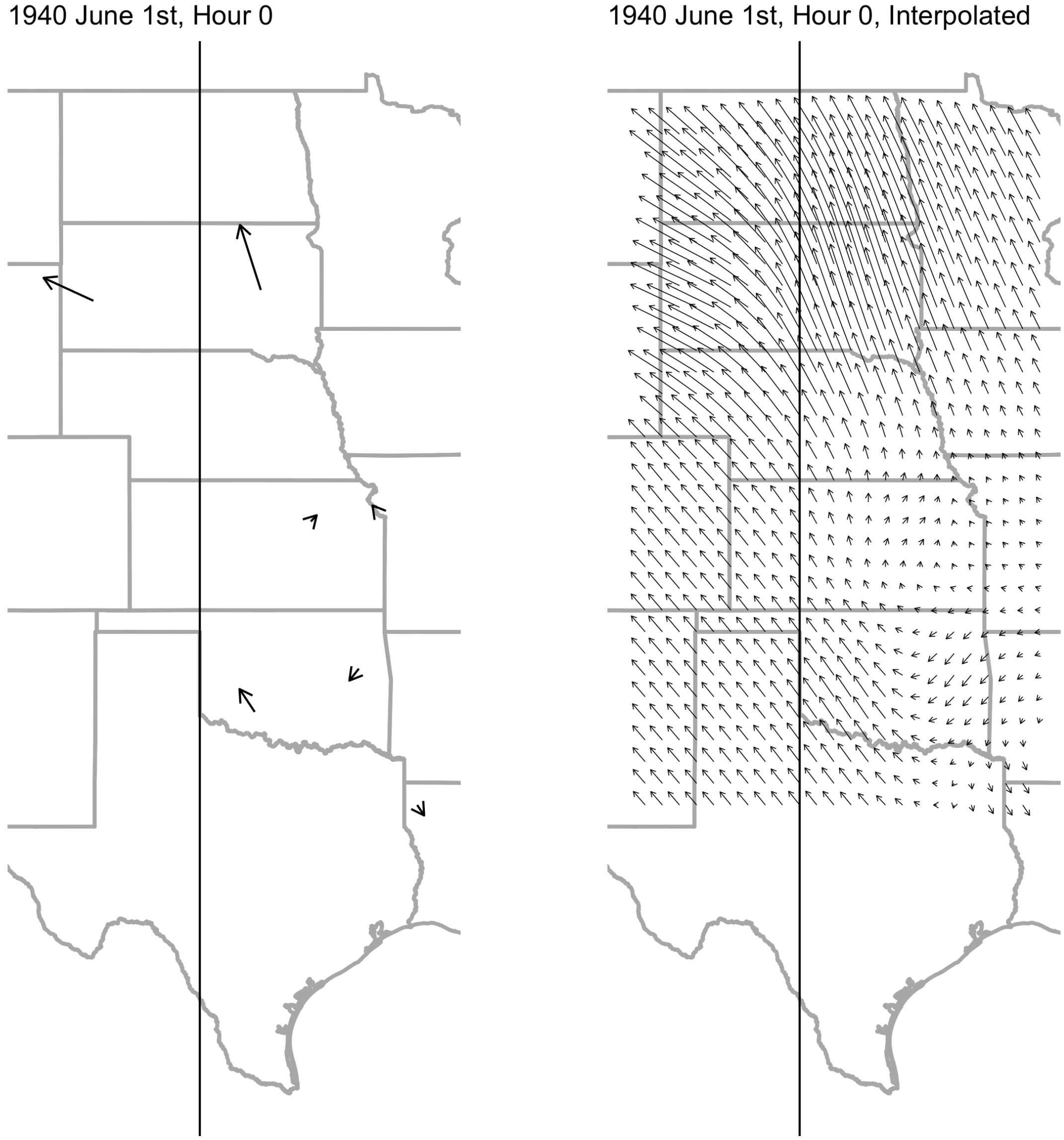
Notes: Figure plots the number of trees planted in each year of the Shelterbelt project implementation. Figures for 1940 and 1941 are estimates based on overall count of trees planted.

Figure A4: Climate Results with Alternate Fixed Effects



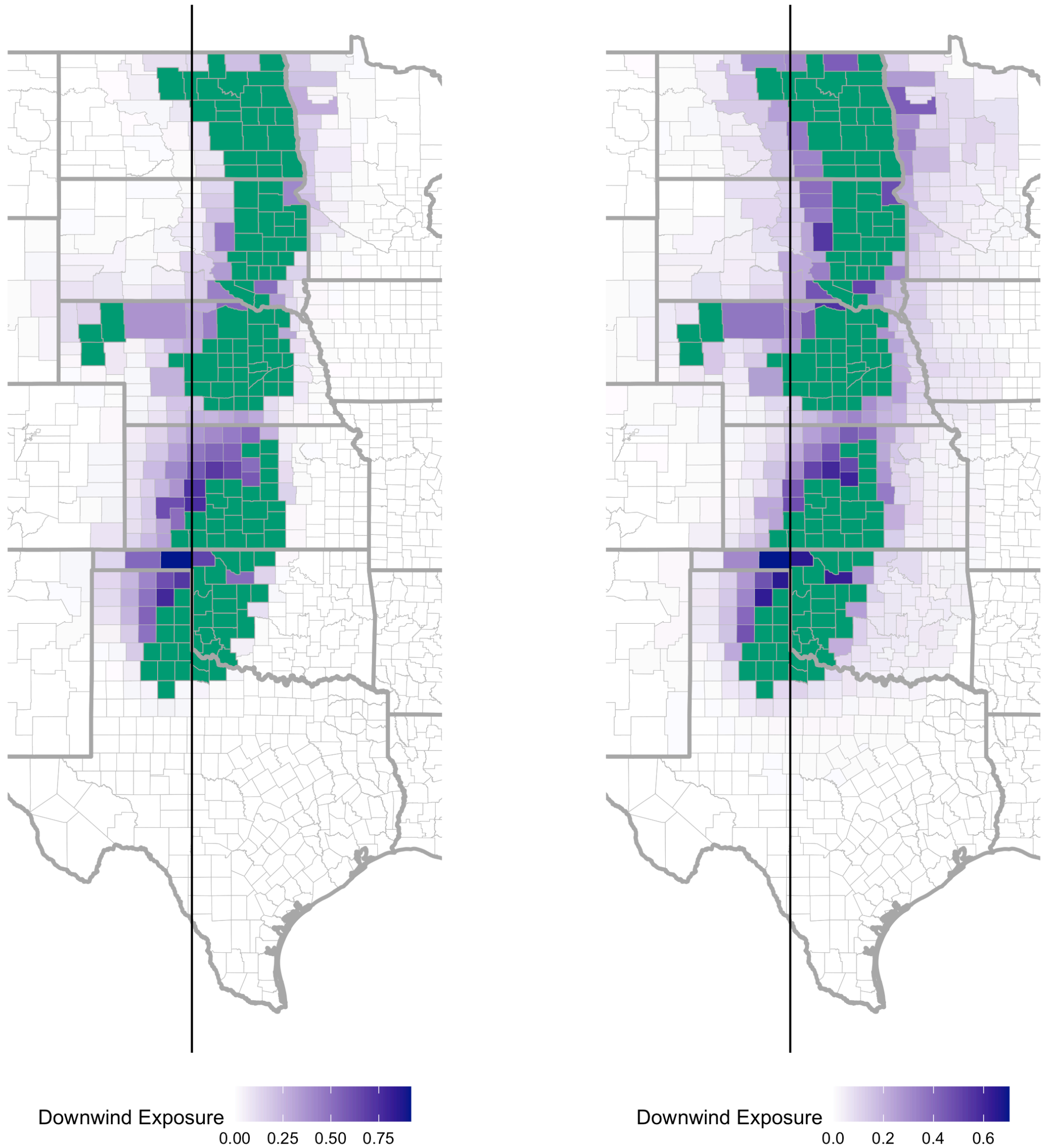
Notes: Figures plot coefficient estimates and 95% confidence intervals for mean summer precipitation and maximum summer temperatures across three specifications. In red, we show our main results with state-by-year (and county) fixed effects. In green, we include only year (and county) fixed effects. In blue, we include principal component quadrant by year fixed effects. To create these quadrants, we perform principal component analysis using county-level data on 1920s and 1930s population, ustolls share of county area, and Great Plains ecoregion share of county area, and average precipitation, maximum and minimum temperatures in the 1930s. We then create quadrants based on the main principal component.

