Rain follows the forest: Land use policy, climate change, and adaptation*

Florian Grosset-Touba, Anna Papp, and Charles A. Taylor†

August 2024

Abstract

Human actions can alter the climate via land use. We analyze the 1930s Great Plains Shelterbelt, a large-scale forestation program across the US Midwest. The program increased precipitation and decreased temperatures for decades. Changes extended 200km downwind – enabling us to study climate adaptation. Improved growing conditions allowed farmers to expand corn acreage, adopt water-intensive practices, and reduce crop failures. In a period of farm consolidation, this contributed to the survival of small farms but less farm machine usage. The findings underscore the endogeneity of climate to land use change and the long-term impacts of tree planting on agricultural development.

*This paper greatly benefited from comments by Francis Annan, Douglas Almond, Price Fishback, Eyal Frank, Robert Heilmayer, Rick Hornbeck, Solomon Hsiang, Gary Libecap, Kyle Meng, Ben Olken, Wolfram Schlenker, Jeffrey Shrader, Aaron Smith, Marco Tabellini, Andrew Waxman, Andrew Wilson, Brian Wright, and participants at the ASSA Annual Meeting, NBER Summer Institute (Energy and Environmental Economics; Development of the American Economy), World Bank-GWU-UVA Economics of Sustainable Development Conference, LSE Environment Week, CEEP-Federal Reserve Bank of New York Environmental Economics and Policy Conference, Harvard Climate Economics Pipeline Workshop, Occasional Workshop in Environmental and Resource Economics (UCSB), Stanford GSB Climate Conference, Simon Agriculture & Natural Resource Seminar (UC Berkeley and UC Davis), AERE Summer Conference, Northeast Workshop on Energy Policy and Environmental Economics, Seminar in Planetary Management, and Sustainable Development Colloquium. Aidan McCullen and Yixian Liu provided excellent research assistance. We are grateful to Dr Meagan Snow for sharing digitized Shelterbelt data. All errors and omissions are our own.

†Grosset-Touba: CREST - ENSAE Paris (florian.grosset@ensae.fr); Papp: Columbia University (corresponding author: ap3907@columbia.edu); Taylor: Harvard University (ctaylor@hks.harvard.edu).

1 Introduction

Tree planting programs are widely popular among policy-makers and companies worldwide. Seeking to reduce their net carbon emissions, governments have pledged 500 million hectares of land for tree-planting by 2050 under the Paris Agreement, more than the areas of South Africa, India, and Turkey combined (Self et al. 2023), while the World Economic Forum launched a One Trillion Trees initiative. In addition, large-scale tree planting is occurring in urban settings to provide local shade and cooling, and in rural areas to mitigate soil erosion, dust storms, and landslides.

Another potential outcome of large-scale tree planting has been proposed by the natural science literature, but garnered less attention in public discourse: a change in the regional climate, driven by the impact of trees on energy and water fluxes. Atmospheric models predict an increase in precipitation where trees are planted, as well as in downwind areas (Bonan 2008).[1] This potential policy-induced change in the local climate implies that large-scale tree planting could also affect economic outcomes through both mechanical effects (e.g., more favorable weather increases crop yields) and responses from individuals and firms (e.g., climate adaptation). These economic effects can manifest locally where trees are planted, but also in locations downwind that are not directly affected by the policy but experience a policy-induced change in climate nonetheless.

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 qualitative climate predictions from atmospheric models in response to afforestation, and estimate the resulting magnitudes. We then study the consequences of this policy-induced climate change on agricultural development, and assess the role of climate adaptation.

We focus on the Great Plains Shelterbelt in the United States. Planned in response to the Dust Bowl, this 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. The trees were grown in windbreaks, which consisted of numerous strips of trees planted between fields and farms, occupying only 0.3% of the total area of the affected counties despite the program's scale. The resulting 'belt' of trees bisected the US from north to south, spanning 1,700km and crossing six states from North Dakota to Texas.

[1] For temperature, the net local effect depends on land characteristics. Trees can increase evapotranspiration, which reduces temperatures. But since trees are generally darker than the land they are planted on (e.g., cropland or grassland), they can decrease albedo and surface reflection, thus raising temperatures.

The largest afforestation effort of its time, the Great Plains Shelterbelt is now rivaled in scope by multiple tree-planting projects worldwide. While it was implemented over 80 years ago, we note that the socioeconomic conditions of the US Midwest in the 1940s are comparable to many lower and middle-income countries where similar programs are being designed and implemented today. We therefore focus on this specific program to leverage its unique characteristics. The historical context provides the long time frame required for a direct study of the drivers and consequences of climate change, i.e., changes in the *distribution* of weather events over time. By combining USDA census data with information on climate and land use, we can 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.

The short and delimited policy implementation period allows for simple and clean identification strategies. We use a difference-in-differences strategy that exploits prevailing winds, which is the primary physical mechanism by which trees planted in a given location affect climate in nearby areas where the program is not implemented. We construct a wind exposure measure based on large-scale prevailing summer winds to approximate a given location's exposure to winds arriving from areas afforested under the Shelterbelt. We then use variation in this wind measure to compare the evolution in outcomes between areas that are, on average, more exposed to summer winds from afforested areas, to areas that are less exposed. We augment the simple difference-in-differences specification with a set of baseline controls to satisfy the identification requirements of our strategy.

We demonstrate that our empirical strategy is valid, and our results robust to potential threats to identification, including the Dust Bowl and medium-term climate fluctuations, the correlation of wind patterns with spatially differentiated climate trends, the strategic location of tree planting, spatial general equilibrium effects, the timing of the effects from planting trees, and irrigation. Among other approaches, this includes designing and implementing an instrumental variable strategy, a long differences, a synthetic difference-in-differences, and running various tests on subsamples and outcomes. The results we present below are robust to these potential confounds.

In a first step, we show that large-scale tree planting substantially alters the climate. To assess effect size, we compare counties in the 75$^{\text{th}}$ percentile of exposure to summer winds blowing through the Shelterbelt afforested areas to those in the 25$^{\text{th}}$ percentile. We find that precipitation increased by 3%, or 2.1mm per month, during the summer months ($p < 0.001$), and maximum temperature decreased by 0.9% (-0.28°C, $p < 0.001$) as well (Table 2. Extreme heat, which has a strong negative impact on yields, decreased even more dramatically, with degree days above 29°C falling 7% ($p < 0.001$) in counties more exposed to winds from the

Shelterbelt. The direction of these effects is consistent with atmospheric model predictions. Importantly, they are not limited to where the trees are planted: we find similar effects of exposure to winds blowing through the Shelterbelt in neighboring areas.

Having established that the Shelterbelt project induces climate change, our second step involves estimating the consequences of this climate change on the economy and assessing the role of adaptation. We limit our analysis to areas near, but not directly afforested under the Shelterbelt project, to isolate the effect of climate change from other changes potentially associated with Shelterbelt participation. We focus on agriculture, a sector highly exposed to climate and representative of a large share of the economy of the post-war US Midwest.

We find that the production of corn, the key crop in the US Midwest, strongly increased in response to this policy-induced climate change in counties downwind from the Shelterbelt. Corn production increased by 30% in counties in the 75$^{\text{th}}$ percentile of wind exposure compared to counties in the 25$^{\text{th}}$ percentile ($p = 0.001$). This effect is mostly driven by an expansion in the area of corn harvested by 25% ($p = 0.005$), with a more modest increase in yields by 5% ($p = 0.053$).

We can explain this large increase in corn production by analyzing both a climate adaptation response from farmers and a mechanical increase in production following improved growing conditions. We find that crop failure decreased downwind from the Shelterbelt ($p = 0.004$), consistent with a reduction in extreme temperatures and increased precipitation. In addition, we observe a reallocation of cropland away from less water-intensive crops (e.g., wheat, $p < 0.001$) and towards more water-intensive crops (e.g., corn, $p < 0.001$), while total cropland remains fixed ($p = 0.497$). Overall, the increase in corn production is primarily explained by climate adaptation, with farmers updating their crop mix decisions when faced with a different climate.

These changes took place in a period of rapid farm consolidation in the US, where by 1965 the number of farms halved, and the average farm size doubled (Dimitri et al. 2005). While much of this 'exit from agriculture' was driven by secular trends in agricultural technology—including the use of machines on larger farms—and structural transformation, we investigate whether the downwind effects of the Shelterbelt can explain spatial differences in farm consolidation.

The relative number of small farms increased in counties downwind from the Shelterbelt ($p = 0.035$), at the expense of mid-sized farms. The improved climate from afforestation slowed down consolidation—likely through the reduction in crop failure events, which has been shown to drive farmer exit and migration (Hornbeck 2012).[2] The relative increase in the number of farms during this period of consolidation shows the potential role climate adaptation can play in smallholder farmer resilience.

This reduced farm consolidation, together with crop switching, led to changes in the choice of inputs used in the production process. Areas exposed to the improved climate exhibit higher spending on fertilizer ($p = 0.009$)—consistent with the switch from wheat to corn, which typically requires more fertilizer to maximize yields. They also exhibit lower spending on hired machines ($p = 0.008$) while retaining similar spending on hired labor ($p = 0.478$)—consistent with a story of lower returns to mechanization on smaller farms. But we also find that this resulted in lower farm values (3.9% lower overall value of agricultural land and buildings, $p = 0.018$), suggesting lower productivity and a potential 'lock in' into agriculture during a period of structural transformation. Overall, our results indicate that improving the climate through land use policy has significant consequences for long-term agricultural development.

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 outcomes; we provide new evidence that this is not the case.[3] 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 deforestation,[4] and then models farmer responses in terms of land use and agricultural productivity. Taken together, these recent working papers confirm the external validity of the endogeneity of climate to land use changes in a range of settings, and the potential follow-on socioeconomic impacts. However, neither paper maps to an explicit policy choice contemplated by governments around the world in response to climate change: large-scale tree planting.

Next, we describe the methodological implications that extend from our findings on climate

[2] Crop insurance did not become widespread in the US until the Federal Crop Insurance Act of 1980.

[3] 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.

[4] A large body of natural science work has investigated the local and regional climate impacts of deforestation (Spracklen and Garcia-Carreras 2015), generally finding it reduces precipitation.

endogeneity. The response of agricultural production to changes in the climate is a key parameter to assessing the economic consequences of climate change, with implications for food security, structural transformation, migration, and trade flows. As detailed below, we propose a reduced-form approach to estimating this response using a policy-induced change in the long-run climate to measure productivity effects, inclusive of adaptive responses. This resulting elasticity comprises both i) the direct mechanical effect of weather shocks drawn from a different distribution (i.e., climate change) and ii) the effects of adaptation to the new climate.

In terms of the direct impact of climate change, our findings have implications for the vast body of work that uses 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 change from short-term weather shocks presents challenges (Hsiang 2016; Kolstad and Moore 2020; Lemoine 2021).[5]

One approach to assessing adaptation involves accounting for how responses to climate shocks vary across space by average climate (Butler and Huybers 2013; Heutel et al. 2021; Auffhammer 2022; Hultgren et al. 2022), the idea being that if the same extreme heat event causes less deaths in a warm climate than a cold climate, that difference is (partly) due to adaptation. This useful and intuitive approach still faces concerns about potential confounders across geographies, as well as the "weather-vs-climate" issue discussed above. Another way to get at adaptation is through "long differences": 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 trends as a 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 use standard empirical tools, such as

[5] 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).

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 enables researchers to argue more convincingly for causal identification of climate effects, particularly in locations downwind or otherwise not directly affected by the policy.[6]

In an agricultural context, existing research provides valuable insights on how economic agents respond to productivity shocks, 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. There is a robust body of work on US crop yield responses and adaptation to climate change, with mixed results.[7] Most of our current knowledge of mechanisms for agricultural adaptation to climate comes from observational studies.[8]

Our work relates to studies on adaptation to medium-to-long-term fluctuations in the monsoon regime in India (Kala 2017; Taraz 2017; Liu et al., forthcoming). These generally combine agricultural and economic data over several decades with five- to ten-year changes in the timing and intensity of monsoons 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). Our paper also builds on work studying the Great Plains Shelterbelt over the long term, and its effect on local agriculture practices and outcomes (Li 2021; Howlader 2023).

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 in locations downwind from the policy itself. We also find strong evidence of climate adaptation by farmers. The geographic scale of these

[6] Our findings also have implications for our understanding of place-based policies involving localized changes in productivity (Kline and Moretti 2014; Bustos et al. 2016; Bustos et al. 2020; Asher et al. 2022; Hornbeck and Moretti 2023). 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.

[7] See, for instance, Schlenker and Roberts 2009; Butler and Huybers 2013; Annan and Schlenker 2015; Burke and Emerick 2016; Malikov et al. 2020; Yu et al. 2021.

[8] Such adaptive channels include 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).

effects are large, encompassing an area twice 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. There are many valid concerns about 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. 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. This short implementation period, combined with a defined target area, makes this program an ideal candidate to identify the causal effects of large-scale tree planting on climate and agricultural development.

Franklin D. Roosevelt (FDR) conceived the Shelterbelt idea while running for president in 1932, upon observing on the campaign trail the damages from the destructive Dust Bowl (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, he 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.[9] FDR's plan called for a shelterbelt 100 miles across and 1,300 miles long, roughly bisecting the continental US from North Dakota to Texas along the country's 18-inch rainfall line.

FDR signed an executive order in 1934, and the first tree was planted in 1935 in Oklahoma. The program continued until 1942, when funding cuts resulting from the US's World War II effort brought it to a stop (Droze 1977). Planting happened mostly as shelterbelts rather

[9] Another common conservation tool involved rotating portions of fields into 'fallowed strips' that are not plowed in a given year and thus secure the soil and provide a small windbreak (Hansen and Libecap 2004).

than patches of forest, according to the plan. Overall, the geographic boundaries from the original plan were not fully respected: Figure S9 shows both the planned and actual zones for Shelterbelt planting. Note that our empirical strategy directly addresses the potential endogeneity of farmer uptake and the location of tree planting, addressing concerns about prior exposure to the Dust Bowl and strategic location choice accounting for expected climate spillovers. These factors are unlikely to be driving the effects we estimate, as explained in Section 4.

Early on, there was interest in the Great Plains project's potential influence on local climate. When first reporting on the initiative, the *New York Times* described it as an "experiment in climate control to combat the ravages of drought" ("Tree Belt in West to Fight Droughts" 1934), and Snow (2019) presents the controversy around the program as a battle between 'ecological foresters' who believed that policy decisions influence local climate and environmental conditions and 'determinist geographers' who saw climate as static.

Specific implementation procedures were key to the program's success. For the most part, seedlings from nurseries were planted instead of seeds to increase survival rates. 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. In considering the program's impact on the water cycle, it is important to note that irrigation was not used to establish the trees. 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 Shelterbelt laborers to be hired from the relief rolls.

3 Data

Our main analysis is based on a county-by-year panel dataset, constructed from four types of data: digitized historical maps of Shelterbelt plantings, 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. In our main analysis, we focus on the period from 1930 to 1965.[10] Our results are robust to using different start and end years.

[10] We start in 1930 due to concerns about data quality and availability before that time (Knappenberger et al. 2001; Kunkel et al. 2007). We end in 1965 to limit the overlap with other agricultural changes, including the expansion of irrigation and urbanization, which could be influenced by tree planting and could influence the climate themselves.

Shelterbelt data: We digitize maps of "areas of concentrated Shelterbelt planting" from Read (1958) and overlay them with county boundaries. This is our best available source of data contemporaneous with the tree-planting program, as there are no official statistics on the area of trees planted in each county. We classify a county as a Shelterbelt county if over 5% of its total area is covered by this concentrated planting (the 5% cutoff corresponds to the 20^{th} percentile among counties with non-zero tree planting). 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 the actual Shelterbelt plantings that survived several years to decades after planting, from the United States Geological Survey (USGS) Topographic Map Quadrangles.[11] We calculate each county's area covered by the Shelterbelt from her digitized shapefiles to compare with our main measure. Appendix Figure S10 plots the two measures side-by-side and shows the consistency in geographic coverage. The correlation is high at 0.86.

Wind data: Wind is an essential driver of atmospheric transport and regional climate change in relation to afforestation. Trees usually release water 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 counties are most likely to have their climate influenced by the Shelterbelt project.

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 at 10 meters above the surface level.

Using the NLDAS-2 data, we create a time-invariant approximate measure of how exposed each county is to winds blowing from the Shelterbelt in the summer (w_i). To do so, we project an imaginary particle at a given speed and direction, and record all counties it crosses over the course of 24 hours. We project these particles from each vertex of each Shelterbelt

[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 to official project totals by state.

[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.

county, and repeat it for each summer hour (June through August) of each year between 1981 and 2010.[13] We focus on summer months given the importance of climatological conditions during that period for agricultural production. For each particle projected, we use the speed and direction of the wind at that specific origin vertex and time.

We assign each particle a weight, to avoid a Shelterbelt county's shape from influencing its importance in the wind exposure measure, and to better reflect exposure to wind across through trees planted under the Shelterbelt project. Each particle's weight is therefore a product of the inverse of the number of vertices in the original county, the share of the county's area covered by concentrated Shelterbelt planting, and a quality measure of the shelterbelts in that area.[14] We then count, for each county, how many (weighted) particles originating from Shelterbelt counties crossed it during the projections. Finally, we rescale the metric by dividing it by its maximum value. Figure 2 illustrates the construction of the wind metric and shows the resulting wind exposure measure. Additional information about its construction is provided in Appendix S.2.1. The resulting wind exposure metric $w_i \in [0, 1]$ is a time-invariant approximate measure of how exposed a county i is to winds blowing through all the trees planted under the Shelterbelt project.

Temperature and precipitation data: We construct a county-by-year panel of precipitation and temperature based on daily weather station 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 create a balanced panel of stations reporting between 1930 and 1965 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 the average daily precipitation, average daily maximum temperature, average daily minimum temperature, and total number of daily degree days at various thresholds for each month. To aggregate this county-by-month dataset to county-by-year, we take the average of these measures over the summer months (June through August). Details on the construction of this dataset are available in Appendix S.3.

We consider degree days as a climatological outcome, since they have been shown to be

[13] High-resolution wind data is only available starting in 1979. Section 4.2 provides evidence that using post-treatment period wind data to measure exposure does not bias our estimates.

[14] In addition to the maps, Read 1958 provides the proportion of shelterbelts in various conditions by north/south of each state (e.g., northern part of North Dakota, southern part of North Dakota), based on surveys of surviving shelterbelts. We use the share of shelterbelts in excellent or good quality in each area as quality measure.

a relevant measure of temperature when studying impacts on crops or physiology, often performing better than maximum or mean temperature. Degree days have been widely used in economics following work by Schlenker and Roberts (2006; 2009), who demonstrated that yields increase gradually with temperature up to a critical threshold, and decrease sharply with any further temperature increase. For corn, our main crop of interest, the critical threshold is 29°C. We therefore include 29°C degree days as one of our main climate outcome variables.

Standard gridded weather datasets with historical coverage, such as NOAA's NClimDiv and PRISM, do not include degree days. They provide data at the monthly level, while daily data is necessary to compute degree days manually. These limitations led us to construct our main weather dataset directly from the raw daily station data. Still, we verify the robustness of our results on precipitation and mean and maximum temperature to using the standard NClimDiv dataset, and find them to be robust.

Economic data: We focus on agriculture, the most important sector in the US Midwest during our study period. We use agricultural censuses, conducted roughly every five years by the US Department of Agriculture and digitized by Haines et al. (2018). We prefer using agricultural census data over the USDA's annual surveys because of their spatial coverage. As shown in Appendix Figure S17, only a subset of states and counties, primarily in the northern US, were surveyed prior to 1940. Thus, we would lack baseline data for all other areas if we did not use the census data.

4 Empirical approach

Our empirical analysis exploits the timing and geographic location of tree-planting under the Shelterbelt project, together with prevailing wind patterns. In a first step, we seek to test whether the Shelterbelt project changed the climate—including in areas downwind from where trees were planted, but not directly afforested themselves. In a second step, we ask whether this policy-induced change in the climate influenced agricultural development in the region, through direct and adaptation channels.

We use the same empirical strategy for the two steps of the analysis. Given the clear temporal and geographic boundaries of the Shelterbelt program, our primary analysis relies on a difference-in-differences framework: comparing the change in climate and economic outcomes–before and after the program–across counties more or less exposed to winds blowing from the Shelterbelt. Our preferred specification augments the classic difference-in-differences with a set of controls, in order to satisfy the causal identification requirements of our approach. Ex-post, we find our main results to be qualitatively similar whether we use controls, subsets of our controls only, or no controls at all in our specification.

We explicitly address a number of potential confounds, and find our results to be robust to these potential threats. Specifically, we address the timing of the tree-planting effects, the strategic choice of tree-planting location, the correlation of wind patterns with spatially differentiated climate trends, the Dust Bowl and mean-reversion, irrigation, spatial general equilibrium effects, and the potential endogeneity of wind patterns.

Below, we provide more details on our preferred empirical specification (4.1) and approaches to address its main potential threats (4.2). We then present our results on the climate impacts of the Shelterbelt (5.1) and its economic consequences (5.2). Finally, we demonstrate that these results are valid and robust (5.3).

4.1 Main empirical strategy

Our main empirical strategy is to use a difference-in-differences model, with a continuous treatment measure:

$$y_{it} = \beta(w_i \times P_t) + \gamma(\mathbf{X}_i \times Y_t) + \delta_{st} + \nu_i + \epsilon_{it} \quad (1)$$

where y_{it} is the outcome of interest at the county-year level, w_i is the wind exposure measure ($w_i \in [0, 1]$) described in Section 3, and P_t is an indicator variable equal to one for years after 1942.[15] $\mathbf{X}_i$ is a vector of controls, described below, interacted with year fixed effects Y_t. We also include county ν_i and state-by-year δ_{st} fixed effects. Using fixed effects at the state-by-year level, instead of year as in classic TWFE specifications, allows us to ensure that potentially differential historical trends in climate or agricultural development across states that could correlate with wind exposure would not bias our results.

Our coefficient of interest is β, which measures the change in outcomes post-1942 induced by a unit increase in wind exposure (w). This unit increase corresponds to moving from having no exposure to winds coming from the Shelterbelt to being the county with the most

[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 S11 for the timing.) We can expect the impact of tree planting to increase over time, as trees grow. We therefore make the conservative choice of using 1943 as the first year 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.

exposure. To aid interpretability, we provide in our tables or figures the difference in wind exposure between the 25^{th} and 75^{th} percentile of that measure among our sample counties.

The effects we identify when estimating β are equilibrium effects. 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 can in itself 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.

We do not have a staggered treatment: the post-treatment period is defined to be the same for all units. However, our use of a continuous (rather than binary) treatment variable w_i requires a "strong parallel trends assumption" to hold for causal identification (Callaway et al. 2021). In our setting, this assumption is that the change in outcomes between the baseline and post-treatment periods would be the same, on average, for the counties with wind exposure w_d and for all other counties, had they also had a wind exposure level of w_d.

The identification assumption is satisfied if (a) counties with different levels of wind exposure would have had the same *trends* in climate and agricultural outcomes absent the Shelterbelt tree planting, and (b) counties with different levels of wind exposure have similar baseline *levels* of climate and agricultural outcomes. Requirement (a) corresponds to the classic parallel trends assumption in binary difference-in-differences. Adding (b) is required for those outcomes where the effects of being exposed to winds blowing through the Shelterbelt vary with the baseline levels of the outcome. For instance, the relationship between temperature and crop yields is known to be highly non-linear, so that the effect on agricultural productivity of a given level of Shelterbelt wind exposure (inducing a given change in the climate) would likely be different for counties with different baseline climates. To satisfy the causal identification assumption, we thus need counties with different levels of wind exposure to have similar baseline levels of crop yields.

While we cannot directly test for requirement (a), we can provide suggestive evidence on baseline trends. Figure 3 classifies counties into above- and below-median values of Shelterbelt wind exposure, and plots the average values of the climate and agricultural variables for each group and each year. For improved visibility, given the high year-to-year variability of rainfall and temperature, we show three-year moving averages for these variables. In the baseline period (up to 1942), the two groups of counties exhibit parallel trends.

In Table 1, we provide evidence that requirement (b) holds once we control for county geospatial and topographic characteristics, as well as baseline erosion and irrigation levels.[16] We therefore include these variables in the vector of controls $\mathbf{X}_i$. We interact these controls with year fixed effects, as they would otherwise be collinear with the county fixed effects. In doing so, we flexibly allow counties with different baseline characteristics to have different changes in outcomes over time without violating our strong parallel trends assumption.

Ex-post, we find that the choice of controls does not qualitatively influence our main results: they are robust to using all controls, no controls at all, or either one of the four sets of controls only (Figures 7 and 8, Panel A). Likewise, using year fixed effects rather than state-by-year fixed effects produces similar results (Figures 7 and 8, Panel B).

4.2 Potential threats to identification

We now present the main threats to the internal validity of our empirical strategy, along with how we address these threats.

Timing of the effects. In the difference-in-differences specification, we define P_t as an indicator variable equal to one for years after 1942. However, it is ex-ante unclear when trees planted under the Shelterbelt program will start influencing the climate and agricultural development. On the one hand, tree planting started as early as 1935, so some effects may also start then. On the other hand, trees need time to grow, and evapotranspiration is a function of tree biomass, so the effects of tree planting may only start materializing after several years. In both cases, this uncertainty around the specific treatment start time would bias our estimated effects towards 0, relative to the true long-term effects of the program.

To alleviate this potential concern, we implement a long differences strategy and estimate:

$$\Delta y_i = \beta^{LD} w_i + \gamma^{LD} \mathbf{X}_i + \psi_s^{LD} + \Delta\epsilon_i \tag{2}$$

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, w_i is the wind exposure measure that approximates exposure to summer winds from the afforested Shelterbelt counties. We also include state fixed effects,

[16] For geospatial characteristics, we use a latitude-longitude grid quartile (with indicators for being in each grid cell), an indicator for being a Shelterbelt county, an indicator for having above-median distance to the nearest Shelterbelt county, and county size. For topographic characteristics, we use elevation and ruggedness. For baseline erosion, we use indicators for experiencing medium or high erosion levels during the Dust Bowl (from Hornbeck 2012). For baseline irrigation, we use the share of county overlapping with the Ogallala aquifer as proxy for irrigation potential, and the share of county actually irrigated in the pre-period 1935.

ψ_s, to control for unobserved state-level trends, as well as the same county-level controls ($\mathbf{X}_i$) as in our main specification (Equation 1).

Strategic choice of tree-planting location. A second threat to identification stems from the potential strategic behavior of Shelterbelt participants. If they took into account the program's potential climate spillovers when deciding where to plant trees, then our strong parallel trends assumption would be violated: trees might have been planted upwind from areas expected to have some specific future climate or economics trends. Note that this would bias our point estimates away from zero only if the trees were strategically planted upwind from areas expected to already witness a relative improvement in their climatic growing conditions.

We address this potential concern with an instrumental variable strategy. Similar to Li (2021), we use the planned Shelterbelt planting zone–an approximately 100-mile wide strip of land between 100°W and 98°W–which is shown in the gray shaded area in Figure S9. The choice of this planting zone was unrelated to any potential impacts on downwind areas. The western border of the planned area was determined by the 18-inch precipitation line, since it was determined by foresters that trees planted in areas further west, where rainfall is lower, would likely not survive. Somewhat arbitrarily, the eastern border was drawn exactly 100-miles to the east of the western border.[17]

We treat all counties that overlap with the planned area as the hypothetical Shelterbelt. We then reproduce the wind exposure measure construction steps described in Section 3, except we replace Shelterbelt counties with the planned counties. We use this planned wind exposure measure (w_i^p) as an instrument for the continuous treatment variable (w_i) in our difference-in-differences model. Figure S19 shows the wind exposure instrument next to the actual wind exposure measure. The instrument is strong, with a F-stat of 91.7 (Appendix Table S7, Col 6).

We estimate a two-stage least squares (2SLS) regression, where the first stage is:

$$w_i = \xi_1 w_i^p + \theta \mathbf{X}_i + \phi_s^{IV} + e_i \tag{3}$$

where w_i is the actual wind exposure measure for each county, w_i^p is the planned wind exposure measure for each county, $\mathbf{X}_i$ is the set of time-invariant controls included in our main specification, and ϕ_s is state fixed effects. The model for the second-stage estimation

[17] Unfortunately, there is no clear discontinuity in the likelihood of Shelterbelt tree planting around the eastern border, so we cannot use a spatial discontinuity design.

is then:

$$y_i = \beta^{IV}(w_i \times P_t) + \gamma^{IV}(\mathbf{X}_i \times Y_t) + \delta_{st}^{IV} + \nu_i^{IV} + \epsilon_{it} \tag{4}$$

where w_i is instrumented by w_i^p, and all other variables are as defined in Equation 1.

Spatially-differential climate trends. It is well established that oceanic oscillations influence the 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). Likewise, global warming differentially affects regions across the US. Our estimates of climate impacts downwind from the Shelterbelt could be biased if the spatial patterns of wind exposure happened to be correlated with spatially differential climate trends.

The set of controls in our main specification (Equation 1) is designed to alleviate these concerns. We create a spatial grid based on latitude and longitude quartiles across our sample region, with each resulting grid cell having an area of 350km^2, and include indicator variables for being in a grid cell, interacted with year fixed effects. Likewise, we include state-by-year fixed effects. This specification allows us to compare counties that are spatially close, hence unlikely to be exposed to differential climate trends absent the Shelterbelt tree planting, but that face differential wind exposure—thereby addressing the potential concern. As we expect with this approach, we find that counties with different levels of wind exposure have on average similar baseline climates (Table 1). Note that our main results hold without these very granular spatial fixed effects.

Dust Bowl and mean reversion. The Shelterbelt project was conceived and implemented in response to the Dust Bowl—a major climatic episode that spanned much of the 1930s.[18] One might wonder, consequently, whether a reversion to non-shock conditions might have occurred around the time of tree planting. This would bias our estimates if a change in the climate in the Shelterbelt area would affect the climate downwind, even absent trees being planted (for instance, because of increased water vapor in the atmosphere). We address this potential concern in several ways.

First, the set of controls in our main specification includes Dust Bowl measures of erosion levels from Hornbeck 2012, which can be taken as proxy for the local severity of the Dust Bowl episode. As such, we identify the downwind effects from the Shelterbelt tree planting

[18] Interestingly, climate scientists argue that the Dust Bowl 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).

by comparing counties with similar Dust Bowl exposure. More broadly, given the balance achieved across counties once we include our main set of controls, our effects are identified by comparing counties with similar climates during our pre-period 1930-1942, which overlaps with the Dust Bowl.

Second, we confirm that the Dust Bowl (or other differential trends) is unlikely to bias the validity of our results, by using an alternative strategy to compare counties with similar baseline trends. Instead of including controls in our difference-in-differences specification, we implement a synthetic difference-in-differences specification: we compare the set of counties with above-median wind exposure to a composite set of the counties with below-median wind exposure, weighted such that the two groups have similar baseline trends, on average.[19] Such synthetic methods require a sufficiently long time period to match the baseline trends, and therefore require us to expand our study period to start in 1910.[20] We note that our main sample does not start this early given concerns about the availability and quality of pre-1930 climate and agricultural data (Knappenberger et al. 2001; Kunkel et al. 2007).

Third, we can replicate our main difference-in-differences specification with different time periods, to omit the Dust Bowl era. Within our preferred 1930-1965 timeframe, we can drop the peak Dust Bowl years in terms of climate anomalies (1934, 1936, 1939). Once we expand the study period prior to 1930, and despite the concerns with data quality, we run our main analysis using Equation 1 with a start year of 1910. We also revise the long difference approach in Equation 2 to compare 1925-1930 to 1960-1965, to address concerns that the early 1930s were atypical. Similarly, we also compare 1930-1935 to 1950-1955 to show that our results are not driven by any potentially atypical climate in the Great Plains during 1960-1965.

The results from these exercises are presented in Section 5.3. They each indicate that our results are neither driven nor biased by the Dust Bowl, or other spatially differentiated climate trends.

Irrigation. If tree planting is spatially correlated with the expansion of irrigation, it could be that our results are 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 potential concerns: first, that trees planted as part of

[19] See Section S.10 for more details.

[20] In order to replicate our analysis for 1910 through 1965, we repeat the construction of a county-by-year panel of precipitation and temperature from weather stations with daily readings as detailed in Section S.3, except using a balanced panel of stations reporting between 1910 and 1965 instead of 1930 and 1965.

the Shelterbelt may have been directly irrigated, and second, that the Shelterbelt region and downwind areas were more likely to be irrigated even if the trees themselves were not.

To the first concern, Barton (1936) describes precisely the cultivation of the trees planted under the Shelterbelt project. He describes everything from the preparation of the ground to enhance rainfall capture to post-planting weeding—without any mention of irrigation. This 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 directly test whether irrigation was correlated with Shelterbelt planting or wind exposure. The results are illustrated in Figure S20. We find a marginally significant negative correlation between pre-period irrigation, Shelterbelt tree planting, and wind exposure. Focusing on irrigation expansion, we find no significant correlation between irrigation in the post-treatment period and either Shelterbelt tree-planting or wind exposure. Given the baseline imbalance, we include pre-period irrigation in the vector of controls $\mathbf{X}_i$ in our preferred specification (Equation 1) to ensure that our effects are identified by comparing comparable counties.

We also directly test whether irrigation drives our results. To do this, we use the fact that almost all of the increase in irrigation in the region was attributed to the Ogallala aquifer. Therefore, we interact the wind exposure term in our main regression (Equation 1) with a dummy variable set to 1 for counties within the Ogallala. We can test whether the effects are concentrated in the counties within the Ogallala aquifer (which would indicate that irrigation may be driving the results), or whether they are also present in counties outside the aquifer, where irrigation did not develop.

Spatial general equilibrium. Our preferred empirical strategy compares the change of the climate and agricultural outcomes over time between counties more or less exposed to winds from the Shelterbelt. Our estimate could therefore capture spatial general equilibrium effects. For instance, improved growing conditions due to high Shelterbelt wind exposure in area A could lead an agent owning farms in areas A and B to reduce investment in B and to allocate it to A, which would further increase yields in area A and reduce them in B. Our estimate would then overestimate the aggregate effect of tree planting on overall agricultural production.

We address this common issue with the interpretation of difference-in-differences estimates by replicating our main analysis with binary treatment measures. Specifically, we use our continuous wind exposure measure to classify counties into four mutually exclusive groups:

i) Shelterbelt counties, where the trees were actually planted

ii) Downwind neighbor counties, with centroids within 200km of Shelterbelt counties and *above* median wind exposure from afforested areas[21]

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

The resulting map of this classification can be viewed on the right panel of Figure 6. We can then estimate the following difference-in-differences equation:

$$y_{it} = \beta^1(S_i \times P_t) + \beta^2(D_i \times P_t) + \beta^3(U_i \times P_t) + \gamma^B(\mathbf{X}_i \times Y_t) + \delta^B_{st} + \nu^B_i + \epsilon_{it} \tag{5}$$

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. As before, we add time-invariant county-level controls interacted by year, as well as state-by-year and county fixed effects.[22]

Absent spatial general equilibrium effects, we should expect β^3 to be small and close to zero, although it may still be significantly different from zero if there are some effects from wind exposure, since it includes every county with below-median wind exposure, not counties with no wind exposure at all. Further, $\beta^2 - \beta^3$ identifies the effect of downwind exposure to Shelterbelt tree planting, *net* of spatial general equilibrium effects.

Equation 5 can also be used for climate outcomes, to serve as a placebo check. Once again, we expect β^3 to be small and close to zero (or at least to be significantly smaller than β^2), since it identifies effects for counties with below-median wind exposure only.

We can also implement a version of the long differences approach from Equation 2 with the binary treatment variables:

$$\Delta y_i = \beta^{LD,1}S_i + \beta^{LD,2}D_i + \beta^{LD,3}U_i + \gamma^{LD,B}\mathbf{X}_i + \psi^{LD,B}_s + \Delta\epsilon_i \tag{6}$$

Endogeneity of wind patterns. Since spatially-consistent granular wind data only became available in 1979, our wind exposure measure is not from the baseline period. Rather, we derive it from long-term prevailing wind patterns computed over 1981-2010. Here, we describe why our results are unlikely to be biased by this fact.

[21] See Appendix Figure S16 for the distribution of wind exposure measures for neighbor counties.

[22] We do not include the indicator for latitude-longitude quartile and above-median distance to the nearest Shelterbelt county, as these terms are highly collinear with this categorical assignment of county treatment.

Direct empirical evidence indicates that prevailing winds have remained stable throughout our study period, and our classification of counties thus would likely be 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 0.92 between the two measures—indicating that wind exposure from the Shelterbelt has been stable throughout the period (Figure S15). Going one step further, we implement a long differences on the subsample of observations for which we have baseline and endline wind data, using wind exposure as an outcome. We do not find evidence that Shelterbelt tree planting had an effect on wind patterns.

Beyond this direct evidence, we can also test whether the pattern of our main results is consistent with a bias induced by a misclassification of counties from the use of post-intervention wind data. We do this using our discretized wind exposure measure and the associated specification given in Equation 5. If we assume that the Shelterbelt changes wind patterns in a way that affects climate in neighboring counties, then a bias would occur if we classify as downwind neighbor areas that now receive precipitation from the new wind regime but did not otherwise. However, this new precipitation would be reallocated towards the downwind neighbors from counties that we classify as other (non-downwind) neighbors: ones that used to receive rain from the wind, but do not anymore due to the new wind pattern. If the Shelterbelt was reallocating precipitation in such a way, we should observe an effect of the intervention on the downwind counties of the same magnitude and opposite direction than the effect on the other non-downwind counties. This implication is directly testable: we do not find a negative treatment effect on other non-downwind neighbor counties, so it is unlikely that there was any material reallocation of precipitation.

5 Results

We now present the impacts of Shelterbelt tree-planting on the climate, and the resulting effects on agricultural development. We first show that large-scale tree planting increased precipitation and reduced temperature in downwind areas (5.1). We then discuss the consequences of this policy-induced change in the climate for agricultural development—including productivity and farm consolidation—with a focus on climate adaptation (5.2). Finally, we demonstrate the validity of our identification strategy and robustness of our results (5.3).

[23] The construction procedure is described in Appendix S.2.2. This exercise cannot be conducted meaningfully before 1938 due to the sparsity of weather station data in the Great Plains region then.

5.1 Climate impacts

Table 2 reports our climate results, estimated using our preferred difference-in-differences specification. In Panel A, we consider all regions the program affected, whether directly afforested under the Shelterbelt program or indirectly exposed through winds, for over two decades after its implementation. We find that summer precipitation was 2.1mm higher in counties in the 75$^{\text{th}}$ percentile of Shelterbelt wind exposure relative to counties in the 25$^{\text{th}}$ percentile of wind exposure. This is equivalent to a 3.0% increase relative to the baseline average monthly summer rainfall.[24] We also find summer temperatures decreased: mean and maximum temperatures were 0.7% and 0.9% lower in areas more exposed to winds from afforested areas. Exposure to extreme temperatures that are harmful to crop yields also decreased significantly: average monthly degree days above 29°C declined by 2.6 for an increase in wind exposure from the 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile, equivalent to a 7.0% decrease relative to the mean.

These results show that tree planting resulted in more favorable growing conditions regionally. They 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). We find exactly this: the decreases in maximum temperatures and degree days above 29°C are greater than the decrease in average temperatures.

Importantly, the effects of Shelterbelt tree planting on the climate downwind are not driven by the afforested counties themselves. The climate effects are similar when focusing on the counties that did not experience tree planting under the Shelterbelt program, and for which agricultural census data is available (Table 2, Panel B).

5.2 Economic consequences

Our results so far show that Shelterbelt tree planting affected the regional climate via increased summer rainfall and reduced summer temperatures. We now turn to the economic consequences of this engineered change in the climate, which became more favorable to agriculture. To avoid confounding our estimates with any direct local effect of tree planting, we focus on counties outside the Shelterbelt project area. There, trees were not planted, but the climate did change in areas exposed to Shelterbelt winds.