Figure A5: Wind Interpolation Example



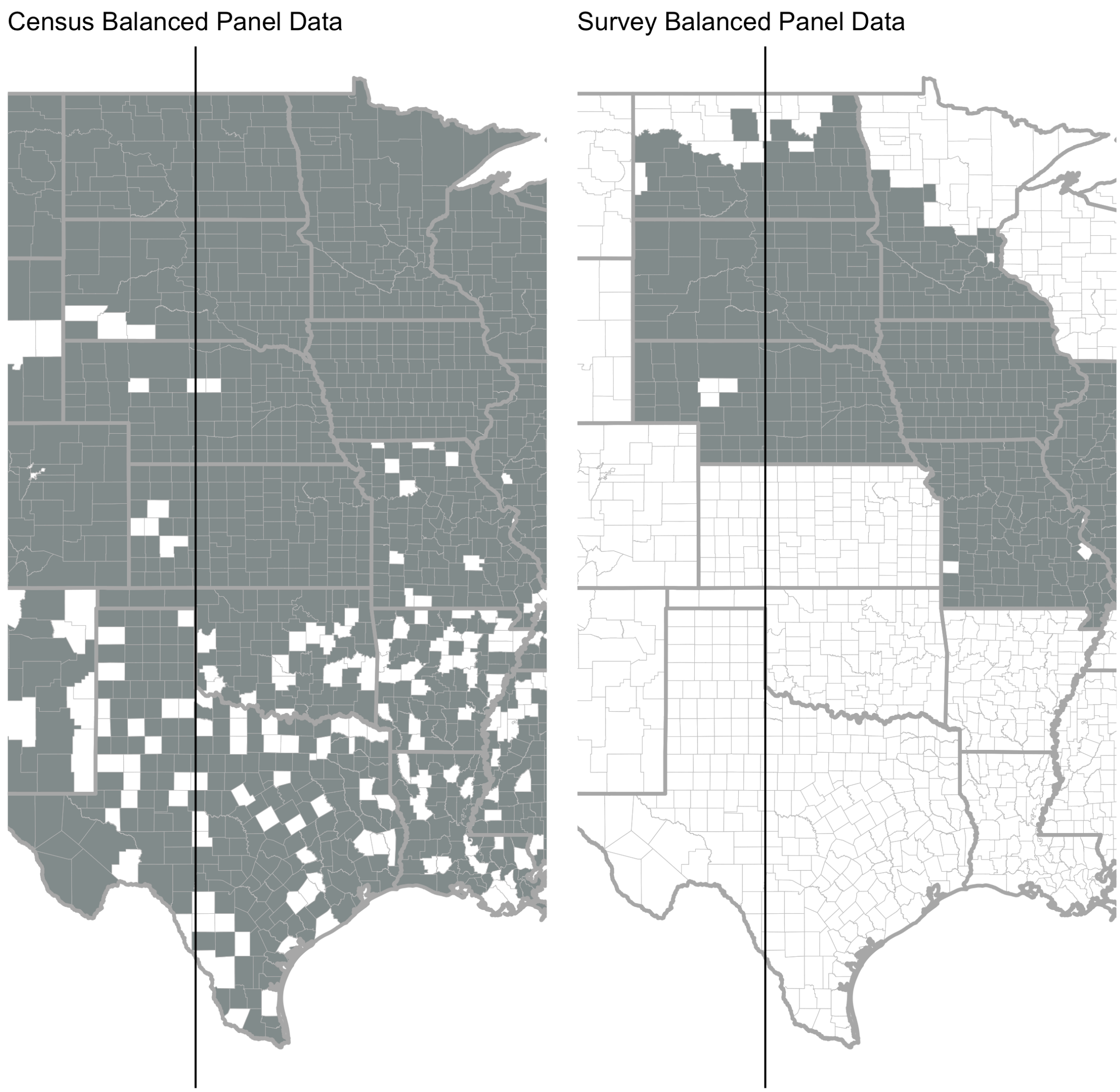
Notes: Figure shows sparse 1938 - 1942 wind station data interpolation for a given hour. The left panel shows wind direction and speeds for available stations in the US Midwest on 1940 June 1st, midnight to 1am. The right panel shows the wind data interpolated to a 0.5 degree grid.

Figure A6: Wind Exposure Measures



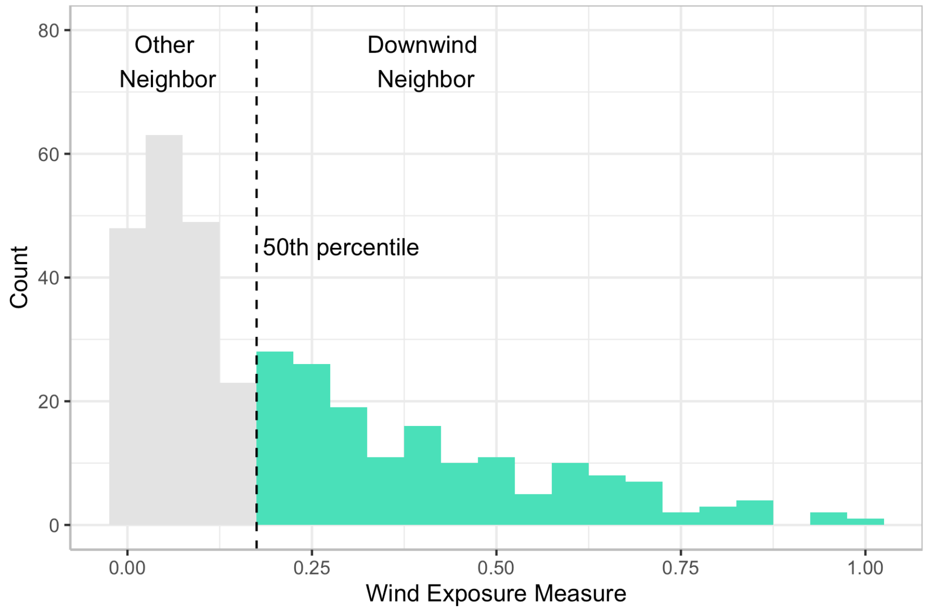
Notes: Maps show two alternate wind exposure metrics. Counties in green are treated Shelterbelt counties while purple shading shows continuous wind exposure measure. The left panel shows our main wind exposure measure based on 1981 - 2010 long-term average winds, while the right panel shows the same measure but using interpolated 1938 - 1942 wind station data. Reassuringly, the two measures are very similar (correlation 0.89).

Figure A7: Agricultural Survey and Census Data



Notes: Figure shows counties for which we have corn yield observations from the agricultural census and surveys for every time period between 1930 and 1965.