[24] To illustrate how such figures are computed using Table 2, Panel A, Col. 1: multiply the "75th-25th Perc. Wind Exp" value (0.21) by the "Wind Exposure:Post 1942" value (0.995), which equals 0.21cm, or 2.1mm. This 0.21cm increase is 3.0% of the sample mean precipitation (7.06cm).

Corn production. We first focus on corn, the most important crop produced in the US Midwest in volume and value. We find that Shelterbelt tree planting greatly increased the production of corn in downwind areas. Table 3 contains the estimates from our preferred difference-in-differences specification (Equation 1). Col. 1 suggests that corn production was 30% higher for counties in the 75th percentile of wind exposure compared to counties in the 25th percentile[25]. Qualitatively similar effects are estimated when using our alternative difference-in-differences, instrumental variable, and long differences specifications, as shown in Figure 4, Panel B.

An increase in corn production (i.e, bushels) can be driven by an increase in the area harvested of corn (i.e., acres), and by an increase in yield (production per area harvested, or bushels per acre). The Shelterbelt tree planting led to a large and significant increase in the area of corn harvested downwind, by 25% in counties in the 75th percentile of wind exposure relative to counties in the 25th percentile (Table 3, Col. 2). Since the percentage difference between the increase in production and in area harvested equals the increase in yields (as illustrated by Figure 5), this implies that most of the corn production increase was driven by the increase in area harvested. The increase in yields was more modest and only marginally significant, at 5% (Table 3, Col. 3).

Climate adaptation. We find strong evidence that farmers downwind from the Shelterbelt respond to the change in climate they experience, including by changing the type of crops they decide to grow. The increase in crop harvested area could indeed come from a decision by the farmers to reallocate land away from dryland crops or pasture to more relatively water-intensive crops like corn (a climate adaptation channel), or mechanically from a reduction in crop failure rates that would lead to an increase in the area harvested while holding the area planted fixed (a physiological channel). Crop failure is driven by factors like weather, insects, and diseases; we can therefore expect to respond to the changes in extreme weather events driven by the Shelterbelt.[26]

Table 4, Panel A provides evidence that both climate adaptation and a physiological response is driving the increase in corn harvested. The increase in the area of corn harvested (Col. 1) does come together with a significant decrease in crop failures by 6,600 acres per county based on the 75th-25th percentile wind exposure difference (Col. 3). If farmers did not adapt to the change in climate, and the entire effect on harvested area was driven by the decrease in crop failures, then we should expect to see an increase in area harvested across all crops—or, at least, no decrease. We therefore consider another major crop grown in the US

[25] Approximated by multiplying the coefficient value (2.273) by the '75th-25th Perc. Wind Exp' value (0.13).
[26] See https://www.ers.usda.gov/data-products/major-land-uses/glossary/#cropfailure

Midwest at the time of the Shelterbelt project: wheat. Contrary to corn, the area harvested of wheat strongly *decreased* in areas downwind from the Shelterbelt following the change in the climate by 6,200 acres per county (Col. 2). While farmers reallocated land between crops, the overall area of cropland did not change (Col. 4).

The USDA agricultural census data we use in this paper provide information on the overall extent of crop failures, but does not disaggregate it by type of crop. However, while much more sparse in its geographical coverage during our time period (see Section S.4), the USDA annual surveys do include information both on the area of corn *planted* and *harvested*. These surveys confirm evidence for both climate adaptation and physiological responses: Appendix Table S6 shows that the overall corn area *planted* by farmers increased significantly (adaptation channel) simultaneous with a decrease in corn failure (physiological channel).

This adaptation behavior following a change in the climate, away from wheat and towards corn, is fully consistent with agronomic evidence. Precipitation has historically been a major determinant of crop choice in the US: 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). When precipitation increases due to the influence of the Shelterbelt, we could therefore expect the share of cropland devoted to more water-intensive crops, such as corn, to increase—which is the behavior we observe empirically.

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.

Agricultural development. The Shelterbelt program had important consequences for the development of US agriculture. The post-War period saw intense concentration in the agricultural sector, with smallholder farms being sold to form larger entities. Over our study period, from 1930 to 1964, the total number of farms in our study region decreased from 819,000 to 468,000 (Appendix Figure S18). We argue that the improved growing conditions induced by Shelterbelt tree planting reduced the extent of this farm consolidation, with the number of small farms significantly increasing in areas more exposed to winds from the Shelterbelt (Table 4, Panel B, Col. 1). This relative increase (i.e., a smaller decline in the number of small farms) appears to at the expense of the mid-sized farms, whose number decreased, albeit the estimate is not statistically significant (Col. 2). The point estimate on the number of large farms is close to 0 (Col. 3). This reduced farm consolidation is associated with a lower overall value of the farms (land and buildings)—potentially through reduced scope for economies of scale (Col. 4).

These climate-induced changes have implications for the use of key inputs: farms exposed to winds from the Shelterbelt spend significantly less on hired machines, but significantly more on fertilizers (Table 5, Cols. 2-3). Spending on hired labor is not significantly affected (Table 5, Col. 1). These effects can be induced either by the new choice of crops (corn typically requires more fertilizer than wheat, for instance), or the smaller size of the farms (hiring machines may only be profitable for farms with fields of sufficient scale).

Overall, these results indicate a key role played by policy-induced climate change on agricultural development, in areas not directly targeted by the tree-planting policy but downwind from it.

5.3 Validity and robustness

The validity of our empirical approach could be threatened by the timing of the tree planting effects, the strategic choice of tree planting location, the correlation of wind patterns with spatially-differentiated climate trends, the Dust Bowl, irrigation, spatial general equilibrium effects, and the potential endogeneity of wind patterns. We refer the reader to Section 4.2 for a detailed discussion of these potential confounds, and our strategies to address them. Below, we introduce the results from these strategies and demonstrate that our empirical approach is valid, and our results robust.

Timing of the effects; Strategic location decisions. Figure 4 presents the effects of the Shelterbelt tree planting on the downwind climate (Panel A) and its economic consequences (Panel B), showing together the estimates from our preferred difference-in-difference approach (Equation 1), the long differences approach (Equation 2), and the instrumental variable approach (Equation 4). For each of these approaches, we present the estimates from the specification with and without the main set of baseline controls. We find similar effects whether we use the difference-in-differences or long differences specifications, which indicates that our results are robust to our choice of 1942 as the cutoff between the baseline and post-treatment periods.

We also find that the instrumental variable estimates with controls, designed to address a potential strategic choice of Shelterbelt program uptake and tree-planting location, are not smaller than our preferred difference-in-differences estimates with controls. This indicates that our preferred estimates are not driven by a strategic selection of tree planting location.

If anything, the IV estimates are larger when considering climate outcomes, suggesting that trees may have been selectively planted upwind from areas that would have suffered from worsening climatic conditions absent the Shelterbelt project—which would bias the OLS estimates towards zero.

Spatially-differential climate trends; Dust Bowl. In Section 4.2, we explain how our set of controls helps ensure that spatially-differential climate trends or the Dust Bowl episode do not bias our results, since identification comes from comparing counties in the same region (unlikely to face differential large-scale, medium-term climate oscillations) and with similar baseline exposure to the Dust Bowl. The resulting balance of the baseline climate by wind exposure levels demonstrates the validity of this approach (Table 1).

To reinforce this argument, and present direct evidence that the Dust Bowl or climate trends do not bias our results, Section 4.2 presents two different strategies that are based on a sample with a start date expanded back to 1910. First, Appendix Table S11 presents the results from the synthetic difference-in-differences analysis, implemented in periods 1910-1965 and 1919-1965. Once again, with this different approach to addressing potentially differential trends, we find similar effects on downwind precipitation relative to our preferred difference-in-differences. Temperature results are lower in magnitude, but also directionally consistent with our main results.

Second, we verify the robustness of our main results by using alternative time periods that omit the Dust Bowl era. We rerun our analyses separately by dropping the project implementation years (1936 to 1942) and peak Dust Bowl years (1934, 1936, 1939) from our baseline period. Appendix Tables S8 and S9 show the results are generally consistent with our main findings. We also conduct long difference estimates (Equation 2) with alternative time windows. In Panel A of Appendix Table S12, we compare 1925-1930 (instead of 1930-1935) to 1960-1965 to address concerns that the early 1930s were still heavy drought periods. In Panel B, we compare 1930-1935 to 1950-1955 (instead of 1960-1965) to compare two general drought periods in the Great Plains in the pre- and post-planting periods. In both cases, the estimates are qualitatively similar to our main long differences results.

Note that our main analysis starts in 1930 due to quality concerns for earlier data periods. Nonetheless, replicating our main difference-in-differences analysis on the 1910-1965 sample instead of our preferred 1930-1965 results produces similar results, though somewhat less precise and lower in magnitude (Appendix Table S10).

Taken together, this consistent set of results derived from different empirical strategies indicates that our results are not driven by spatially differential climate trends, or by the Dust

Bowl episode.

Irrigation. In Section 4.2, we explain how our baseline controls ensure that a correlation between irrigation and either tree planting or wind exposure do not bias our results. We confirm that irrigation does not drive our main results in Appendix Tables S13 and S14, in which we show that the downwind effects of the Shelterbelt tree planting on climate and agricultural development are similar whether we consider counties outside the Ogallala aquifer–where irrigation was far less likely to develop, and counties atop the aquifer—where increase expanded rapidly in the post-War period.

Spatial general equilibrium. Figure 6 presents results from the difference-in-differences strategy with a discretized wind exposure measure (Equation 5), which allows us to conduct placebo checks on the climate outcomes and to test for spatial general equilibrium effects on the economic outcomes—as introduced in Section 4.2. Consistent with our main results, we find strong and significant effects of the Shelterbelt tree planting on neighboring counties with above-median wind exposure. Further, we find little to no effects on neighboring counties with below-median exposure, for both the climate and economic outcomes. This validates the placebo check for the climate outcomes and indicates that potential spatial general equilibrium effects have limited influence on our economic outcomes; it therefore need not linger as a concern when interpreting our main treatment effect estimates.

Endogeneity of wind patterns. We have demonstrated in Section 4.2 that measuring wind exposure in the post-treatment period does not bias our estimates, and refer the reader to that section for further detail.

Robustness to choice of controls and fixed effects. The choice of controls does not qualitatively influence our main results. Both our climate and economic estimates are robust to using all controls, no controls at all, or either one of the four sets of controls only (Figures 7 and 8, Panel A). Likewise, using year fixed effects rather than state-by-year fixed effects produces similar results (Figures 7 and 8, Panel B).

Spatial correlation. To address potential concerns about spatial correlation influencing statistical inference, we implement Conley standard errors. Appendix Figure S21 shows that even when using a conservative, large distance cutoff (1000km)–as well as a range of distance cutoffs–our main estimates remain statistically significant with the exception of precipitation, which gets noisy at higher cutoffs.

Hyperlocal analysis. Finally, we seek to directly validate the paper's basic underlying idea: that planting trees changes the local climate. 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 trees (Snow 2019) to calculate the afforested area in the vicinity of each station. 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 S15). These results, though likely partially mitigated by downwind climate spillover effects that we ignore in this exercise, show that the change in climate due to tree planting holds at the local level. Further discussion of these station-level results is provided in Appendix S.9.

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 the 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 more exposed to large-scale prevailing winds from afforested areas in the Shelterbelt to those less exposed to these winds. We find that rainfall increased and temperature decreased with higher exposure to winds from afforested areas. Our results are robust to various alternate empirical methods, including instrumental variables, long differences, difference-in-differences with binary treatment variables, and synthetic difference-in-differences 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 2 to the theoretical transpiration rate of trees. Our estimated precipitation coefficient is 0.995 cm per month for a unit increase in wind exposure. Summing this over the three summer months that we analyze from June to August (2.985 cm), multiplying it by the average wind exposure in the total region studied (0.21), and multiplying by the total region studied (1,694,433km^2), results in an increase of 1cm of water per year spread across 1,062,155km^2, which is equivalent to 7.9 million acre-feet of water (2.56 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.[27] 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 roughly in line with the 2.56 trillion gallons attributable to increased precipitation. While this exercise is coarse and simplistic[28], 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 consequences 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 production increased in areas more exposed to winds from the Shelterbelt but not directly afforested. This increase in corn production is mostly driven by an increase in the area harvested of corn, rather than by corn yields. Such increase, in turn, can be explained by a combination of reduced crop failures and climate adaptation: farmers switch from less water-intensive crops like wheat to more water-intensive crops like corn.

The policy-induced improvement of the climate in areas downwind from the Shelterbelt has important consequences for the agricultural development of the US Midwest: in a period of intense farm consolidation and mechanization, we find that areas whose growing conditions improved thanks to the Shelterbelt tree planting witnessed relatively less consolidation, keeping more small farms. But these areas also mechanized less, evidenced by lower use of farm machinery. As a result, farm values were 3.9% lower in terms of the overall value of agricultural land and buildings, suggesting lower productivity and a potential 'lock in' into agriculture during a period of structural transformation.

Our findings are particularly timely given the global enthusiasm for large-scale tree planting as a means of mitigating climate change—especially in light of estimates that such activities could potentially 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.[29]

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

[28] 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.

[29] 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).

There are good reasons for this enthusiasm. Tree planting is a 'simple technology' enjoying high levels of public approval and public participation. 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. Further, forestation efforts can reduce air pollution, particularly in urban settings (Xing et al. 2023). Our paper adds another co-benefit to this list. The increased precipitation and decreased extreme heat that we find during the growing season provide 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) and adaptation (by reducing the negative impact of global warming on agriculture).[30]

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.[31] Some critics worry that massive afforestation efforts could come at the expense of cropland and thus food security, while others are concerned about the dispossession of land from pastoralists 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 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,

[30] 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 of deforestation. By illustrating the challenges to maintain the current tree cover, this evidence base can help guide the design of afforestation programs.

[31] 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 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.

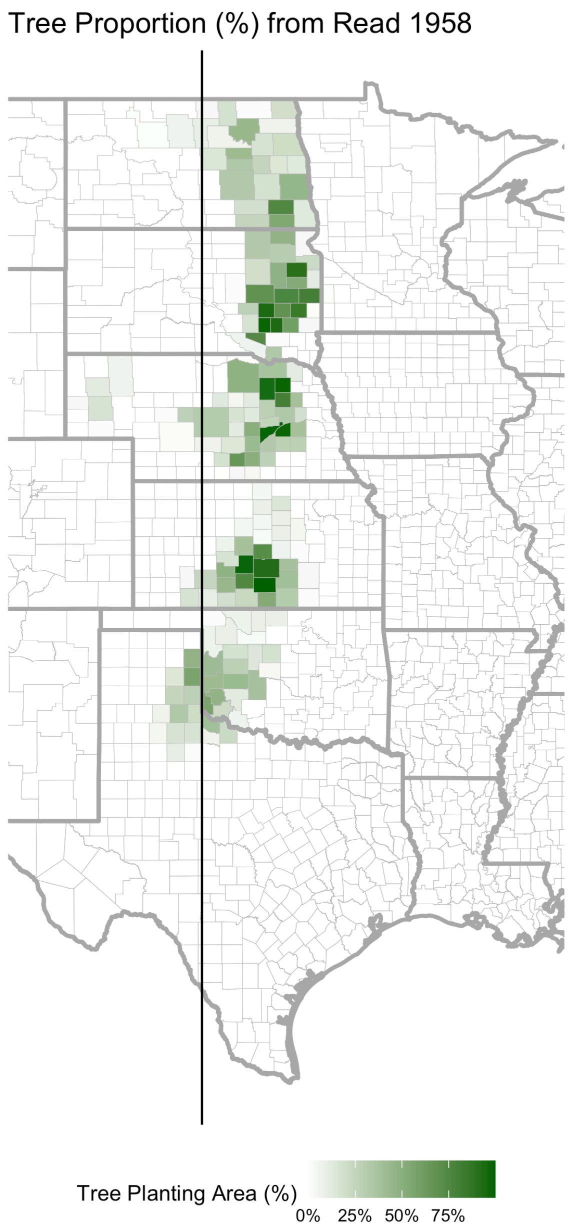
Relatedly, another valid question concerns the external validity of our results and the extent that the Great Plains is similar to other potential tree planting regions of the world. In terms of economic status, we first note that many countries today are still highly dependent on agriculture, like the US Midwest was in the 1940s.[32] In terms of agronomic conditions, the Great Plains Shelterbelt occurred on mollisol soils, which are common throughout rainfall-limited historic grasslands. As shown in Appendix Figure S13, 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 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.

[32] 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 S12).

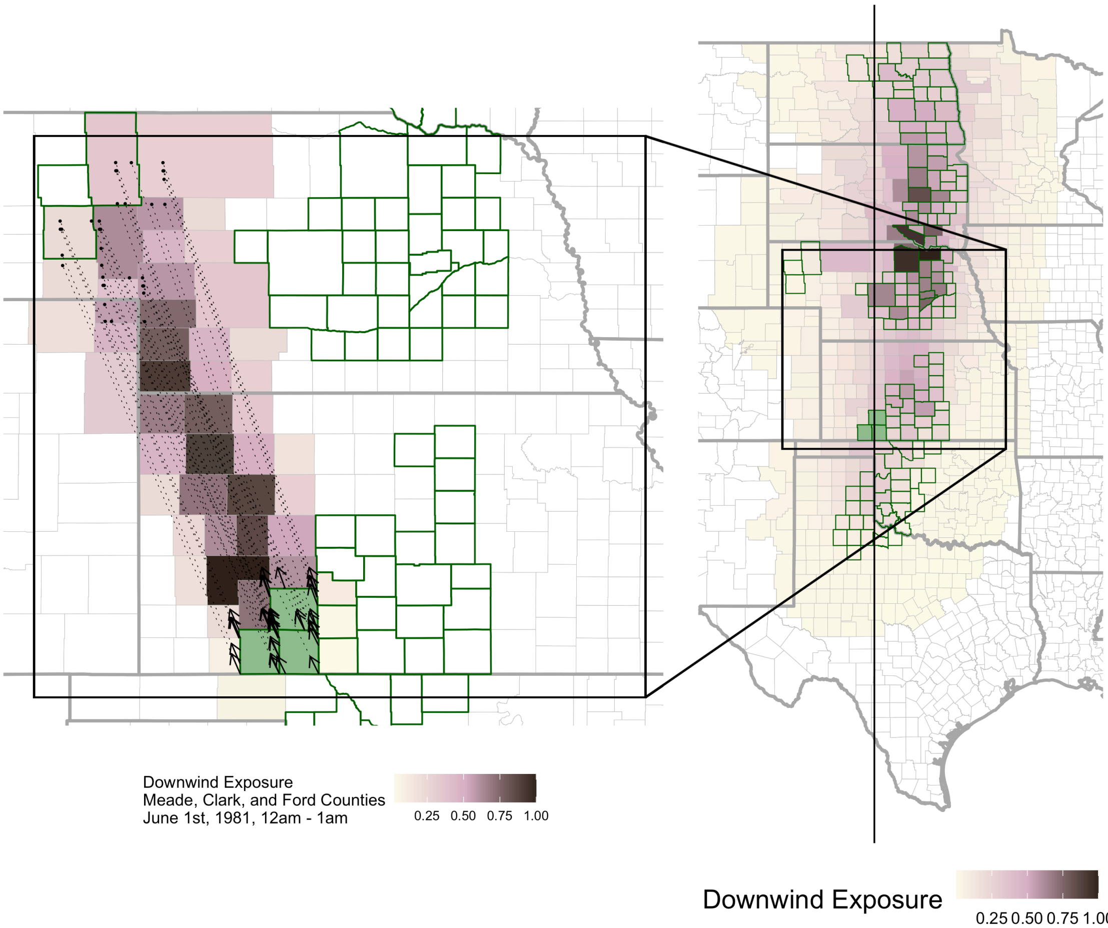
7 Figures

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.

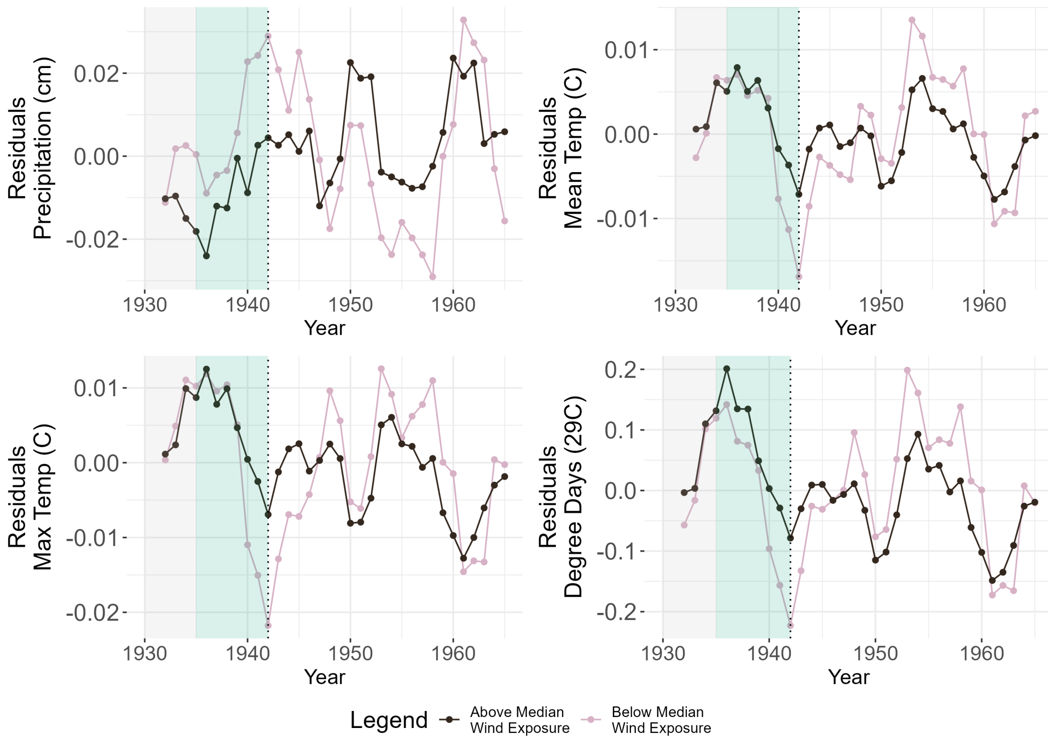
Figure 2: Shelterbelt wind exposure measure



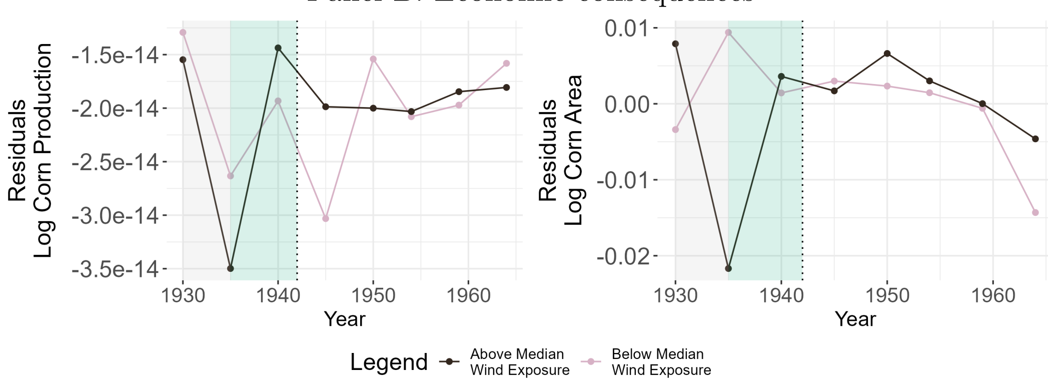
Notes: Figures illustrate the construction of our Shelterbelt wind exposure measure. Counties with green borders are Shelterbelt counties. Purple shading shows continuous wind exposure measure. The left panel shows details of construction for three Shelterbelt counties (Meade, Clark, and Ford, in Kansas). Arrows represent the direction and magnitude of prevailing winds for a given day and hour. Paths of imaginary particles projected from each county's vertices following the wind are shown as dotted lines. A path going through a given county means a higher Shelterbelt wind exposure for that county. Aggregating these paths over all counties and summer hours yields our continuous measure of wind exposure. More details on the variable's construction are provided in Appendix S.2.1. The right panel shows the final continuous wind exposure measure for all counties in the sample.

Figure 3: Trends in outcomes for low and high wind exposure counties

Panel A: Climate outcomes

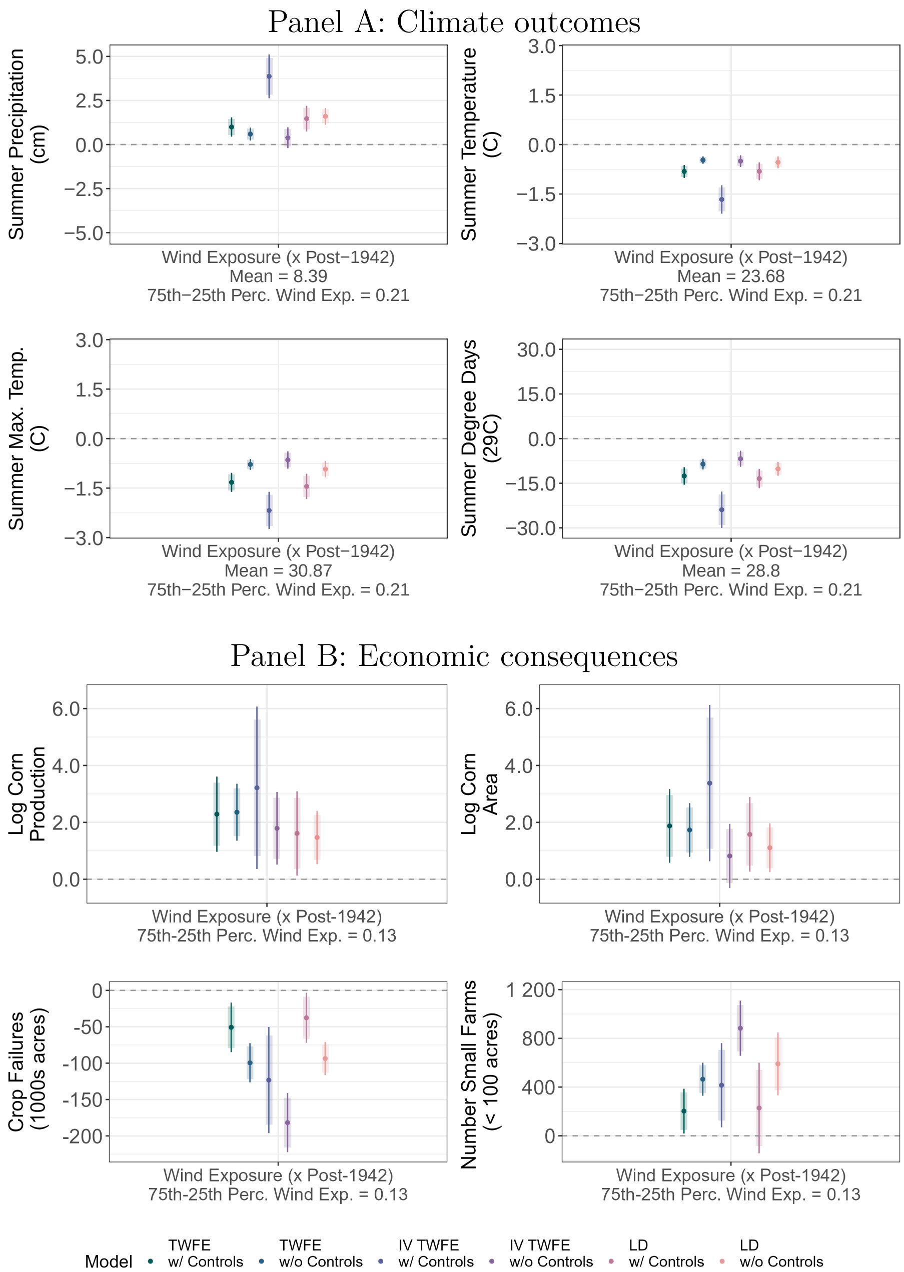


Panel B: Economic consequences



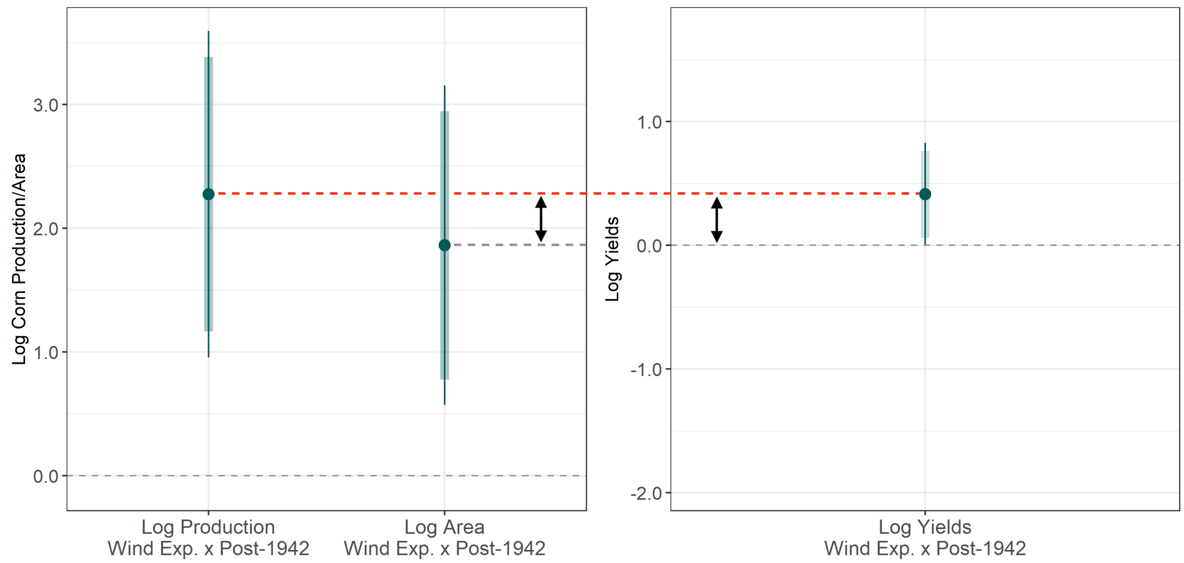
Notes: Figures plot climate and economic variables over the sample period 1930-1965, separately for counties with above-median and below-median wind exposure. The variables are residualized, removing county FE and time-invariant controls interacted by year, including county-level geospatial and topographic characteristics, baseline erosion, and baseline irrigation. Panel A shows summer precipitation, mean and maximum summer temperature, and 29C summer degree days. 3-year rolling averages are reported due to high variation in annual weather outcomes. Panel B shows log corn production and area harvested. Our baseline period encompasses the period before the project started (1930-1935, gray-shaded) and the tree planting years (1936-1942, green-shaded).

Figure 4: Climate and economic results summary



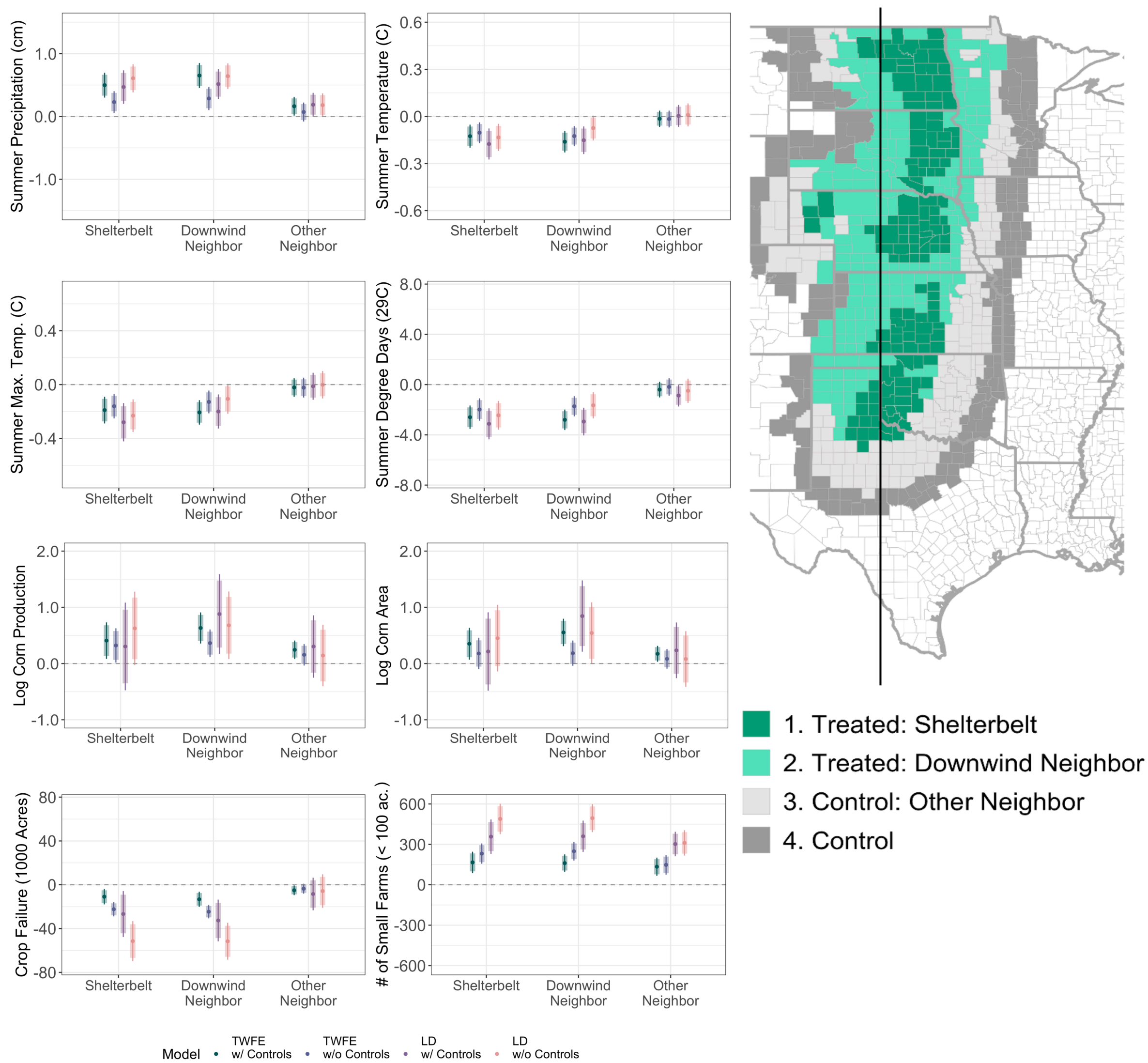
Notes: Figures plot coefficient estimates and 95% (thin line) and 90% (thick line) confidence intervals across three different models: two-way fixed effects (TWFE) (Equation 1), instrumental variables TWFE (Equation 4), and long differences (LD) (Equation 2), each with and without controls. The main independent variable is wind exposure (w_i), which measures approximate exposure to winds from afforested areas, interacted by a post-treatment dummy for the TWFE models. "75^{th}-25^{th} Perc. Wind Exp" shows the difference between the 75^{th} and 25^{th} percentile of the continuous wind exposure measure. Time-invariant controls include the county's geospatial and topographic characteristics, baseline erosion, and baseline irrigation. County and state-by-year (or state, for LD) FE is included. In Panel A, dependent variables are summer precipitation, mean and maximum temperature, and 29C degree days (June - August averages). In Panel B, dependent variables are log corn production and area, crop failure in acres, and number of farms with a size below 100 acres.

Figure 5: Effects on corn production, area, and yield



Notes: Figure shows results from estimating Equation 1, for log corn production and area (left panel) and log corn yields (right panel) for 479 counties, with centroids within 300km of the centroids of Shelterbelt counties, dropping directly afforested areas. The main independent variable is wind exposure (w_i), which measures approximate exposure to winds from afforested areas, interacted by a post-treatment dummy. Time-invariant controls include the county's geospatial and topographic characteristics, baseline erosion, and baseline irrigation. County and state-by-year FE is included. The difference between log production increase and log area increase is equal to the log yield increase. Coefficient estimates and 95% (thin line) and 90% (thick line) confidence intervals are reported.

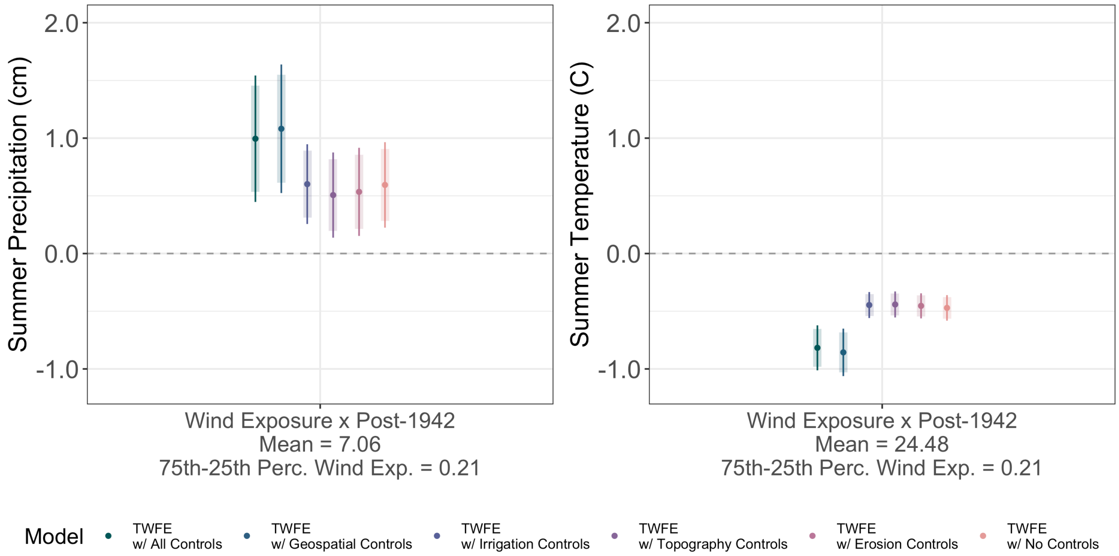
Figure 6: Results using binary treatment instead of continuous wind exposure measure



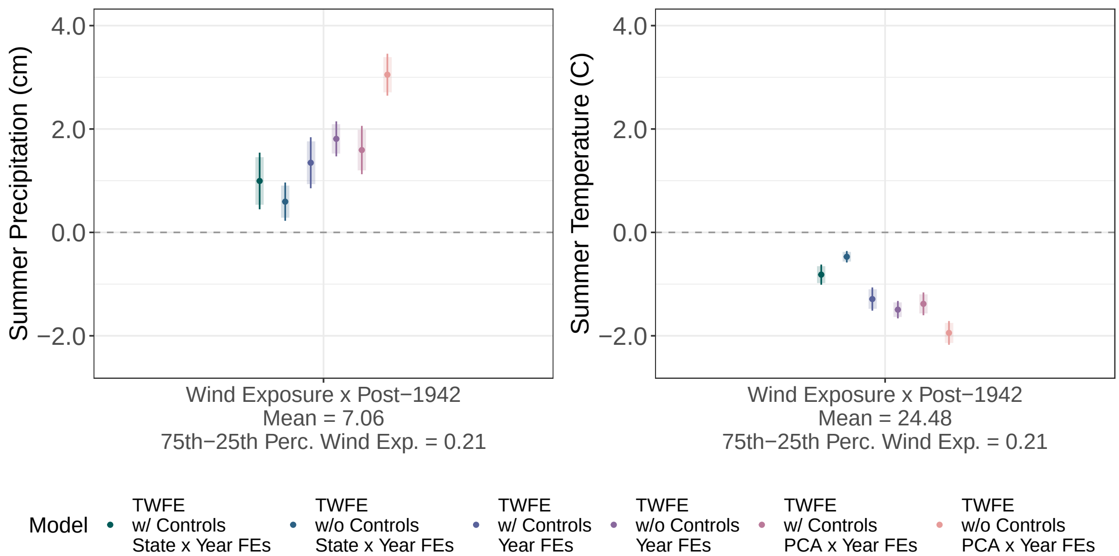
Notes: Figure shows results from estimating the model with binary treatment variables instead of continuous treatment variable. Based on the distance to the tree planting and summer wind exposure measure (w_i) from the Shelterbelts, we group counties within 300km of afforested areas into four categories. These include afforested counties (Shelterbelt), non-afforested counties with above-median wind exposure, centroids within 200km of the centroid of the closest Shelterbelt county (Downwind Neighbor), non-afforested counties with below-median wind exposure, centroids within 200km of the centroid of the closest Shelterbelt county (Other Neighbor), and pure control counties with centroids between 200 and 300km of the centroid of the closest Shelterbelt county. We use the Other Neighbor counties as a placebo check, as we expect limited climate effects in areas with little wind exposure from tree planting. The right panel shows each county's assigned group. We estimate a difference-in-differences model (Equation 5) and a long differences model (Equation 6) both with and without time-invariant controls (interacted by year for the difference-in-differences). Time-invariant controls include the county's geospatial and topographic characteristics, baseline erosion, and baseline irrigation. County and state-by-year (or state, for LD) FE is included. The left panel then plots coefficient estimates and 95% (thin line) and 90% (thick line) confidence intervals for summer precipitation, mean and maximum temperature, 29C degree days (top), and log corn production and area and crop failure measures (bottom).