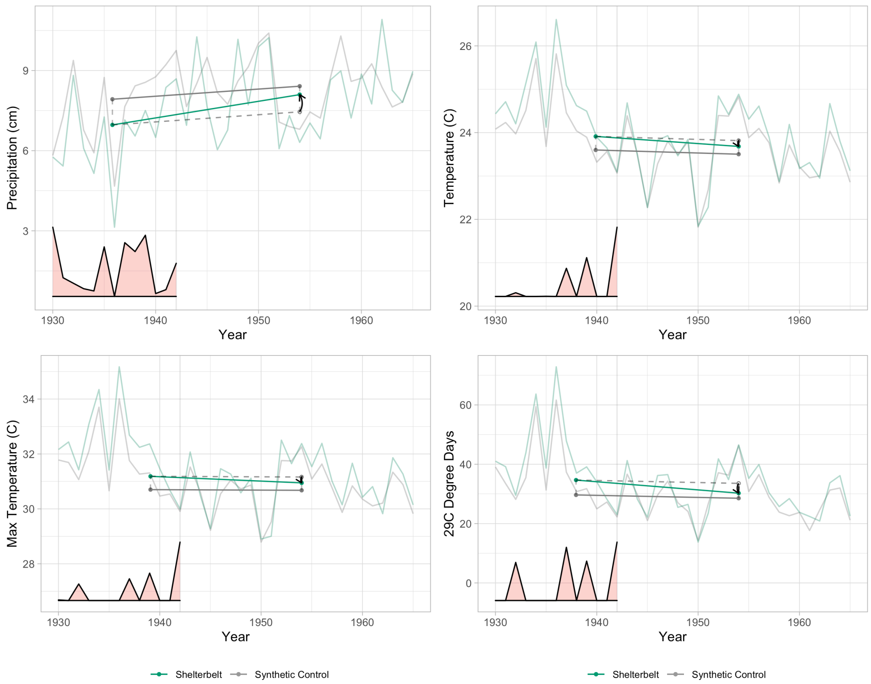
Figure A8: Shelterbelt Neighbor Wind Exposure



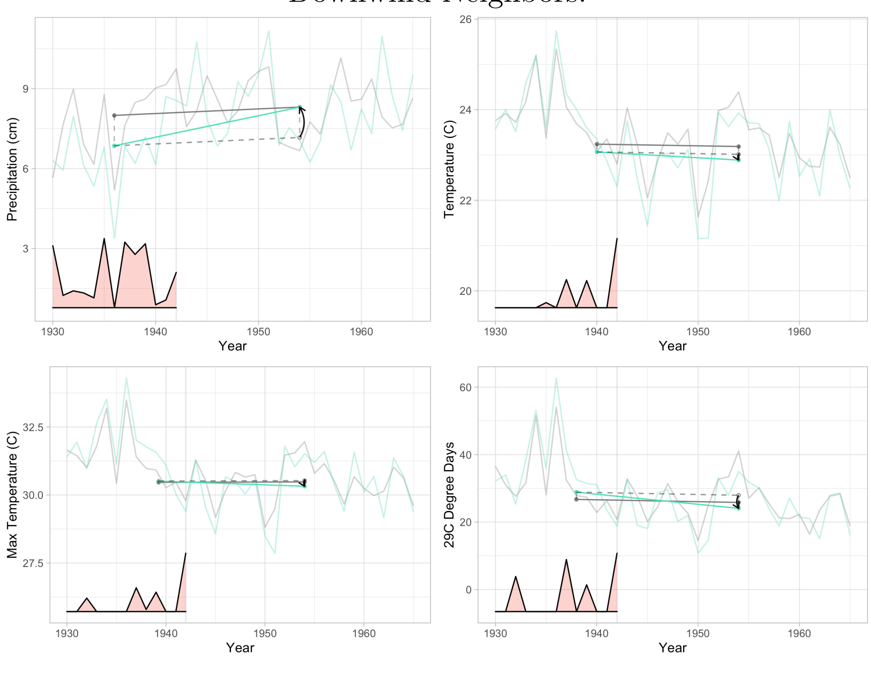
Notes: Figure shows histogram of the wind exposure measure for counties within 200km of afforested areas. Counties with wind exposure above the median measure are classified as downwind neighbor counties, while the rest are classified as other neighbors.

Figure A9: Climate Synthetic Difference-in-Differences Graphs

Shelterbelt:



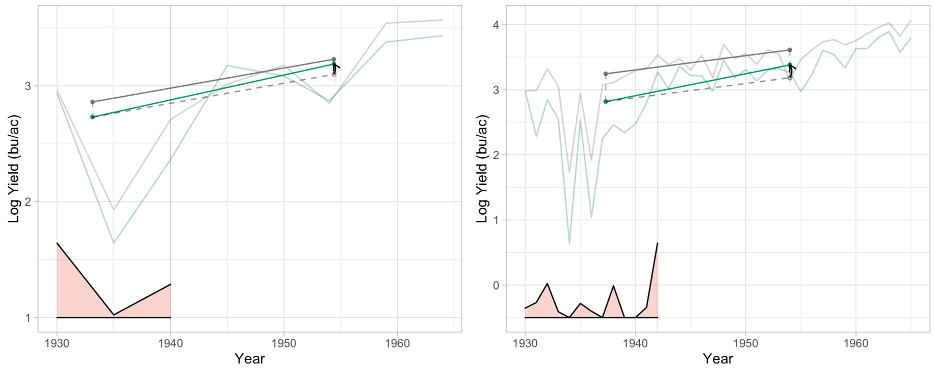
Downwind Neighbors:



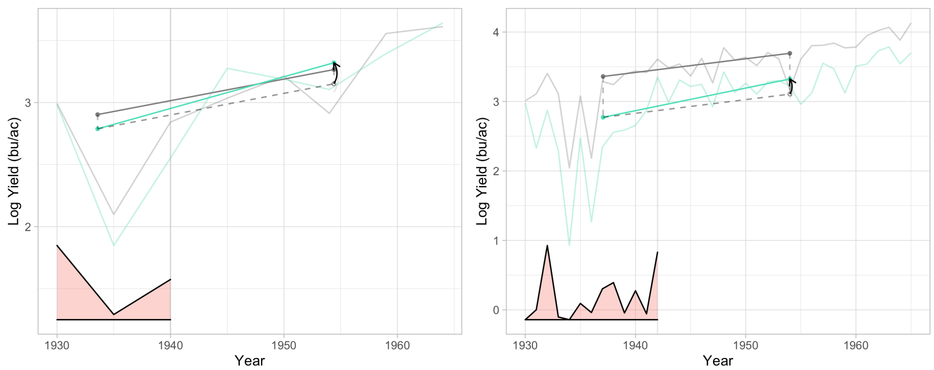
Notes: Figure shows climate synthetic difference-in-differences results graphically. Shelterbelt (top panel) and downwind neighbor (bottom panel) precipitation and temperature trends are plotted along with their respective synthetic controls trends; weights used to average pretreatment time periods are shown at the bottom of the graphs in red. The synthetic difference-in-differences method emphasizes periods that are on average more similar to treated periods, therefore the synthetic control trend (gray) is further adjusted using the weights shown at the bottom of the graphs. The estimated effect is indicated by the arrow.