Figure 7: Climate results robustness

Panel A: Alternate controls



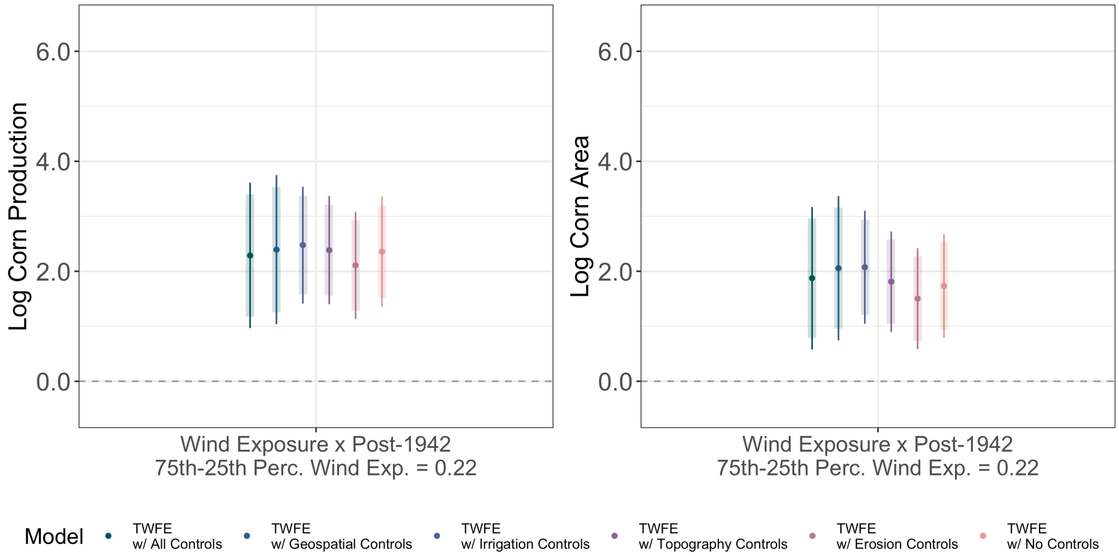
Panel B: Alternate fixed effects



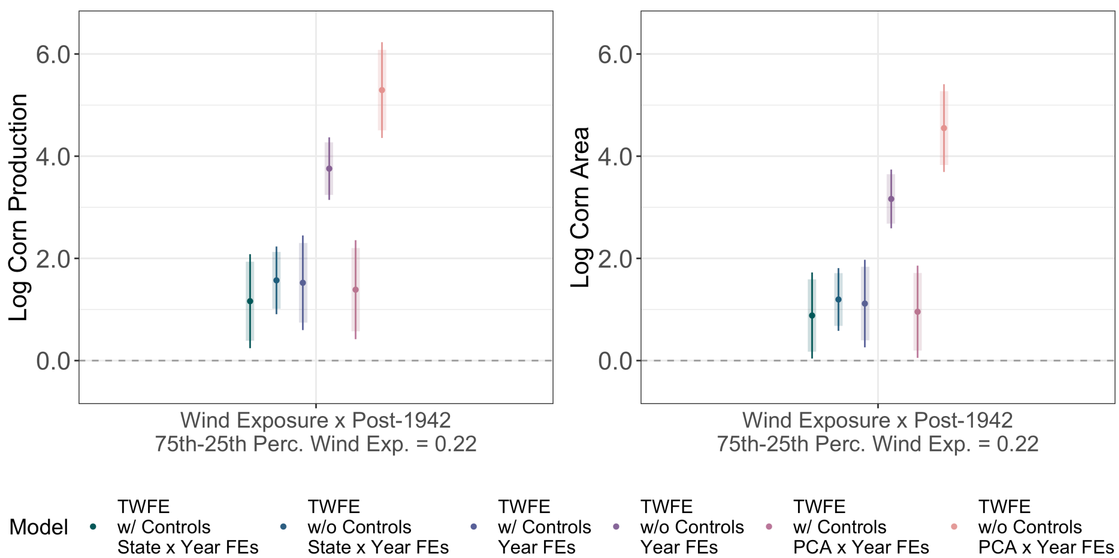
Notes: Figures plot coefficient estimates and 95% (thin line) and 90% (thick line) confidence intervals for mean summer precipitation and mean summer temperatures. In Panel A, we show robustness across five versions of estimating Equation 1 with various controls. First, we show our main results with all controls. Next, we only include, in turn, geospatial controls, baseline irrigation controls, topographic controls, and baseline erosion controls. Finally, we remove all controls. In Panel B, we show robustness across six specifications (based on Equation 1) with various fixed effects. First, we show our main results with state-by-year (and county) fixed effects, with and without controls. Next, we include only year (and county) fixed effects. Finally, we include principal component quadrant by year fixed effects. To create these quadrants, we perform principal component analysis using county-level data on each of our controls, as well as average precipitation and temperature. We then create quintiles based on the main principal component.

Figure 8: Corn production and area results robustness

Panel A: Alternate controls



Panel B: Alternate fixed effects



Notes: Figures plot coefficient estimates and 95% (thin line) and 90% (thick line) confidence intervals for log corn production and area harvested. In Panel A, we show robustness to five specifications (based on Equation 1) with various controls. First, we show our main results with all controls. Next, we include only the county area irrigated in 1935, Dust Bowl erosion measures, crop suitability, and soil type controls. Finally, we drop all controls. In Panel B, we do the same with six specifications with various fixed effects. First, we show our main results with state-by-year (and county) fixed effects, with and without controls. Next, we include only year (and county) fixed effects. Finally, we include principal component quadrant by year fixed effects. To create these quadrants, we perform principal component analysis using county-level geospatial and topographic characteristics, baseline erosion, baseline irrigation, average precipitation, and maximum and minimum temperatures. We then create quintiles based on the main principal component.

8 Tables

Table 1: Balance table

Outcomes	Sample Mean	Without Controls		With Controls	
		Coef.	P-Val.	Coef.	P-Val.
	(1)	(2)	(3)	(4)	(5)
Panel A: Climate Outcomes, Monthly Average Jun-Aug					
Precipitation (cm)	7.1	-1.212	$<$0.001	-0.366	0.110
Mean Temp (C)	24.5	-2.167	$<$0.001	-0.046	0.860
Max Temp (C)	32	-1.306	0.017	0.307	0.292
Degree Days (29C)	37.8	-7.1	0.069	1.957	0.321
Panel B: Agricultural Outcomes, Corn					
Log Production (bushels)	11.6	-1.321	0.113	1.424	0.167
Log Area Harvested (acres)	9	-0.67	0.359	1.23	0.206
Log Yields (bushels per acre)	2.6	-0.651	0.001	0.195	0.341

Notes: Table provides summary statistics and shows the balance of outcomes by levels of wind exposure. Sample is of the 678 counties with centroids within 300km of the centroids of Shelterbelt counties (Panel A), and their subset of 479 counties having agricultural census data and excluding directly afforested counties (Panel B). The outcomes are listed in the left side of the table. Column (1) reports their sample average over the baseline period 1935-1942. Columns (2) and (3) report, respectively, the OLS point estimate and associated p-value from the cross-sectional regression of the outcome on the county's wind exposure measure. Columns (4) and (5) also report the OLS point estimate and associated p-value when regressing the outcome on the wind exposure measure, when adding controls to the regression. These controls are: indicators for being a Shelterbelt county; for having above-median distance to the nearest Shelterbelt county; county size; share of county overlapping with the Ogallala aquifer; share of county irrigated in 1935; indicators for having medium or high Dust Bowl erosion levels; elevation; ruggedness; latitude and longitude (indicators for the sample quartiles, and their interactions); and state fixed effects.

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

	Dependent variable:			
	Precipitation (cm)	Mean Temp (C)	Max Temp (C)	Degree Days (29C)
	(1)	(2)	(3)	(4)
Panel A: All Counties and Years				
Wind Exposure:Post 1942	0.995***	−0.817***	−1.326***	−12.557***
	(0.279)	(0.099)	(0.147)	(1.492)
	[0.000]	[0.000]	[0.000]	[0.000]
Mean	7.06	24.48	31.97	37.82
Std.Dev.	2.82	2.82	2.94	23.37
75th-25th Perc. Wind Exp	0.21	0.21	0.21	0.21
Observations	24,408	24,408	24,408	24,408
Panel B: Non-Shelterbelt Counties Only, with Agricultural Census Available				
Wind Exposure:Post 1942	1.161	−1.472***	−2.295***	−23.778***
	(0.921)	(0.238)	(0.326)	(2.953)
	[0.209]	[0.000]	[0.000]	[0.000]
Mean	7.65	23.79	31.09	31.89
Std.Dev.	2.99	2.46	2.51	16.77
75th-25th Perc. Wind Exp	0.13	0.13	0.13	0.13
Observations	3,539	3,539	3,539	3,539

Notes: Table shows results for estimating Equation 1. Sample is of the 678 counties with centroids within 300km of the centroids of Shelterbelt counties (Panel A), and a subset of the 479 counties with agricultural census data available and that were not directly afforested (Panel B). Dependent variables are the annual average of each month's average climate for June, July, and August. For clarity, for the 'Mean' row Panel A: (1) precipitation of 7.06cm is the average monthly cumulative rainfall, averaged across June-August; (2) mean temperature of 24.48C is the monthly average of daily mean temperatures, averaged across June-August; (3) max temperature of 31.97C is the monthly average of daily maximum temperatures, averaged across June-August; (4) degree days (29C) of 37.82 is the monthly sum of daily degree days exceeding 29C (i.e., a 32C day would contribute 3 degree days to that month), averaged across June-August. The main independent variable is wind exposure (w_i), which measures approximate exposure to winds from afforested areas, interacted by a post-treatment dummy. "75th-25th Perc Wind Exp" shows the difference between the 75th and 25th percentile of the continuous wind exposure measure in the sample. Time-invariant controls, interacted by year, include county-level geospatial and topographic characteristics, baseline erosion, and baseline irrigation. County and state-by-year FE is included. Standard errors are clustered at the county level, shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01).

Table 3: Impact of Great Plains Shelterbelt on corn production, area harvested, and yields using USDA 5-year agricultural census data, 1930 to 1964

	Dependent variable:		
	Log Production	Log Area	Log Yields
	(1)	(2)	(3)
Wind Exposure:Post 1942	2.273***	1.861***	0.412*
	(0.672)	(0.657)	(0.212)
	[0.001]	[0.005]	[0.053]
75th-25th Perc. Wind Exp	0.13	0.13	0.13
Observations	3,539	3,539	3,539

Notes: Table shows results for estimating Equation 1 for 479 counties, with centroids within 300km of the centroids of Shelterbelt counties, dropping directly afforested areas. Dependent variables are from USDA 5-year agricultural censuses (8 censuses between 1930 and 1964) for log corn production in bushels (Col. 1), log area of corn harvested in acres (Col. 2), and log corn yields (bushels per acre). The main independent variable is wind exposure (w_i), which measures approximate exposure to winds from afforested areas, interacted by a post-treatment dummy. “75th-25th Perc Wind Exp” shows the difference between the 75th and 25th percentile of the continuous wind exposure measure. Time-invariant controls, interacted by year, include county-level geospatial and topographic characteristics, baseline erosion, and baseline irrigation. County and state-by-year FE is included. Standard errors clustered at the county level are shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01).

Table 4: Impact of Great Plains Shelterbelt on agricultural development, 1930 to 1964

	(1)	(2)	(3)	(4)
Panel A: Agricultural Output	*Dep. var.:* Cropland area (1000s acres)			
	Corn Harvested	Wheat Harvested	Crop Failures	Total Cropland
Wind Exposure:Post 1942	36.741***	−47.460***	−50.698***	−15.561
	(8.293)	(10.646)	(17.361)	(22.853)
	[0.000]	[0.000]	[0.004]	[0.497]
Panel B: Farm Consolidation	*Dep. var.:* Number of Farms, by Farm Size			Farms Value
	$<$ 100 acres	100-499 acres	$\geq$ 500 acres	(Log)
Wind Exposure:Post 1942	196.153**	−60.303	−3.753	−0.300**
	(92.735)	(114.545)	(42.006)	(0.125)
	[0.035]	[0.599]	[0.929]	[0.018]
75th-25th Perc. Wind Exp	0.13	0.13	0.13	0.13
Observations	3,539	3,539	3,539	3,539

Notes: Table shows results for estimating Equation 1 for 479 counties, with centroids within 300km of the centroids of Shelterbelt counties, dropping directly afforested areas. Dependent variables are from USDA 5-year agricultural censuses (8 censuses between 1930 and 1964). The main independent variable is wind exposure (w_i), which measures approximate exposure to winds from afforested areas, interacted by a post-treatment dummy. "75th-25th Perc Wind Exp" shows the difference between the 75th and 25th percentile of the continuous wind exposure measure. "Farms Value" corresponds to the log of the total value of farmland and buildings at the county-year level. Time-invariant controls, interacted by year, include county-level geospatial and topographic characteristics, baseline erosion, and baseline irrigation. County and state-by-year FE included. Standard errors are clustered at the county level shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01).

Table 5: Impact of Great Plains Shelterbelt on input choices, 1930 to 1964

	Dependent variable: Log Spending, on		
	Hired Labor	Hired Machines	Fertilizer
	(1)	(2)	(3)
Wind Exposure:Post 1942	-0.204	-0.703^{***}	3.081^{***}
	(0.287)	(0.263)	(1.159)
	[0.478]	[0.008]	[0.009]
75th-25th Perc. Wind Exp	0.13	0.13	0.13
Observations	2,283	2,283	2,283

Notes: Table shows results for estimating Equation 1 for 479 counties, with centroids within 300km of the centroids of Shelterbelt counties, dropping directly afforested areas. Dependent variables are from USDA 5-year agricultural censuses (8 censuses between 1930 and 1964). The main independent variable is wind exposure (w_i), which measures approximate exposure to winds from afforested areas, interacted by a post-treatment dummy. "75th-25th Perc Wind Exp" shows the difference between the 75th and 25th percentile of the continuous wind exposure measure. Time-invariant controls, interacted by year, include county-level geospatial and topographic characteristics, baseline erosion, and baseline irrigation. County and state-by-year FE is included. Standard errors are clustered at the county level, shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01).

References

Alkama, Ramdane, and Alessandro Cescatti. 2016. “Biophysical climate impacts of recent changes in global forest cover.” *Science* 351 (6273): 600–604.

Annan, Francis, and Wolfram Schlenker. 2015. “Federal crop insurance and the disincentive to adapt to extreme heat.” *The American Economic Review Papers and Proceedings* 105 (5): 262–66.

Araujo, Rafael. 2023. “When clouds go dry: an integrated model of deforestation, rainfall, and agriculture.”

Araujo, Rafael, Francisco Costa, and Marcelo Sant’Anna. 2022. “Efficient forestation in the Brazilian Amazon: Evidence from a dynamic model.”

Arkhangelsky, Dmitry, Susan Athey, David A. Hirshberg, Guido W. Imbens, and Stefan Wager. 2021. “Synthetic Difference-in-Differences.” *The American Economic Review* 111 (12): 4088–4118.

Asher, Sam, Alison Campion, Douglas Gollin, and Paul Novosad. 2022. “The long-run development impacts of agricultural productivity gains: Evidence from irrigation canals in india.” *Working Paper.*

Auffhammer, Maximilian. 2022. “Climate Adaptive Response Estimation: Short and long run impacts of climate change on residential electricity and natural gas consumption.” *Journal of Environmental Economics and Management* 114:102669.

Balboni, Clare, Aaron Berman, Robin Burgess, Benjamin A Olken, Brian Copeland, Robert Heilmayr, Allan Hsiao, et al. n.d. “The economics of tropical deforestation.” Prepared, *Annual review of economics.*

Balboni, Clare, Robin Burgess, and Benjamin A Olken. 2021. “The origins and control of forest fires in the tropics.”

Barton, Thomas F. 1936. “The Great Plains Tree Shelterbelt Project.” *Journal of Geography* 35:125.

Bastin, Jean-Francois, Yelena Finegold, Claude Garcia, Danilo Mollicone, Marcelo Rezende, Devin Routh, Constantin M Zohner, and Thomas W Crowther. 2019. “The global tree restoration potential.” *Science* 365 (6448): 76–79.

Blakeslee, David, Ram Fishman, and Veena Srinivasan. 2020. “Way Down in the Hole: Adaptation to Long-Term Water Loss in Rural India.” *The American Economic Review* 110 (1): 200–224.

Bonan, Gordon B. 2008. “Forests and Climate Change: Forcings, Feedbacks, and the Climate Benefits of Forests.” *Science* 320 (5882): 1444–1449.

Braun, Thomas, and Wolfram Schlenker. 2023. “Cooling Externality of Large-Scale Irrigation.” *NBER Working Paper,* Working Paper Series, no. 30966.

Burgess, Robin, Francisco J M Costa, and Ben Olken. 2019. “The Brazilian Amazon’s double reversal of fortune.”

Burgess, Robin, Matthew Hansen, Benjamin A Olken, Peter Potapov, and Stefanie Sieber. 2012. “The Political Economy of Deforestation in the Tropics.” *The quarterly journal of economics* 127 (4): 1707–1754.

Burke, Marshall, and Kyle Emerick. 2016. “Adaptation to climate change: Evidence from US agriculture.” *American Economic Journal: Economic Policy* 8 (3): 106–40.

Burlig, Fiona, Louis Preonas, and Matt Woerman. 2021. “Energy, Groundwater, and Crop Choice.” *NBER Working Paper,* no. 28706.

Bustos, Paula, Bruno Caprettini, and Jacopo Ponticelli. 2016. “Agricultural productivity and structural transformation: Evidence from Brazil.” *The American Economic Review.*

Bustos, Paula, Gabriel Garber, and Jacopo Ponticelli. 2020. “Capital accumulation and structural transformation.” *The Quarterly Journal of Economics.*

Butler, Ethan E, and Peter Huybers. 2013. "Adaptation of US maize to temperature variations." *Nature Climate Change* 3 (1): 68–72.

Callaway, Brantly, Andrew Goodman-Bacon, and Pedro H. C. Sant'Anna. 2021. *Difference-in-Differences with a Continuous Treatment.* arXiv: 2107.02637 `[econ.EM]`.

Carleton, Tamma A., and Solomon M. Hsiang. 2016. "Social and economic impacts of climate." *Science* 353 (6304): aad9837.

Cook, Benjamin I., Ron L. Miller, and Richard Seager. 2009. "Amplification of the North American Dust Bowl drought through human-induced land degradation." *Proceedings of the National Academy of Sciences* 106 (13): 4997–5001.

Cui, Xiaomeng. 2020. "Climate change and adaptation in agriculture: Evidence from US cropping patterns." *Journal of Environmental Economics and Management* 101:102306.

DeAngelis, Anthony, Francina Dominguez, Ying Fan, Alan Robock, M Deniz Kustu, and David Robinson. 2010. "Evidence of enhanced precipitation due to irrigation over the Great Plains of the United States." *Journal of Geophysical Research: Atmospheres* 115 (D15).

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken. 2012. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century." *American Economic Journal: Macroeconomics* 4 (3): 66–95.

———. 2014. "What Do We Learn from the Weather? The New Climate-Economy Literature." *Journal of Economic Literature* 53 (3): 740–798.

Deryugina, Tatyana, Garth Heutel, Nolan H. Miller, David Molitor, and Julian Reif. 2019. "The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction." *The American Economic Review* 109 (12): 4178–4219.

Devaraju, N., Govindasamy Bala, and Angshuman Modak. 2015. "Effects of large-scale deforestation on precipitation in the monsoon regions: remote versus local effects." *Proceedings of the National Academy of Sciences* 112 (11): 3257–3262.

Dimitri, Carolyn, Anne Effland, and Neilson C Conklin. 2005. "The 20th century transformation of US agriculture and farm policy."

Dooley, Kate, Heather Keith, Anne Larson, Georgina Catacora-Vargas, Wim Carton, Kirstine Lund Christiansen, Ojong Enokenwa Baa, Alain Frechette, Sonia Hugh, Nathan Ivetic, et al. 2022. "The Land Gap Report."

Droze, Wilmon H. 1977. *Trees, prairies, and people: A history of tree planting in the Plains States.* Texas Woman's University.

Georgescu, Matei, David B Lobell, and Christopher B Field. 2011. "Direct climate effects of perennial bioenergy crops in the United States." *Proceedings of the National Academy of Sciences* 108 (11): 4307–4312.

Haines, Michael, Price Fishback, and Paul Rhode. 2018. *United States Agriculture Data, 1840 - 2012.*

Hansen, Zeynep K, and Gary D Libecap. 2004. "Small farms, externalities, and the Dust Bowl of the 1930s." *Journal of Political Economy* 112 (3): 665–694.

Heutel, Garth, Nolan H Miller, and David Molitor. 2021. "Adaptation and the mortality effects of temperature across US climate regions." *Review of Economics and Statistics* 103 (4): 740–753.

Hornbeck, Richard. 2012. "The enduring impact of the American Dust Bowl: Short-and long-run adjustments to environmental catastrophe." *The American Economic Review* 102 (4): 1477–1507.

Hornbeck, Richard, and Pinar Keskin. 2014. “The historically evolving impact of the ogallala aquifer: Agricultural adaptation to groundwater and drought.” *American Economic Journal: Applied Economics* 6 (1): 190–219.

Hornbeck, Richard, and Enrico Moretti. 2023. “Estimating who benefits from productivity growth: local and distant effects of city productivity growth on wages, rents, and inequality.” Forthcoming, *The Review of Economics and Statistics.*

Horner, GM, WA Starr, and JK Patterson. 1957. “The Pacific Northwest wheat region.” *The Yearbook of Agriculture (Washington, DC: US Department of Agriculture),* 475–481.

Howlader, Aparna. 2023. “Determinants and consequences of large-scale tree plantation projects: Evidence from the Great Plains Shelterbelt Project.” *Land Use Policy* 132:106785.

Hsiang, Solomon. 2016. “Climate Econometrics.” *Annual Review of Resource Economics* 8 (1): 43–75.

Hua, Fangyuan, Lin Wang, Brendan Fisher, Xinlei Zheng, Xiaoyang Wang, W Yu Douglas, Ya Tang, Jianguo Zhu, and David S Wilcove. 2018. “Tree plantations displacing native forests: The nature and drivers of apparent forest recovery on former croplands in Southwestern China from 2000 to 2015.” *Biological Conservation* 222:113–124.

Hultgren, Andrew, Tamma Carleton, Michael Delgado, Diana R Gergel, Michael Greenstone, Trevor Houser, Solomon Hsiang, Amir Jina, Robert E Kopp, Steven B Malevich, et al. 2022. “Estimating global impacts to agriculture from climate change accounting for adaptation.” *Available at SSRN 4222020.*

Jayachandran, Seema, Joost de Laat, Eric F Lambin, Charlotte Y Stanton, Robin Audy, and Nancy E Thomas. 2017. *Cash for carbon: A randomized trial of payments for ecosystem services to reduce deforestation,* 6348.

Kala, Namrata. 2017. “Learning, adaptation, and climate uncertainty: Evidence from Indian agriculture.” *MIT Center for Energy and Environmental Policy Research Working Paper* 23.

Kline, Patrick, and Enrico Moretti. 2014. “Local economic development, agglomeration economies, and the big push: 100 years of evidence from the Tennessee Valley Authority.” *Quarterly Journal of Economics.*

Knappenberger, Paul C., Patrick J. Michaels, and Robert E. Davis. 2001. “Nature of observed temperature changes across the United States during the 20th century.” *Climate Research* 17 (1): 45–53.

Kolstad, Charles D, and Frances C Moore. 2020. “Estimating the Economic Impacts of Climate Change Using Weather Observations.” *Review of Environmental Economics and Policy* 14 (1): 1–24.

Kunkel, Kenneth E., Michael A. Palecki, Kenneth G. Hubbard, David A. Robinson, Kelly T. Redmond, and David R. Easterling. 2007. “Trend Identification in Twentieth-Century U.S. Snowfall: The Challenges.” *Journal of Atmospheric and Oceanic Technology* (Boston MA, USA) 24 (1): 64–73.

Kurukulasuriya, Pradeep, and Robert Mendelsohn. 2008. “Crop switching as a strategy for adapting to climate change.” *African Journal of Agricultural and Resource Economics* 2 (311-2016-5522): 105–126.

Lemoine, Derek. 2021. “Estimating the Consequences of Climate Change from Variation in Weather.” *NBER Working Paper,* Working Paper Series, no. 25008.

Leverkus, Alexandro B, Simon Thorn, David B Lindenmayer, and Juli G Pausas. 2022. “Tree planting goals must account for wildfires.” *Science* 376 (6593): 588–589.

Li, Tianshu. 2021. “Protecting the breadbasket with trees? The effect of the great plains shelterbelt project on agriculture.” *Land Economics* 97 (2): 321–344.

Liu, Maggie, Yogita Shamdasani, and Vis Taraz. Forthcoming. “Climate Change and Labor Reallocation: Evidence from Six Decades of the Indian Census.” *American Economic Journal: Economic Policy.*

Loarie, S R, D B Lobell, G P Asner, Q Mu, et al. 2011. “Direct impacts on local climate of sugar-cane expansion in Brazil.” *Nature climate change.*

Lobell, David B, Celine J Bonfils, Lara M Kueppers, and Mark A Snyder. 2008. “Irrigation cooling effect on temperature and heat index extremes.” *Geophysical Research Letters* 35 (9).

Malikov, Emir, Ruiqing Miao, and Jingfang Zhang. 2020. “Distributional and temporal heterogeneity in the climate change effects on U.S. agriculture.” *Journal of environmental economics and management* 104:102386.

McKinsey Global Institute. 2022. *The net-zero transition: what it would cost, what it could bring.* Technical report. https://www.mckinsey.com/capabilities/sustainability/our-insights/the-net-zero-transition-what-it-would-cost-what-it-could-bring.

Montesquieu, Charles de. 1750. *The Spirit of the Laws.* Thomas Nugent.

Mueller, Nathaniel D, Ethan E Butler, Karen A McKinnon, Andrew Rhines, Martin Tingley, N Michele Holbrook, and Peter Huybers. 2016. “Cooling of US Midwest summer temperature extremes from cropland intensification.” *Nature Climate Change* 6 (3): 317–322.

Neild, Ralph E, and James E Newman. 1987. *Growing season characteristics and requirements in the Corn Belt.* Cooperative Extension Service, Iowa State University.

Peng, Shu-Shi, Shilong Piao, Zhenzhong Zeng, Philippe Ciais, Liming Zhou, Laurent Z. X. Li, Ranga B. Myneni, Yi Yin, and Hui Zeng. 2014. “Afforestation in China cools local land surface temperature.” *Proceedings of the National Academy of Sciences* 111 (8): 2915–2919.

Read, Ralph A. 1958. “Great Plains shelterbelt in 1954.” *Great Plains Agricultural Council.*

Schlenker, Wolfram, and Michael J Roberts. 2006. “Nonlinear Effects of Weather on Corn Yields.” *Applied Economic Perspectives and Policy* 28 (3): 391–398.

———. 2009. “Nonlinear temperature effects indicate severe damages to US crop yields under climate change.” *Proceedings of the National Academy of Sciences* 106 (37): 15594–15598.

Schulte, Lisa A, Jarad Niemi, Matthew J Helmers, Matt Liebman, J Gordon Arbuckle, David E James, Randall K Kolka, Matthew E ONeal, Mark D Tomer, John C Tyndall, et al. 2017. “Prairie strips improve biodiversity and the delivery of multiple ecosystem services from corn–soybean croplands.” *Proceedings of the National Academy of Sciences* 114 (42): 11247–11252.

Self, Alister, Rebecca Burdon, Jared Lewis, Peter Riggs, and Kate Dooley. 2023. *The Land Gap Report: 2023 Update.* Technical report.

Sloat, Lindsey L, Steven J Davis, James S Gerber, Frances C Moore, Deepak K Ray, Paul C West, and Nathaniel D Mueller. 2020. “Climate adaptation by crop migration.” *Nature Communications* 11 (1): 1–9.

Smith, C, J C A Baker, and D V Spracklen. 2023. “Tropical deforestation causes large reductions in observed precipitation.” *Nature* 615 (7951): 270–275.

Snow, Meagan. 2019. “The Shelterbelt "Scheme": Radical Ecological Forestry and the Production of Climate in the Fight for the Prairie States Forestry Project.” PhD diss., University of Minnesota.

Spracklen, DV, and LJGRL Garcia-Carreras. 2015. “The impact of Amazonian deforestation on Amazon basin rainfall.” *Geophysical Research Letters* 42 (21): 9546–9552.

Taraz, Vis. 2017. “Adaptation to climate change: Historical evidence from the Indian monsoon.” *Environment and Development Economics* 22 (5): 517–545.

Taylor, Charles A. 2022. “Irrigation and Climate Change: Long-Run Adaptation and its Externalities.” *Working paper.*

"Tree Belt in West to Fight Droughts." 1934. *The New York Times,* 1.

Xing, Jianwei, Zhiren Hu, Fan Xia, Jintao Xu, and Eric Zou. 2023. *Urban Forests: Environmental Health Values and Risks.* Technical report. National Bureau of Economic Research.

Yu, Chengzheng, Ruiqing Miao, and Madhu Khanna. 2021. "Maladaptation of U.S. corn and soybeans to a changing climate." *Scientific reports* 11 (1): 1–12.

Zebiak, Stephen E, and Mark A Cane. 1987. "A model el niñ–southern oscillation." *Monthly Weather Review* 115 (10): 2262–2278.

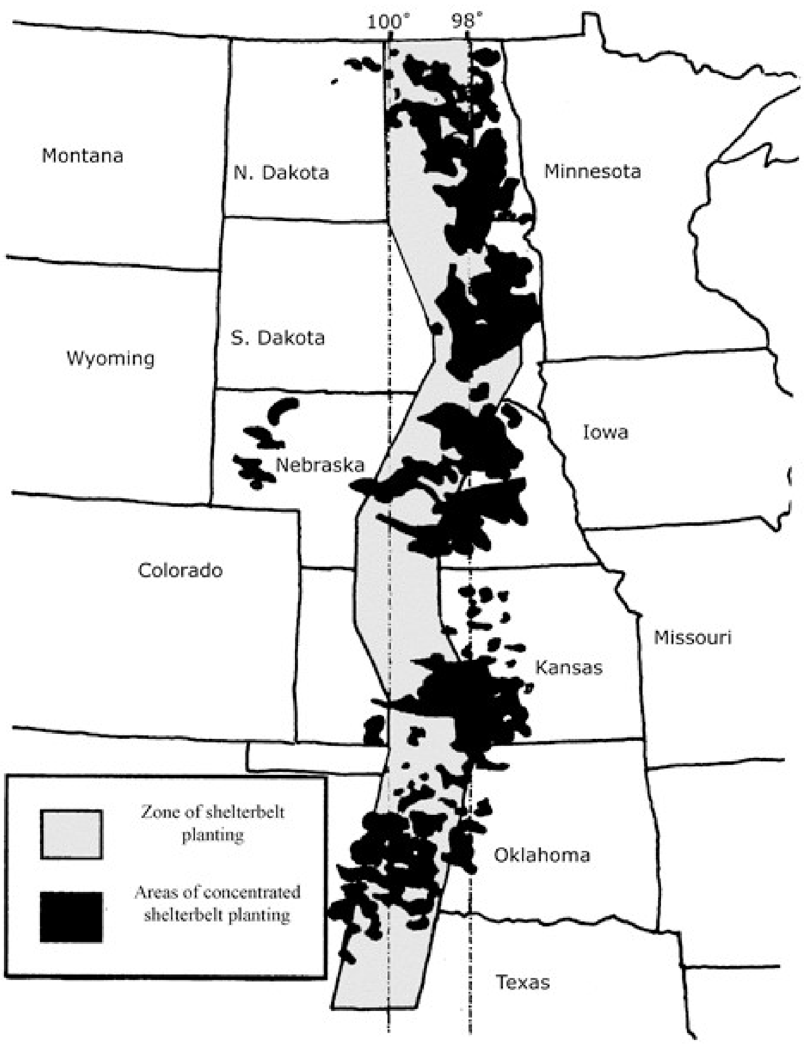
S Supplementary Appendix - For Online Publication

This Appendix contains the following supplementary materials:

S.1 Additional background and context

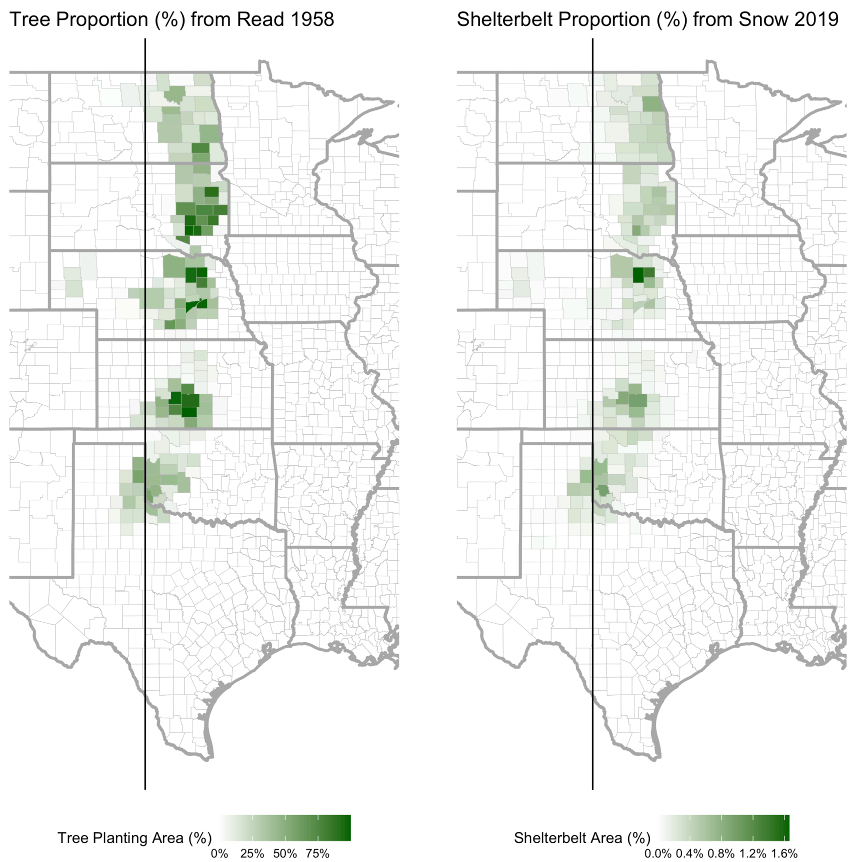
In this section, we present additional information on the history of the Great Plains Shelterbelt project. Figure S9 shows a map of concentrated Shelterbelt planting that we digitize and use as our main measure of treatment. The resulting county-level measure (share of area covered by concentrated tree planting) is shown in the left panel of Figure S10. We also check the robustness of our results using an alternate measure of digitized Shelterbelt shapefiles from Snow 2019, which is shown in the right panel of Figure S10. Figure S11 shows the approximate numbers of trees planted in each year of the program.

Figure S9: Shelterbelt planned area and realized concentrated planning



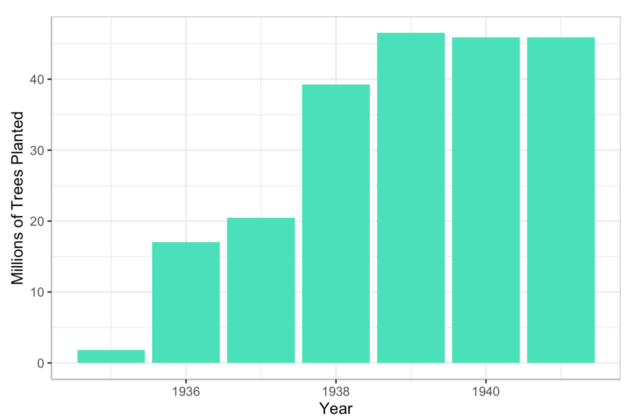
Notes: Map shows planned zone of Shelterbelt planning and areas of concentrated Shelterbelt planning according to Read 1958. Our Shelterbelt definition is based on county areas covered by the areas of concentrated tree planting.

Figure S10: Shelterbelt measures



Notes: Figure compares our main measure of Shelterbelt treatment from Read (1958) and the alternate measure from Snow (2019) used for robustness checks. The two measures are similar (correlation 0.86).

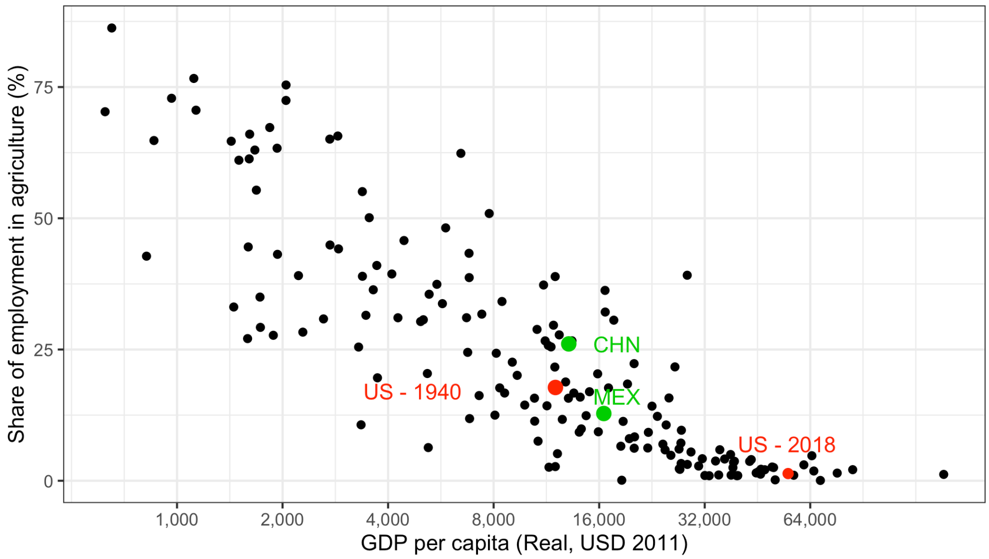
Figure S11: Shelterbelt tree planting over time



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.