Figure A10: Corn Yields Synthetic Difference-in-Differences Graphs

Shelterbelt:



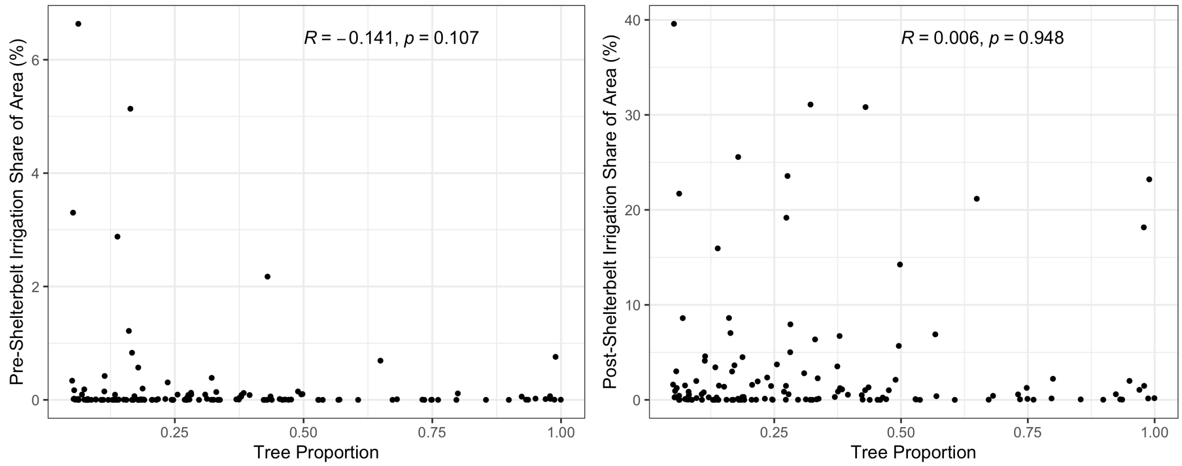
Downwind Neighbors:



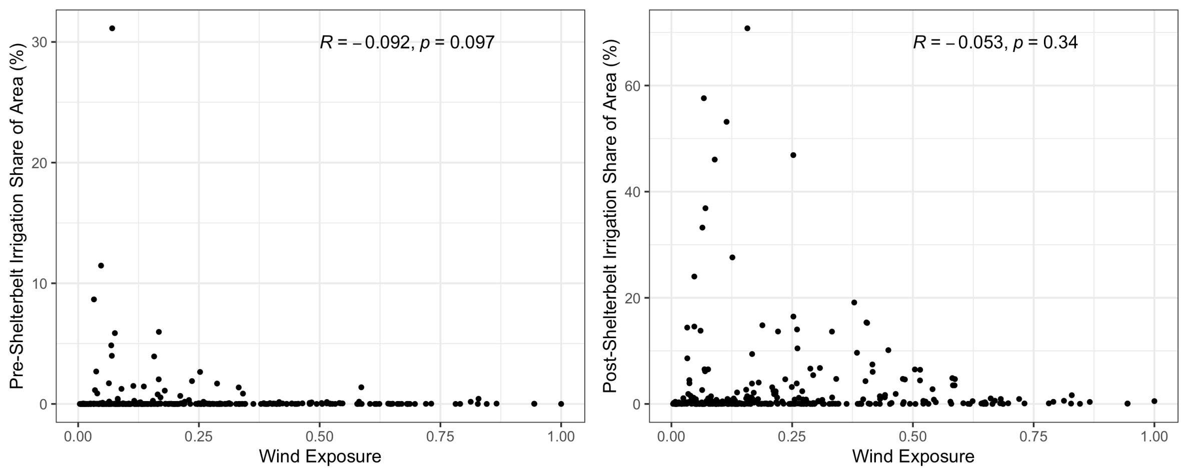
Notes: Figure shows corn yield synthetic difference-in-difference results graphically. Shelterbelt (top panel) and downwind neighbor (bottom panel) yields from the census (left panel) and agricultural surveys (right panel) are plotted along with their respective synthetic controls trends; weights used to average pretreatment time periods are shown at the bottom of the graphs in red. The synthetic difference-in-differences method emphasizes periods that are on average more similar to treated periods, therefore the synthetic control trend (gray) is further adjusted using the weights shown at the bottom of the graphs. The estimated effect is indicated by the arrow.

Figure A11: Irrigation and Shelterbelt Planting

Panel A:

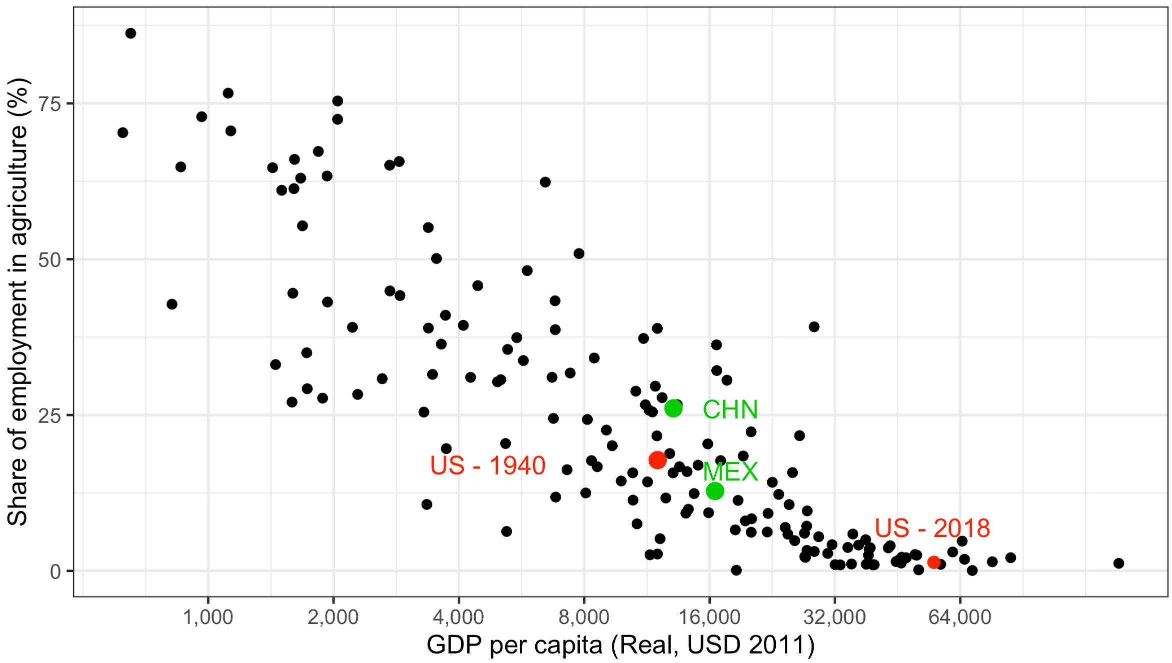


Panel B:



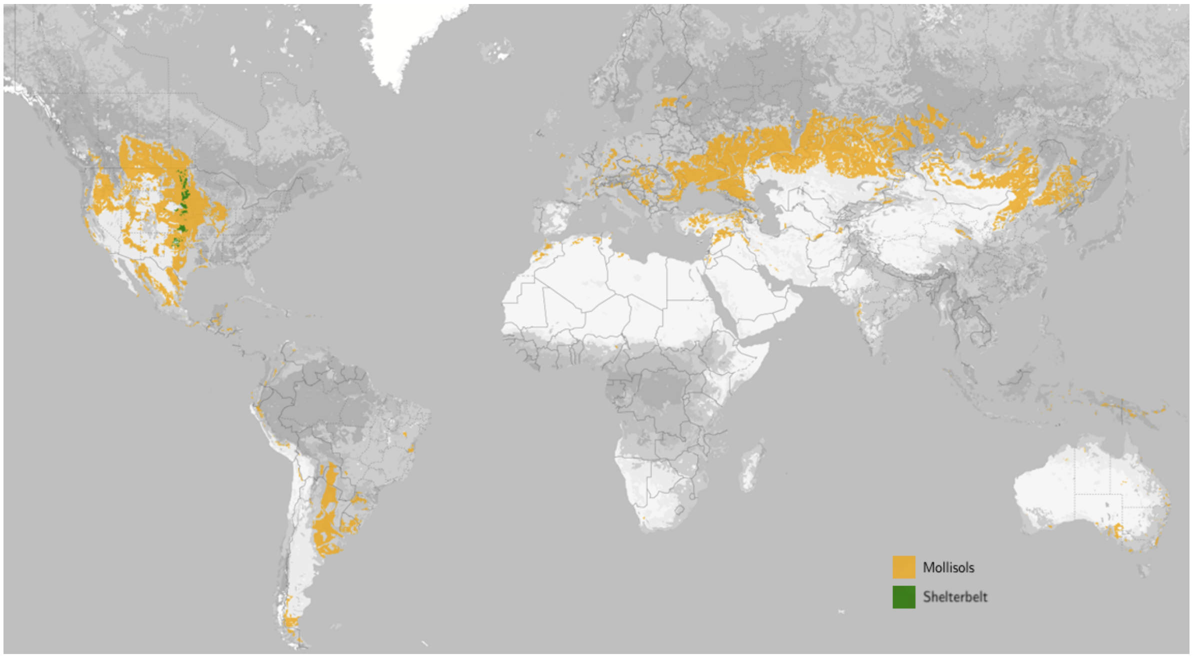
Notes: Panel A shows scatterplots of concentrated Shelterbelt planting as a share of county area on the x axis and irrigated land as a share of county area on the y axis. Panel B shows wind exposure measure from the Shelterbelts on the x axis and irrigated land as a share of county area on the y axis. Left plots shows irrigation prior to the Shelterbelt project (1935), while the right plots shows irrigation post afforestation (1959).

Figure A12: United States in 1940, compared to countries in 2018



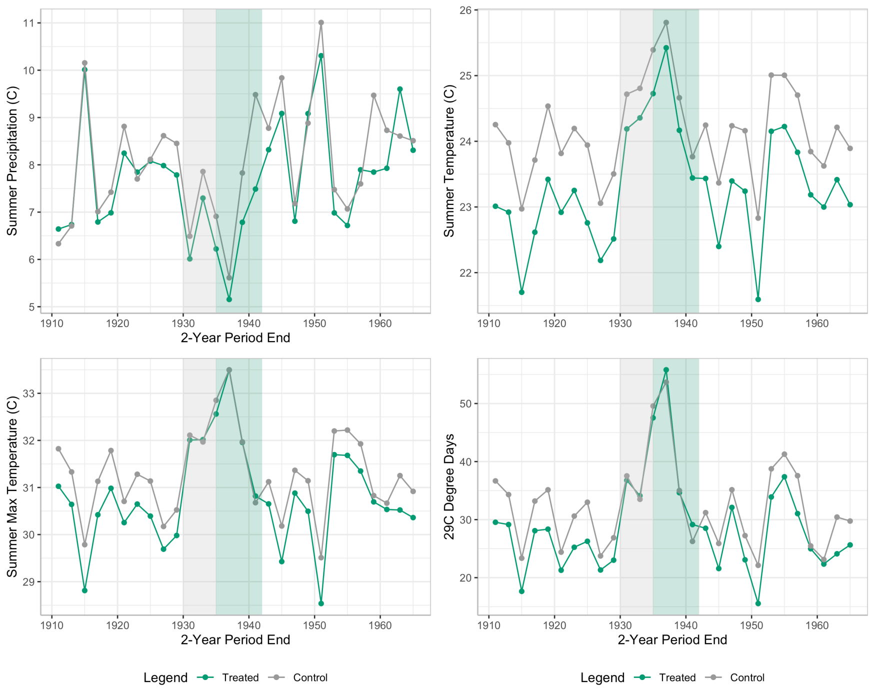
Notes: GDP per capita from the Maddison Project Database (2018 and 1940). Share of employment in agriculture from the US Census (1940, IPUMS) and the World Development Indicators (2018, WB).

Figure A13: Distribution of Mollisols



Notes: Soil map derived from USDA NRCS.

Figure A14: Trends in Climate Outcomes for Affected and Control Counties, 1910 - 1965



Notes: Figures plot mean summer precipitation, mean/maximum summer temperatures, and 29C degree days for all affected areas (Shelterbelt and downwind neighbors) and pure control counties for 1910-1965. Climate outcomes are averaged for two year periods in order to smooth high year-to-year variation. Gray shaded area shows pure baseline period (without tree planting), green shaded area shows Shelterbelt project years.

Appendix Tables

Table A1: Impact of Great Plains Shelterbelt on Jun-Aug crop water availability, 1930 to 1965

	Dependent variable:	
	Palmer Drought Severity Index (PDSI)	
	(1)	(2)
Shelterbelt:Post 1942	0.642***	0.785***
	(0.064)	(0.110)
	[0.000]	[0.000]
Downwind Neighbor:Post 1942	0.522***	0.833***
	(0.055)	(0.093)
	[0.000]	[0.000]
Other Neighbor:Post 1942	0.302***	0.147
	(0.054)	(0.113)
	[0.000]	[0.193]
Shelterbelt=Neighbor	p = 0.030	p = 0.635
Downwind=Other	p = 0.000	p = 0.000
Control Post-1942 Mean	0.01	0.01
Control Post-1942 Std.Dev.	1.79	1.79
FE	County, State-by-Year	County, Year
Observations	24,408	24,408

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets. Table shows results for estimating equation 2. Dependent variables are June - August averages.

Table A2: Impact of Great Plains Shelterbelt on Jun-Aug county climate, 1930 to 1965

	Dependent variable:			
	Precipitation	Temperature (C)		
	(cm)	Mean	Max	29C Degree Days
	(1)	(2)	(3)	(4)
Wind Exposure:Post 1942	1.044***	−0.548***	−0.696***	−7.977***
	(0.255)	(0.074)	(0.109)	(1.121)
	[0.000]	[0.000]	[0.000]	[0.000]
Control:Post Mean	8.60	23.61	30.59	26.91
Control:Post Std.Dev.	4.05	3.30	3.28	23.02
Observations	19,404	19,404	19,404	19,404

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets. Table shows results for estimating a modified version of equation 2, $y_{it} = \beta_2(w_i \times P_t) + \gamma_{st} + \mu_i + \epsilon_{it}$, where w_i is the continuous wind exposure measure described in Section 3. We drop Shelterbelt counties but keep all counties within 300km of Shelterbelt counties. Dependent variables are June - August averages. County and state-by-year FE included.

Table A3: Impact of Great Plains Shelterbelt on Jun-Aug county climate, 1930 to 1965 (Excluding 1936-1942)

	Dependent variable:			
	Precipitation	Temperature (C)		
	(cm)	Mean	Max	29C Degree Days
	(1)	(2)	(3)	(4)
Shelterbelt:Post 1942	0.024	-0.130^{***}	-0.154^{***}	-1.688^{***}
	(0.094)	(0.036)	(0.050)	(0.510)
	[0.798]	[0.000]	[0.003]	[0.001]
Downwind Neighbor:Post 1942	0.007	-0.146^{***}	-0.116^{**}	-1.141^{**}
	(0.102)	(0.036)	(0.048)	(0.472)
	[0.944]	[0.000]	[0.017]	[0.016]
Other Neighbor:Post 1942	−0.006	0.0002	0.049	0.402
	(0.083)	(0.030)	(0.042)	(0.417)
	[0.939]	[0.995]	[0.243]	[0.336]
Shelterbelt=Neighbor	p = 0.821	p = 0.546	p = 0.361	p = 0.207
Downwind=Other	p = 0.888	p = 0.000	p = 0.000	p = 0.000
Control:Post Mean	8.60	23.61	30.59	26.91
Control:Post Std.Dev.	4.05	3.30	3.28	23.02
Observations	24,408	24,408	24,408	24,408

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets. Table shows results for estimating equation 2. Dependent variables are June - August averages. County and state-by-year FE included.