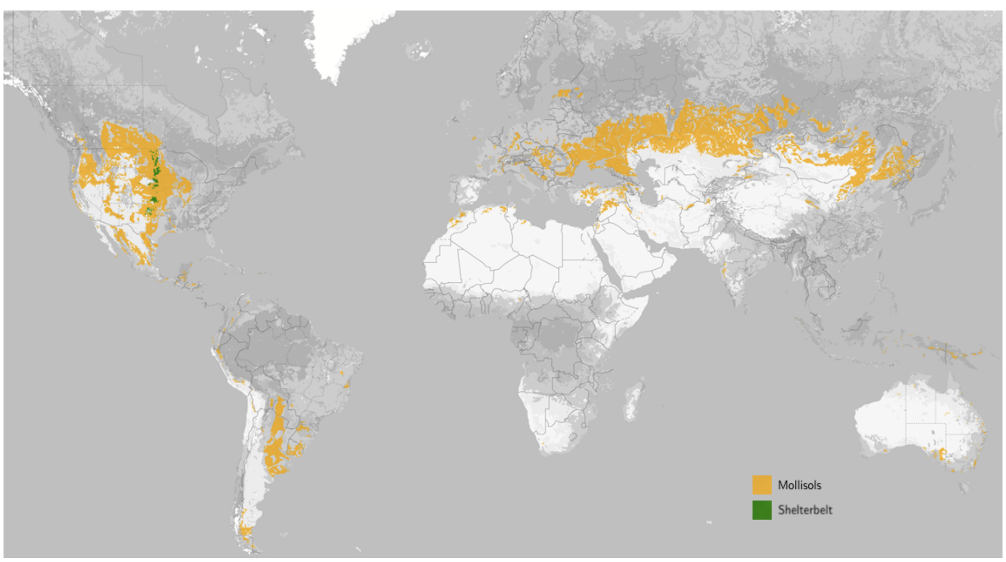
Figures S12 and S13 offer contextual evidence supporting the external validity of our results and illustrate economic and agronomic parallels between the Great Plains and various contemporary global contexts.

Figure S12: 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 S13: Distribution of Mollisols



Notes: Soil map derived from USDA NRCS.

S.2 Wind exposure construction details

S.2.1 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. We also multiply this measure by the area of concentrated Shelterbelt planting in the outgoing county (s_j) and the average quality of the trees planted (q_j) coming from Read (1958).

$$p_{ijh} = \frac{\sum_c p_{ijch}}{V_j} \times (s_j \times q_j)$$

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.

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

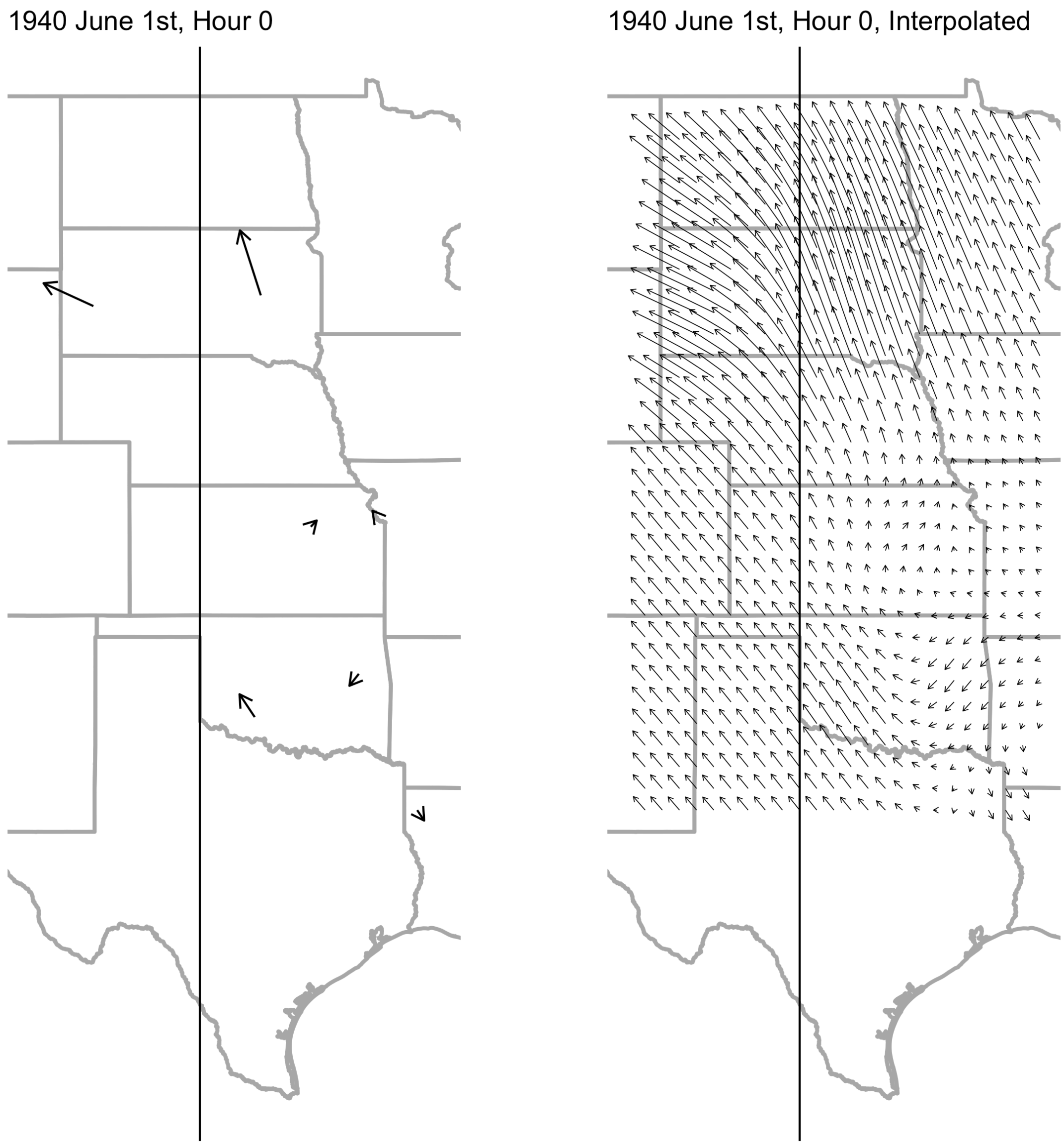
The resulting value $w_i \in [0, 1]$ is the time-invariant approximate measure of exposure to winds from the shelterbelt.

S.2.2 Wind interpolation for 1938-1942

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 S14 shows what the data look like before and after interpolation. We then take the same steps, described in Section S.2.1, in constructing an alternate wind exposure metric as with the 1981-2010 gridded wind data.

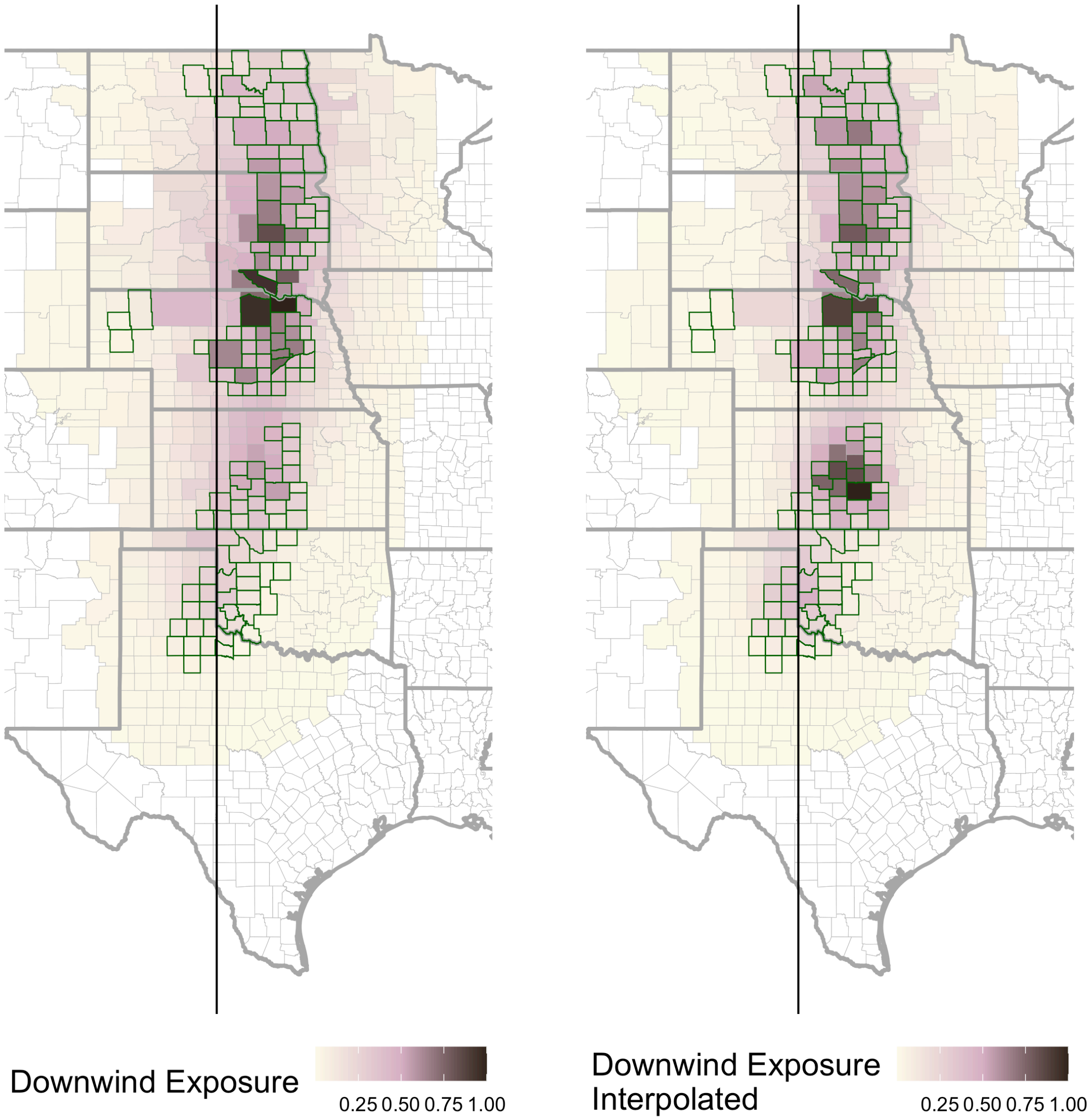
Appendix Figure S15 compares the two resulting downwind exposure metrics. Reassuringly, the measures are very similar with a correlation of 0.92.

Figure S14: 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 S15: Wind exposure measures

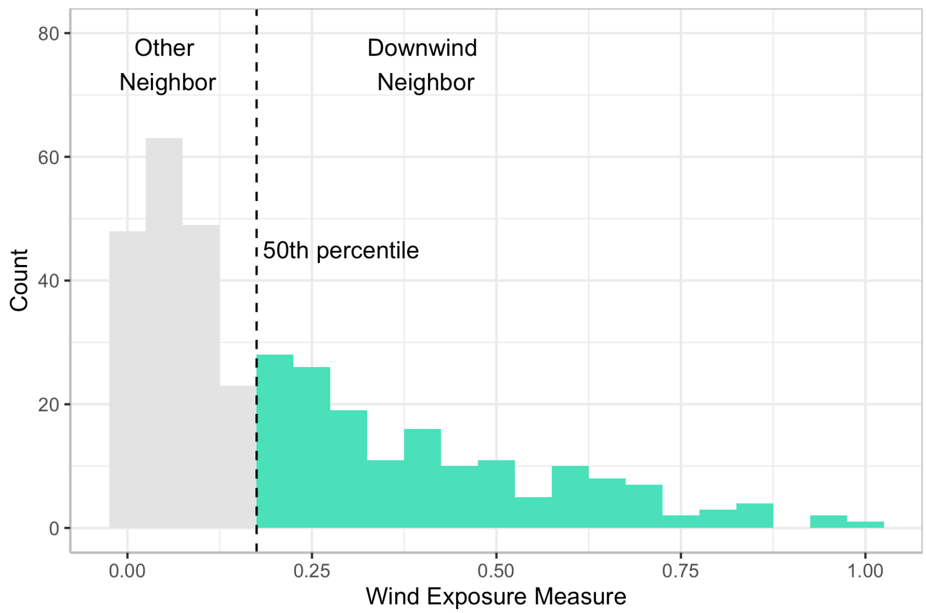


Notes: Maps show two alternate wind exposure metrics. Counties with green borders are treated Shelterbelt counties while shading shows continuous wind exposure measure. The left panel shows our main wind exposure measure based on 1981-2010 long-term average winds, while the right panel shows the same measure but using interpolated 1938-1942 wind station data. Reassuringly, the two measures are very similar (correlation 0.92).

S.2.3 Discretized wind exposure details

Figure S16 shows the construction of our discretized wind exposure categories based on our continuous wind exposure measure. As detailed in Section 4.2, we use the binary difference-in-difference analysis to address concerns regarding the interpretation of the continuous difference-in-differences results. We classify counties into Shelterbelt counties, downwind neighbor counties, other neighbor counties, and pure control counties. Figure S16 shows a histogram of our continuous wind exposure measure and how we divide counties into the above-median (downwind) and below-median (other control) groups.

Figure S16: 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.

S.3 Climate data construction

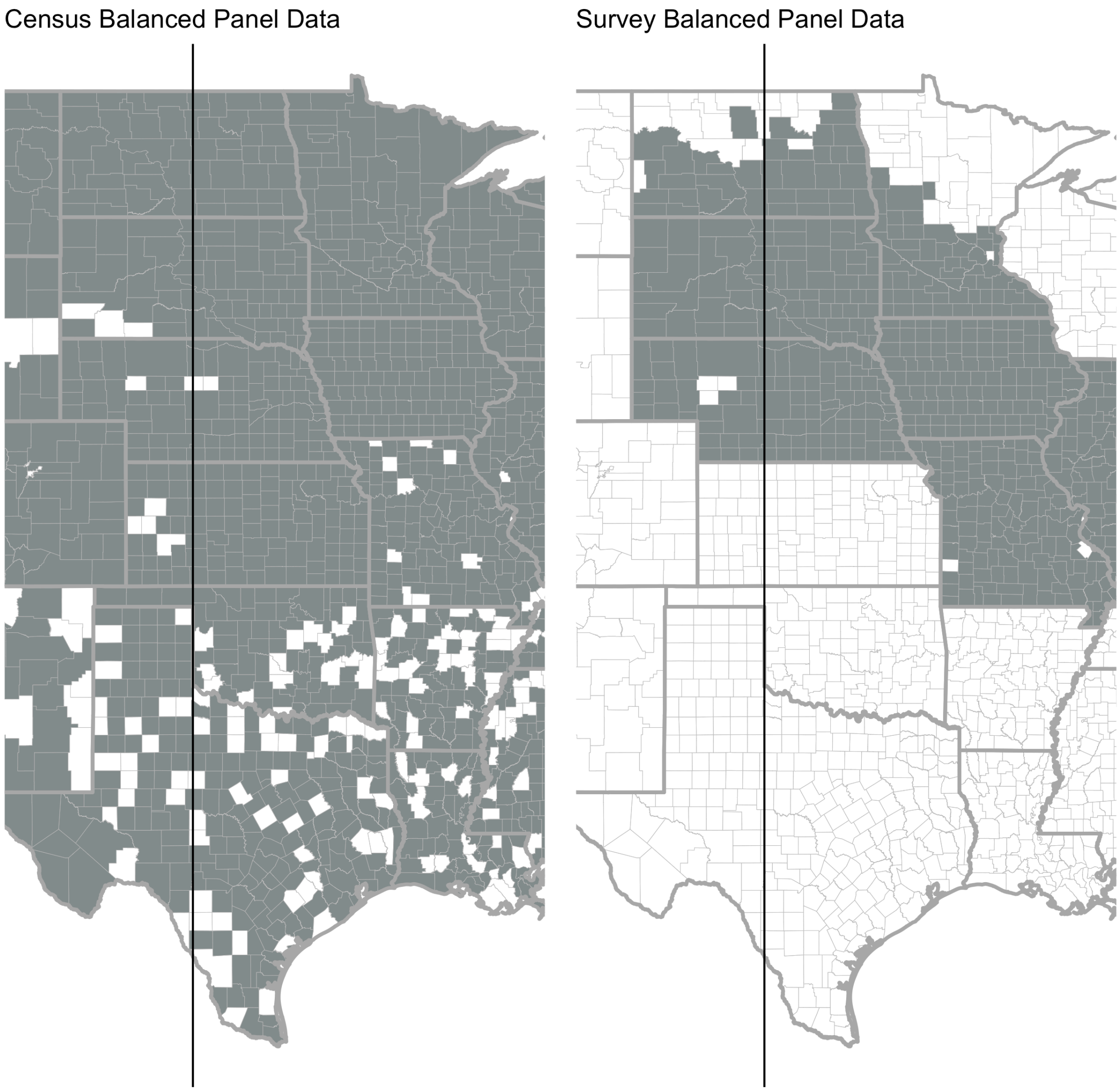
We build our main weather data from daily station data using a methodology inspired by Schlenker and Roberts (2006). We use NOAA's Global Historical Climatology Network daily (GHCNd) data to create a balanced panel of stations with availability between 1930 and 1965. We take the following steps to construct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

S.4 Agricultural census and survey data details

Figure S17 illustrates the geographical coverage of USDA agricultural census (conducted every approximately 5 years) and survey (conducted annually) data between 1930 and 1964. We use agricultural census data in our main analysis, as it offers a more comprehensive coverage of the region.

Figure S17: Agricultural census and survey 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 1964.

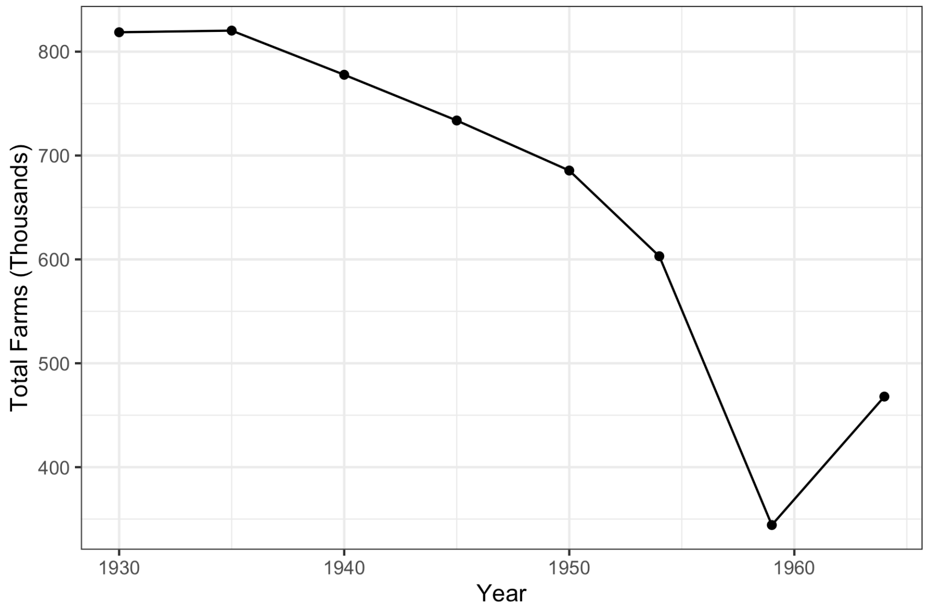
However, the survey data enables us to study differences between corn area *planted* and *harvested*, and show that farmers adapted on the extensive margin by planting more corn in areas more exposed to winds from the Shelterbelt (Table S6). Additionally, the data provides a robustness check of the yield results (Col. 4 of Table S6).

Table S6: Impact of Great Plains Shelterbelt on Corn Acreage, 1930-1965 (USDA Annual Surveys)

	Dependent variable:			
	Corn Area (1000s acres)			Log
	Planted	Harvested	Failure	Yields
	(1)	(2)	(3)	(4)
Panel A: No Controls				
Wind Exposure:Post 1942	20.033**	27.082***	−7.049**	0.729***
	(9.638)	(7.709)	(3.066)	(0.168)
	[0.040]	[0.001]	[0.023]	[0.000]
Panel B: Controls				
Wind Exposure:Post 1942	22.822**	26.946***	−4.124	0.860***
	(9.549)	(8.970)	(4.241)	(0.275)
	[0.018]	[0.004]	[0.333]	[0.003]
75th-25th Perc. Wind Exp	0.20	0.20	0.20	0.20
Observations	5,249	5,249	5,249	5,249

Notes: Table shows results for estimating Equation 1 for 181 counties (outside of the direct afforested areas) with data in the USDA annual surveys. Corn area planted includes all types of corn; corn area harvested is a sum of grain, silage, and forage corn; corn failure is calculated as the difference between the area planted and harvested. Main independent variable is wind exposure (w_i), which measures approximate exposure to winds from afforested areas, interacted by a post-treatment dummy. "75th-25th Perc Wind Exp" shows the difference between the 75th and 25th percentile of the continuous wind exposure measure. Panel A includes no controls beyond county and state-by-year FE. Panel B adds time-invariant controls, interacted by year, including county-level geospatial and topographic characteristics, baseline erosion, and baseline irrigation. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01).