Table A4: Impact of Great Plains Shelterbelt on Jun-Aug county climate, 1930 to 1965 (Excluding 1934, 1936, and 1939)

	Dependent variable:			
	Precipitation (cm)	Temperature (C)		
		Mean	Max	29C Degree Days
	(1)	(2)	(3)	(4)
Shelterbelt:Post 1942	0.545***	−0.107***	−0.166***	−2.075***
	(0.087)	(0.031)	(0.043)	(0.391)
	[0.000]	[0.001]	[0.000]	[0.000]
Downwind Neighbor:Post 1942	0.559***	−0.146***	−0.165***	−2.329***
	(0.096)	(0.030)	(0.040)	(0.361)
	[0.000]	[0.000]	[0.000]	[0.000]
Other Neighbor:Post 1942	0.129*	−0.001	0.010	0.172
	(0.075)	(0.025)	(0.036)	(0.312)
	[0.086]	[0.978]	[0.786]	[0.581]
Shelterbelt=Neighbor	p = 0.848	p = 0.126	p = 0.969	p = 0.207
Downwind=Other	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Control:Post Mean	8.60	23.61	30.59	26.91
Control:Post Std.Dev.	4.05	3.30	3.28	23.02
Observations	24,408	24,408	24,408	24,408

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets. Table shows results for estimating equation 2. Dependent variables are June - August averages. County and state-by-year FE included.

Table A5: Impact of Great Plains Shelterbelt on Jun-Aug county climate, 1930 to 1965 (North and South Separately)

	Dependent variable:			
	Precipitation (cm)	Temperature (C) Mean	Max	29C Degree Days
	(1)	(2)	(3)	(4)
Panel A: North of 40°N only				
Shelterbelt:Post 1942	−0.004	−0.051	−0.243***	−1.987***
	(0.114)	(0.048)	(0.068)	(0.600)
	[0.969]	[0.288]	[0.000]	[0.002]
Downwind Neighbor:Post 1942	−0.070	−0.027	−0.112*	−1.244***
	(0.102)	(0.042)	(0.058)	(0.471)
	[0.489]	[0.517]	[0.056]	[0.009]
Other Neighbor:Post 1942	0.164*	−0.016	−0.115**	−0.756*
	(0.096)	(0.037)	(0.055)	(0.444)
	[0.089]	[0.663]	[0.039]	[0.090]
Observations	12,780	12,780	12,780	12,780
Panel A: South of 40°N only				
Shelterbelt:Post 1942	0.358***	−0.131***	−0.063	−1.833***
	(0.133)	(0.046)	(0.062)	(0.672)
	[0.008]	[0.006]	[0.315]	[0.007]
Downwind Neighbor:Post 1942	0.719***	−0.248***	−0.191***	−2.501***
	(0.155)	(0.049)	(0.064)	(0.684)
	[0.000]	[0.000]	[0.004]	[0.000]
Other Neighbor:Post 1942	0.030	−0.026	0.052	0.164
	(0.125)	(0.040)	(0.052)	(0.550)
	[0.811]	[0.521]	[0.317]	[0.766]
Observations	11,628	11,628	11,628	11,628

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets. Table shows results for estimating equation 2. Dependent variables are June - August averages. County and state-by-year FE included.

Table A6: Impact of Great Plains Shelterbelt on Jun-Aug county climate, 1930 to 1965 (Conley standard errors)

	Dependent variable:			
	Precipitation (cm)	Temperature (C) Mean	Max	29C Degree Days
	(1)	(2)	(3)	(4)
Shelterbelt:Post 1942	0.229	-0.104	-0.160^{**}	-1.986^{**}
	(0.270)	(0.073)	(0.081)	(0.910)
	[0.397]	[0.155]	[0.050]	[0.030]
Downwind Neighbor:Post 1942	0.285	-0.125^{*}	-0.129^{*}	-1.727^{**}
	(0.314)	(0.075)	(0.067)	(0.786)
	[0.364]	[0.095]	[0.054]	[0.028]
Other Neighbor:Post 1942	0.071	-0.016	-0.022	-0.184
	(0.117)	(0.046)	(0.066)	(0.598)
	[0.548]	[0.723]	[0.734]	[0.759]
Control:Post Mean	8.60	23.61	30.59	26.91
Control:Post Std.Dev.	4.05	3.30	3.28	23.02
Observations	24,408	24,408	24,408	24,408

Notes: *p<0.1; **p<0.05; ***p<0.01. Conley standard errors with 1000km distance cutoff in parentheses; p-values shown in brackets. Table shows results for estimating equation 2. Dependent variables are June - August averages. County and state-by-year FE included.

Table A7: Impact of Great Plains Shelterbelt on corn yields, 1930 to 1965

	Dependent variable:
	Log Corn Yields (bu/ac)
All Impacted Areas:Post 1942	0.141***
	(0.033)
	[0.000]
Observations	11,088

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets. Table shows results for estimating equation 2, with (log) corn yields from agricultural surveys as the dependent variable. County and state-by-year FE include.

Table A8: Impact of Great Plains Shelterbelt on corn yields, 1930 to 1965

	Dependent variable:			
	Log Yield (bu/ac)		Log Production (bu)	Log Area (ac)
	(1)	(2)	(3)	(4)
Wind Exposure:Post 1942	0.823***	0.530***	1.515***	0.947**
	(0.168)	(0.110)	(0.417)	(0.380)
	[0.000]	[0.000]	[0.000]	[0.014]
Downwind=Other	p = 0.013	p = 0.012	p = 0.133	p = 0.411
Data Source	Survey	Census	Census	Census
Observations	8,280	4,182	3,706	3,706

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets. Table shows results for estimating a modified version of equation 2, $y_{it} = \beta_2(w_i \times P_t) + \gamma_{st} + \mu_i + \epsilon_{it}$, where w_i is the continuous wind exposure measure described in Section 3. We drop Shelterbelt counties but keep all counties within 300km of Shelterbelt counties. Table shows results using both corn yields from agricultural surveys (annual, column 1) and censuses (every 5-years, columns 2 - 4). County and state-by-year FE included.

Table A9: Weather-Yield Relationship in Great Plains, 1942-1965

	Dependent variable:
	Log Yields
	(1)
Degree Days 10C	0.005***
	(0.0003)
	[0.000]
Degree Days 29C	−0.031***
	(0.001)
	[0.000]
Degree Days 39C	−0.269***
	(0.027)
	[0.000]
Precipitation	0.054***
	(0.007)
	[0.000]
Precipitation^2	−0.003***
	(0.0003)
	[0.000]
Sample	Control
Time	Post-1942
Obs.	2,944

Notes: *p<0.1; **p<0.05; ***p<0.01. Table shows results for estimating equation 8. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets.

Table A10: Synthetic Difference-in-Differences: Impact of Great Plains Shelterbelt on Jun-Aug county climate, 1930 to 1965

	Dependent variable:			
	Precipitation	Temperature (C)		
	(cm)	Mean	Max	29C Degree Days
	(1)	(2)	(3)	(4)
Shelterbelt:Post 1942	0.646***	−0.134***	−0.213***	−3.299***
	(0.065)	(0.032)	(0.045)	(0.340)
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Downwind Neighbor:Post 1942	1.139***	−0.127***	−0.207***	−3.882***
	(0.058)	(0.0529)	(0.038)	(0.277)
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Other Neighbor:Post 1942	0.426***	-0.014	-0.027	-0.256
	(0.093)	(0.028)	(0.040)	(0.316)
	p = 0.000	p = 0.632	p = 0.512	p = 0.426

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors shown in parentheses and calculated using the "jack-nife" standard error estimator described in Section IV of Arkhangelsky et al. (2021); p-values shown in brackets. Table shows results for estimating equation 3. Dependent variables are June - August averages.

Table A11: Synthetic Difference-in-Differences: Impact of Great Plains Shelterbelt on corn yields, 1930 to 1965

	Dependent variable:	
	Log Yield (bu/ac)	
	(1)	(2)
Shelterbelt:Post 1942	0.197***	0.089**
	(0.036)	(0.037)
	[0.000]	[0.037]
Downwind Neighbor:Post 1942	0.218***	0.170***
	(0.034)	(0.035)
	[0.000]	[0.000]
Other Neighbor:Post 1942	0.034	0.100***
	(0.038)	(0.024)
	[0.381]	[0.000]
Data Source	Survey	Census

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors shown in parentheses and calculated using the "jackknife" standard error estimator described in Section IV of Arkhangelsky et al. (2021); p-values shown in brackets. Table shows results for estimating equation 3.

Table A12: Long differences: Impact of Great Plains Shelterbelt on Jun-Aug county climate

	Dependent variable:			
	Precipitation	Temperature (C)		
	(cm)	Mean	Max	29C Degree Days
	(1)	(2)	(3)	(4)
Shelterbelt	0.814***	−0.208***	−0.277***	−2.720***
	(0.114)	(0.044)	(0.062)	(0.612)
	[0.000]	[0.000]	[0.000]	[0.000]
Downwind Neighbor	0.657***	−0.113***	−0.095*	−1.048*
	(0.104)	(0.041)	(0.057)	(0.561)
	[0.000]	[0.006]	[0.093]	[0.063]
Other Neighbor	0.234**	−0.010	0.006	−0.394
	(0.096)	(0.037)	(0.052)	(0.516)
	[0.016]	[0.797]	[0.901]	[0.445]
Downwind=Other	p = 0.000	p = 0.007	p = 0.055	p = 0.213
Controls	-	-	-	-
Observations	678	678	678	678

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors shown in parentheses; p-values shown in brackets. Table shows results for estimating equation 4. Dependent variables are calculated as the difference between 1930-1935 and 1960-1965 June - August averages. State FE included.

Table A13: Long differences: Impact of Great Plains Shelterbelt on Jun-Aug county climate (With Controls)

	Dependent variable:			
	Precipitation (cm)	Temperature (C) Mean	Max	29C Degree Days
	(1)	(2)	(3)	(4)
Shelterbelt	0.668^{***}	-0.189^{***}	-0.281^{***}	-3.193^{***}
	(0.115)	(0.042)	(0.060)	(0.548)
	[0.000]	[0.000]	[0.000]	[0.000]
Downwind Neighbor	0.640^{***}	-0.199^{***}	-0.237^{***}	-3.312^{***}
	(0.109)	(0.040)	(0.057)	(0.519)
	[0.000]	[0.000]	[0.000]	[0.000]
Other Neighbor	0.255^{***}	-0.047	-0.047	-1.102^{**}
	(0.092)	(0.034)	(0.048)	(0.439)
	[0.006]	[0.167]	[0.327]	[0.013]
Downwind=Other	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Controls	Y	Y	Y	Y
Observations	678	678	678	678

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors shown in parentheses; p-values shown in brackets. Table shows results for estimating equation 4. Dependent variables are calculated as the difference between 1930-1935 and 1960-1965 June - August averages. Controls include latitude and longitude, indicator for counties in the Ogallala aquifer, and change in irrigated county area share. State FE also included.

Table A14: Long differences: Impact of Great Plains Shelterbelt on corn yields

	Dependent variable:			
	Log Yields (bu/ac)		Log Production (bu)	Log Area (ac)
	(1)	(2)	(3)	(4)
Shelterbelt	0.243***	0.124***	0.297*	0.173
	(0.085)	(0.047)	(0.169)	(0.151)
	[0.005]	[0.010]	[0.080]	[0.252]
Downwind Neighbor	0.188**	0.098**	0.213	0.115
	(0.077)	(0.044)	(0.156)	(0.139)
	[0.015]	[0.025]	[0.172]	[0.409]
Other Neighbor	0.021	0.079**	0.165	0.085
	(0.076)	(0.039)	(0.141)	(0.126)
	[0.780]	[0.046]	[0.244]	[0.498]
Downwind=Other	p = 0.024	p = 0.637	p = 0.739	p = 0.821
Data Source	Survey	Census	Census	Census
Controls	-	-	-	-
State FEs	-	-	-	-
Observations	307	525	525	525

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors shown in parentheses; p-values shown in brackets. Table shows results for estimating equation 4. Dependent variables are calculated as the difference between 1930-1935 and 1960-1965 averages. State FE included.

Table A15: Long differences: Impact of Great Plains Shelterbelt on corn yields (With Controls)

	Dependent variable:			
	Log Yields (bu/ac)		Log Production (bu)	Log Area (ac)
	(1)	(2)	(3)	(4)
Shelterbelt	0.289***	−0.027	0.211	0.238*
	(0.090)	(0.042)	(0.155)	(0.137)
	[0.002]	[0.528]	[0.175]	[0.083]
Downwind Neighbor	0.216***	−0.053	0.437***	0.491***
	(0.074)	(0.040)	(0.145)	(0.128)
	[0.004]	[0.181]	[0.003]	[0.000]
Other Neighbor	0.014	0.036	0.167	0.131
	(0.073)	(0.033)	(0.123)	(0.108)
	[0.854]	[0.279]	[0.174]	[0.227]
Downwind=Other	p = 0.006	p = 0.015	p = 0.045	p = 0.003
Data Source	Survey	Census	Census	Census
Controls	Y	Y	Y	Y
State FEs	Y	Y	Y	Y
Observations	307	525	525	525

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors shown in parentheses; p-values shown in brackets. Table shows results for estimating equation 4. Dependent variables are calculated as the difference between 1930-1935 and 1960-1965 averages. Controls include latitude and longitude, indicator for counties in the Ogallala aquifer, and change in irrigated county area share. State FE also included.

Table A16: Predicting Shelterbelt Planting

	Dependent variable:
	Shelterbelt County Dummy
Ustolls Share of County Area (%)	0.442***
	(0.033)
	[0.000]
Observations	678
F Statistic	184.353***

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors shown in parentheses; p-values shown in brackets. Table shows results for estimating equation 5.

Table A17: Long Differences with Instrumental Variables: Impact of Great Plains Shelterbelt on Jun-Aug county climate, 1930-1935 to 1960-1965

	Dependent variable:				
	Precipitation (cm)	Temperature (C) Mean	Max	29C DD	All Treated Areas
	(1)	(2)	(3)	(4)	(5)
All Treated Areas	0.656***	−0.115***	−0.159***	−0.704	
	(0.108)	(0.042)	(0.059)	(0.583)	
	[0.000]	[0.007]	[0.008]	[0.228]	
Predicted Treated Areas					0.733***
					(0.026)
					[0.000]
Controls	-	-	-	-	-
Observations	677	677	677	677	678
F Statistic					104.182***

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors shown in parentheses; p-values shown in brackets. Table shows results for estimating equations 6 (Column 5) and 7 (Columns 1 - 4). Dependent variables are calculated as the difference between 1930-1935 and 1960-1965 June - August averages. State FE included.

Table A18: Long Differences with Instrumental Variables: Impact of Great Plains Shelterbelt on Jun-Aug county climate, 1930-1935 to 1960-1965 (With Controls)

	Dependent variable:				
	Precipitation (cm)	Temperature (C)			All Treated Areas
		Mean	Max	29C DD	
	(1)	(2)	(3)	(4)	(5)
All Treated Areas	0.657^{***}	-0.164^{***}	-0.260^{***}	-2.306^{***}	
	(0.125)	(0.046)	(0.065)	(0.592)	
	[0.000]	[0.000]	[0.000]	[0.000]	
Predicted Treated Areas					0.654^{***}
					(0.027)
					[0.000]
Controls	Y	Y	Y	Y	Y
Observations	678	678	678	678	678
F Statistic					86.988^{***}

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors shown in parentheses; p-values shown in brackets. Table shows results for estimating equations 6 (Column 5) and 7 (Columns 1 - 4). Dependent variables are calculated as the difference between 1930-1935 and 1960-1965 June - August averages. Controls include latitude and longitude, indicator for counties in the Ogallala aquifer, and change in irrigated county area share. State FE also included.

Table A19: Long Differences with Instrumental Variables: Impact of Great Plains Shelterbelt on corn yields, 1930-1935 to 1960-1965

	Dependent variable:			
	Log Yields (bu/ac)	All Treated Areas	Log Yields (bu/ac)	All Treated Areas
	(1)	(2)	(3)	(4)
All Treated Areas	0.313***		0.149***	
	(0.076)		(0.045)	
	[0.000]		[0.002]	
Predicted Treated Areas		0.875***		0.739***
		(0.037)		(0.030)
		[0.000]		[0.000]
Data Source	Survey	Survey	Census	Census
Controls	-	-	-	-
State FEs	-	-	-	-
Observations	307	307	525	525
F Statistic		193.100***		84.457***

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors shown in parentheses; p-values shown in brackets. Table shows results for estimating equations 6 (Columns 2 and 4) and 7 (Columns 1 and 3). Dependent variables are calculated as the difference between 1930-1935 and 1960-1965 June - August averages. State FE included.

Table A20: Long Differences with Instrumental Variables: Impact of Great Plains Shelterbelt on corn yields, 1930-1935 to 1960-1965

	Dependent variable:			
	Log Yields (bu/ac)	All Treated Areas	Log Yields (bu/ac)	All Treated Areas
	(1)	(2)	(3)	(4)
All Treated Areas	0.352***		0.026	
	(0.081)		(0.046)	
	[0.000]		[0.574]	
Predicted Treated Areas		0.846***		0.670***
		(0.040)		(0.032)
		[0.000]		[0.000]
Data Source	Survey	Census	Survey	Census
Controls	Y	Y	Y	Y
State FEs	Y	Y	Y	Y
Observations	307	307	525	525
F Statistic		108.788***		73.137***

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors shown in parentheses; p-values shown in brackets. Table shows results for estimating equations 6 (Columns 2 and 4) and 7 (Columns 1 and 3). Dependent variables are calculated as the difference between 1930-1935 and 1960-1965 June - August averages. Controls include latitude and longitude, indicator for counties in the Ogallala aquifer, and change in irrigated county area share. State FE included.

Table A21: Long Differences: Irrigation in the Great Plains, 1930-1935 to 1960-1965

	Dependent variable:		
	Δ Irrigation Area (% of County)		
	(1)	(2)	(3)
Shelterbelt	2.872***	2.929***	2.687***
	(0.748)	(0.812)	(0.817)
	[0.0002]	[0.0004]	[0.002]
Downwind Neighbor	2.206***	2.332***	1.460*
	(0.698)	(0.738)	(0.777)
	[0.002]	[0.002]	[0.061]
Other Neighbor	1.813**	1.334*	1.144
	(0.719)	(0.702)	(0.698)
	[0.012]	[0.058]	[0.102]
State FEs	-	Yes	Yes
Lat/Lon Controls	-	-	Yes
Observations	613	613	613

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors shown in parentheses; p-values shown in brackets. Table shows results for estimating equation 4. Change in irrigated share of county area calculated using 1935 and 1959 measures.

Table A22: Synthetic Difference-in-Differences: Impact of Great Plains Shelterbelt on Jun-Aug county climate

	Dependent variable:			
	Precipitation (cm)	Temperature (C)		
		Mean	Max	29C Degree Days
	(1)	(2)	(3)	(4)
Panel A: 1910 - 1965				
Shelterbelt:Post 1942	0.095*	0.027*	−0.007	−0.430***
	(0.057)	(0.015)	(0.025)	(0.165)
	[0.094]	[0.075]	[0.794]	[0.022]
Downwind Neighbor:Post 1942	0.501***	0.025*	−0.063***	−0.478***
	(0.045)	(0.013)	(0.021)	(0.165)
	[0.000]	[0.054]	[0.003]	[0.004]
Other Neighbor:Post 1942	0.366***	0.076***	0.063**	0.820
	(0.061)	(0.014)	(0.024)	(0.208)
	[0.000]	[0.000]	[0.421]	[0.000]
Panel B: 1919 - 1965				
Shelterbelt:Post 1942	0.248***	−0.059***	−0.115***	−1.544***
	(0.071)	(0.018)	(0.028)	(0.209)
	[0.001]	[0.001]	[0.000]	[0.000]
Downwind Neighbor:Post 1942	0.715***	−0.069***	−0.147***	−2.071***
	(0.050)	(0.015)	(0.025)	(0.167)
	[0.000]	[0.000]	[0.000]	[0.000]
Other Neighbor:Post 1942	0.370***	−0.018	0.004	0.020
	(0.070)	(0.017)	(0.028)	(0.246)
	[0.000]	[0.281]	[0.895]	[0.941]

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors shown in parentheses and calculated using the "jack-nife" standard error estimator described in Section IV of Arkhangelsky et al. (2021); p-values shown in brackets. Table shows results for estimating equation 3. Dependent variables are June - August averages.

Table A23: Long differences: Impact of Great Plains Shelterbelt on Jun-Aug county climate (With Controls)

	Dependent variable:			
	Precipitation (cm)	Temperature (C) Mean	Max	29C Degree Days
	(1)	(2)	(3)	(4)
Shelterbelt	0.784***	−0.221***	−0.308***	−3.602***
	(0.114)	(0.043)	(0.062)	(0.579)
	[0.000]	[0.000]	[0.000]	[0.000]
Downwind Neighbor	0.594***	−0.097**	−0.090	−1.623***
	(0.106)	(0.040)	(0.058)	(0.540)
	[0.000]	[0.017]	[0.121]	[0.003]
Other Neighbor	0.226**	−0.026	−0.017	−0.620
	(0.092)	(0.035)	(0.050)	(0.467)
	[0.014]	[0.455]	[0.730]	[0.185]
Dust Bowl Intensity Measures				
Erosion Intensity	0.113	−0.312***	−0.281***	−5.015***
	(0.144)	(0.054)	(0.079)	(0.732)
	[0.431]	[0.000]	[0.000]	[0.000]
Precipitation Anomaly	−0.150***	0.011	0.001	0.323**
	(0.027)	(0.010)	(0.015)	(0.136)
	[0.000]	[0.280]	[0.924]	[0.019]
Temperature Anomaly	0.496***	−0.292***	−0.360***	−3.794***
	(0.105)	(0.040)	(0.058)	(0.537)
	[0.000]	[0.000]	[0.000]	[0.000]
Downwind=Other	p = 0.000	p = 0.064	p = 0.188	p = 0.052
Controls	Y	Y	Y	Y
Observations	658	658	658	658

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors shown in parentheses; p-values shown in brackets. Table shows results for estimating equation 4. Dependent variables are calculated as the difference between 1930-1935 and 1960-1965 June - August averages. Controls include three measures of Dust Bowl intensity (soil erosion, precipitation and temperature anomalies) shown in table, as well as indicator for counties in the Ogallala aquifer, and change in irrigated county area share. State FE also included.

Table A24: Impact of Great Plains Shelterbelt on Jun-Aug station climate, 1930 to 1965

	Dependent variable:			
	Precipitation	Temperature (C)		
	(cm)	Mean	Max	29C Degree Days
	(1)	(2)	(3)	(4)
Afforested Area (1000 ac) : Post-1942	0.306^{**}	-0.127^{**}	-0.140^{*}	-0.030^{*}
	(0.151)	(0.055)	(0.077)	(0.016)
	[0.047]	[0.025]	[0.077]	[0.067]
Observations	2,880	1,872	1,872	1,872

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the station level shown in parentheses; p-values shown in brackets. Table shows results for estimating equation 2 with a continuous treatment variable for tree planting. This treatment variable is equal to the area afforested within a 25km radius of each station. Dependent variables are June - August averages. Station and year FE included.