Figure S18: Farm count in sample counties from the USDA 5-year agricultural census data, 1930 to 1964

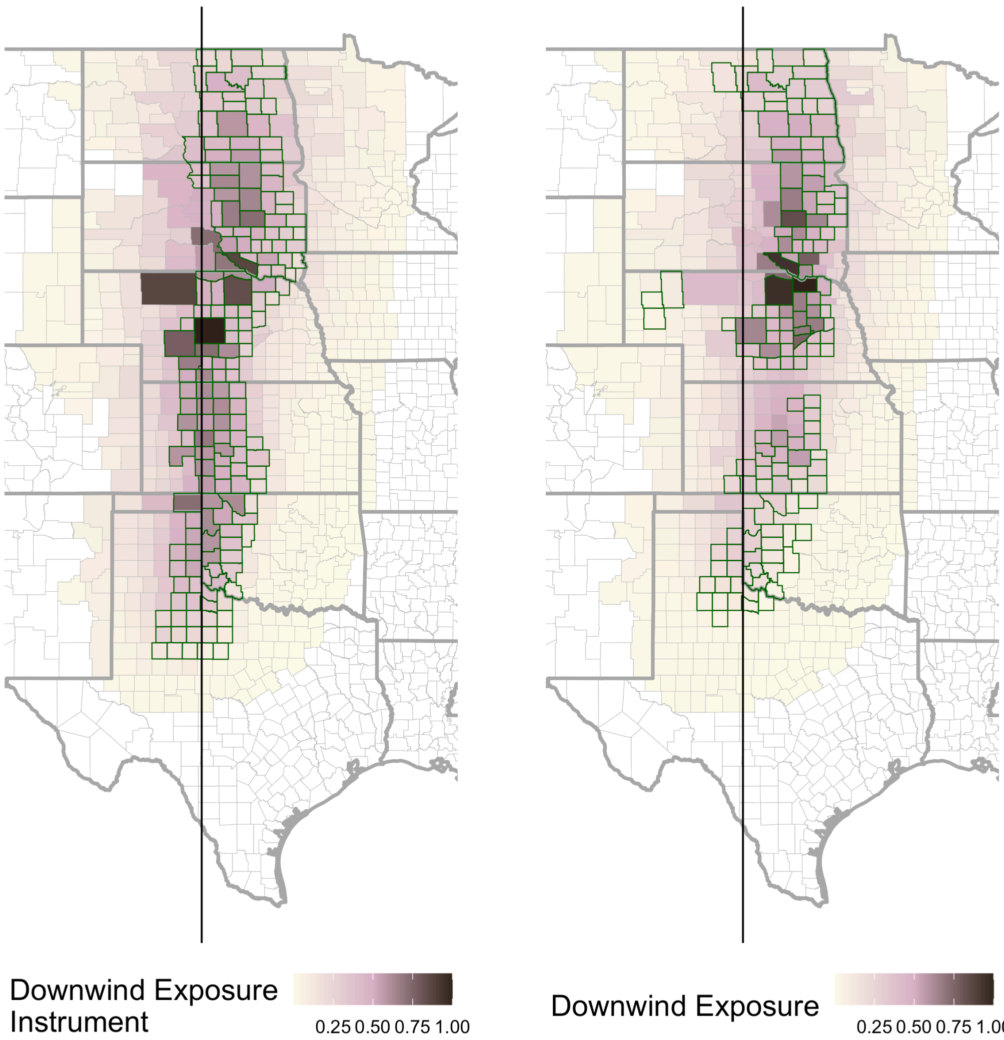


Notes: Figure shows the total farm count in counties for which we have observations from the agricultural census for every time period between 1930 and 1964.

S.5 Instrumental variables approach

This section shows additional details of our instrumental variable approach, presented in Section 4.2, that addresses the potential threat to our main identification strategy from possible strategic planting behavior of the decision-makers involved with the Shelterbelt project. Similar to Li (2021), we use the zone of planned Shelterbelt planting as shown in the gray shaded area in Figure S9.

Figure S19: Wind exposure and wind exposure instrument



Notes: Left panel shows the instrument for the continuous wind exposure measure constructed based on the planned 100-mile Shelterbelt zone. Right panel shows the final continuous wind exposure measure based on realized Shelterbelt planting. Dark green outlines show planned and realized Shelterbelt counties.

We treat all counties that overlap with the planned area as the hypothetical or planned Shelterbelt. We then reproduce the wind exposure measure construction steps described in

Section 3, except replace Shelterbelt counties with the planned counties. We use this planned wind exposure measure (w_i^p) as an instrument for the continuous treatment variable (w_i) in our difference-in-differences model. Figure S19 shows the wind exposure instrument next to the actual wind exposure measure. Our results are robust to this strategy (Table S7) and the instrument is strong, with a F-stat of 91.7 (Table S7, Col. 6).

Table S7: Impact of Great Plains Shelterbelt on Jun-Aug county climate, 1930 to 1965

	Dependent variable:				
	Precip. (cm)	Mean Temp (C)	Max Temp (C)	Degree Days (29C)	Wind Exposure
	(1)	(2)	(3)	(4)	(5)
Wind Exp.:Post 1942	3.871***	-1.664***	-2.177***	-23.91***	
	(0.6340)	(0.2198)	(0.2873)	(3.125)	
	[0.000]	[0.000]	[0.000]	[0.000]	
Wind Exp. IV					0.486***
					(0.046)
					[0.000]
Mean	8.39	23.68	30.87	28.8	-
Std.Dev.	3.49	3.04	3.17	22.46	-
75th-25th Perc. Wind Exp	0.21	0.21	0.21	0.21	-
Observations	24,408	24,408	24,408	24,408	678
F-Stat	-	-	-	-	91.7***

Notes: Table shows results for estimating Equation 4 for 678 counties, with centroids within 300km of the centroids of Shelterbelt counties. Dependent variables are June - August averages. Main independent variable is wind exposure (w_i), which measures approximate exposure to winds from afforested areas, interacted by a post-treatment dummy. This variable is instrumented by the planned wind exposure measure, which reconstructs the wind exposure measure based on the planned 100-mile wide Shelterbelt zone. First stage is shown in Column (5). "75th-25th Perc Wind Exp" shows the difference between the 75th and 25th percentile of the continuous wind exposure measure. Time-invariant controls, interacted by year, include county-level geospatial and topographic characteristics, baseline erosion, and baseline irrigation. County and state-by-year FE included. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01).

S.6 Differential climate trends and the Dust Bowl

This section presents our additional results reinforcing that the Dust Bowl or longer-time climate trends do not bias our results.

S.6.1 Dropping Dust Bowl years

First, we verify the robustness of our main results to omitting the Dust Bowl era. 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. Tables S8 and S9 show the results are generally consistent with our main findings.

Table S8: Impact of Great Plains Shelterbelt on Jun-Aug county climate, 1930 to 1965 (Excluding 1936-1942)

	Dependent variable:			
	Precipitation (cm)	Mean Temp (C)	Max Temp (C)	Degree Days (29C)
	(1)	(2)	(3)	(4)
Wind Exposure:Post 1942	0.841***	−0.866***	−1.370***	−13.010***
	(0.291)	(0.107)	(0.153)	(1.586)
	[0.005]	[0.000]	[0.000]	[0.000]
Mean	6.72	24.67	32.23	39.49
Std.Dev.	2.61	2.8	2.81	23.25
75th-25th Perc. Wind Exp	0.21	0.21	0.21	0.21
Observations	24,408	24,408	24,408	24,408

Notes: Table shows results for estimating Equation 1 for 678 counties, with centroids within 300km of the centroids of Shelterbelt counties. Dependent variables are June - August averages. Main independent variable is wind exposure (w_i), which measures approximate exposure to winds from afforested areas, interacted by a post-treatment dummy. "75th-25th Perc Wind Exp" shows the difference between the 75th and 25th percentile of the continuous wind exposure measure. Time-invariant controls, interacted by year, include county-level geospatial and topographic characteristics, baseline erosion, and baseline irrigation. County and state-by-year FE included. Separate variable included (not shown) for Wind Exposure:Treat, where Treat is set to 1 for 1936-1942. Mean and standard deviation of the outcome measured during the baseline period, excluding 1936-42, are reported. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01).

Table S9: Impact of Great Plains Shelterbelt on Jun-Aug county climate, 1930 to 1965 (Excluding 1934, 1936, and 1939)

	Dependent variable:			
	Precipitation (cm)	Mean Temp (C)	Max Temp (C)	Degree Days (29C)
	(1)	(2)	(3)	(4)
Wind Exposure:Post 1942	1.225***	−0.840***	−1.338***	−13.232***
	(0.317)	(0.093)	(0.136)	(1.324)
	[0.000]	[0.000]	[0.000]	[0.000]
Mean	7.58	24.16	31.49	32.95
Std.Dev.	2.64	2.6	2.63	18.1
75th-25th Perc. Wind Exp	0.21	0.21	0.21	0.21
Observations	24,408	24,408	24,408	24,408

Notes: Table shows results for estimating Equation 1 for 678 counties, with centroids within 300km of the centroids of Shelterbelt counties. Dependent variables are June - August averages. Main independent variable is wind exposure (w_i), which measures approximate exposure to winds from afforested areas, interacted by a post-treatment dummy. "75th-25th Perc Wind Exp" shows the difference between the 75th and 25th percentile of the continuous wind exposure measure. Time-invariant controls, interacted by year, include county-level geospatial and topographic characteristics, baseline erosion, and baseline irrigation. County and state-by-year FE included. Separate variable included (not shown) for Wind Exposure:Peak, where Peak is set to 1 for 1934, 1936, and 1939. Mean and standard deviation of the outcome measured during the baseline period, excluding 1934, 1936, and 1939, are reported. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01).

S.6.2 Longer and alternative time periods

Next, we rerun our analyses over a longer time period, noting that our main analysis starts in 1930 due to quality concerns for earlier data periods. Nevertheless, replicating our main difference-in-differences analysis on the 1910-1965 sample instead of our preferred 1930-1965 results produces similar results, though somewhat less precise and lower in magnitude (Table S10).

Table S10: Impact of Great Plains Shelterbelt on Jun-Aug county climate, 1910 to 1965

	Dependent variable:			
	Precipitation (cm)	Mean Temp (C)	Max Temp (C)	Degree Days (29C)
	(1)	(2)	(3)	(4)
Wind Exposure:Post 1942	0.175	-0.346^{***}	-0.647^{***}	-5.571^{***}
	(0.215)	(0.068)	(0.111)	(0.919)
	[0.416]	[0.000]	[0.000]	[0.000]
Mean	7.55	23.77	31.17	31.77
Std.Dev.	2.92	3.1	3.18	22.76
75th-25th Perc. Wind Exp	0.21	0.21	0.21	0.21
Observations	37,968	37,968	37,968	37,968

Notes: Table shows results for estimating Equation 1 for 678 counties, with centroids within 300km of the centroids of Shelterbelt counties. Dependent variables are June - August averages. Main independent variable is wind exposure (w_i), which measures approximate exposure to winds from afforested areas, interacted by a post-treatment dummy. "75th-25th Perc Wind Exp" shows the difference between the 75th and 25th percentile of the continuous wind exposure measure. Time-invariant controls, interacted by year, include county-level geospatial and topographic characteristics, baseline erosion, and baseline irrigation. County and state-by-year FE included. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01).

To address potential violations to the parallel trends assumption when extending the start date of our analysis back to 1910, we also replicate our synthetic difference-in-differences analyses (detailed in Section S.10). Table S11 shows the results from the synthetic difference-in-differences analysis, implemented on the periods 1910-1965 and 1919-1965. We find similar effects on downwind precipitation than with our preferred difference-in-differences approach with controls. Temperature results are lower in magnitude, but directionally consistent with our main results too.

Table S11: Synthetic Difference-in-Differences: Impact of Great Plains Shelterbelt on Jun-Aug county climate

	Dependent variable:			
	Precipitation (cm)	Mean Temp (C)	Max Temp (C)	Degree Days (29C)
	(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: Table shows results for estimating Equation 8. Dependent variables are June - August averages. Main independent variables are Shelterbelt treatment groups shown in Figure 6. Standard errors shown in parentheses and calculated using the "jacknife" standard error estimator described in Section IV of Arkhangelsky et al. (2021); p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01.).

Finally, we conduct long difference estimates (Eq. 2) with alternative time periods, comparing time periods with similar characteristics. In Panel A of Table S12, we compare 1925-1930 – instead of 1930-1935 – to 1960-1965, to address concerns that the early 1930s were heavy drought periods. In Panel B, we compare 1930-1935 to 1950-1955 – instead of 1960-1965 – to compare two general drought periods in the Great Plains in the pre- and post-planting periods. The estimates are qualitatively similar to our main long differences results.

Table S12: Impact of Great Plains Shelterbelt on Jun-Aug county climate

	Dependent variable:			
	Precipitation (cm)	Mean Temp (C)	Max Temp (C)	Degree Days (29C)
	(1)	(2)	(3)	(4)
Panel A: 1925-1930 vs. 1960-1965				
Wind Exposure	1.585***	−0.451***	−0.854***	−9.025***
	(0.569)	(0.160)	(0.217)	(1.964)
	[0.006]	[0.006]	[0.000]	[0.000]
Mean	6.3	24.34	31.95	38.35
Std.Dev.	1.86	2.69	2.58	20.29
Panel B: 1930-1935 vs. 1950-1955				
Wind Exposure	1.247***	−1.139***	−1.803***	−17.096***
	(0.453)	(0.123)	(0.186)	(1.617)
	[0.007]	[0.000]	[0.000]	[0.000]
Mean	6.92	24.78	32.31	40.12
Std.Dev.	2.65	2.83	2.84	23.89
75th-25th Perc. Wind Exp	0.21	0.21	0.21	0.21
Observations	678	678	678	678

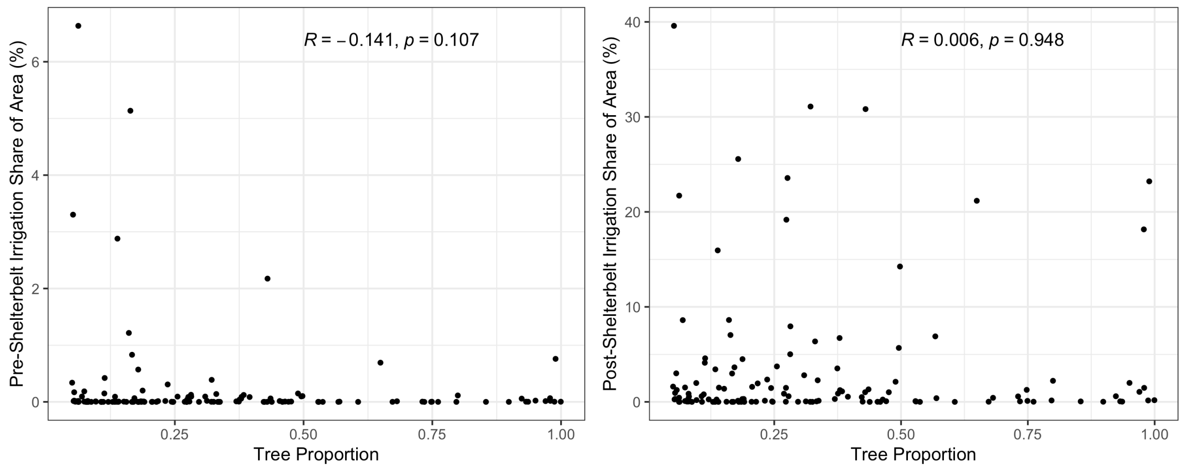
Notes: Table shows results for estimating Equation 2 for 678 counties, with centroids within 300km of the centroids of Shelterbelt counties. In Panel A (B), dependent variables are calculated as the difference between 1925-1930 (1930-1935) and 1960-1965 (1950-1955) June - August averages. Main independent variable is wind exposure (w_i), which measures approximate exposure to winds from afforested areas. "75th-25th Perc Wind Exp" shows the difference between the 75th and 25th percentile of the continuous wind exposure measure. Controls include county-level geospatial and topographic characteristics, baseline erosion, and baseline irrigation. State FE included. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01).

S.7 Irrigation

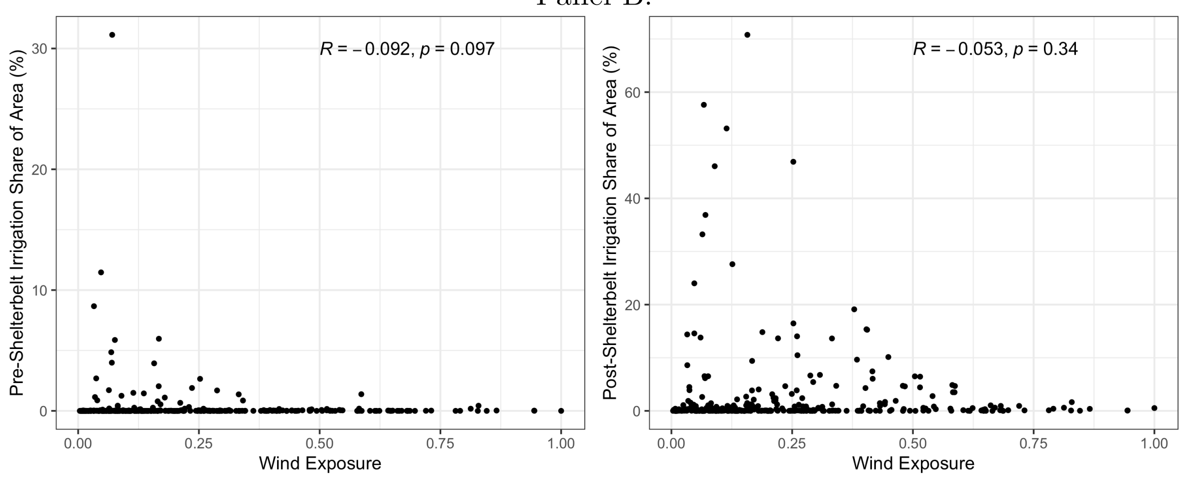
In Section 4.2, we explain how our set of baseline controls ensures that baseline irrigation correlated with tree planting or wind exposure does not bias our results. In Figure S20, we also show that irrigation prior to the project (left) and after the project (right) are not correlated with Shelterbelt planting (Panel A) and our wind exposure measure (Panel B).

Figure S20: 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 post-period irrigation (1959).

We also confirm that irrigation does not drive our main results in Tables S13 and S14, in which we show that the downwind effects of the Shelterbelt tree planting on climate and agricultural development are similar whether we consider counties outside the Ogallala aquifer, where irrigation did not develop, and counties over the aquifer—where almost all increase in irrigation happened.

Table S13: Irrigation: Impact of Great Plains Shelterbelt on Jun-Aug county climate, 1930 to 1965, by aquifer status

	Dependent variable:			
	Precipitation (cm)	Mean Temp (C)	Max Temp (C)	Degree Days (29C)
	(1)	(2)	(3)	(4)
Wind Exposure:Post 1942	0.935^{***}	-0.705^{***}	-1.096^{***}	-10.523^{***}
:Ogallala	(0.339)	(0.109)	(0.154)	(1.604)
	[0.006]	[0.000]	[0.000]	[0.000]
Wind Exposure:Post 1942	1.090^{***}	-0.997^{***}	-1.694^{***}	-15.807^{***}
:Outside Ogallala	(0.286)	(0.110)	(0.172)	(1.581)
	[0.000]	[0.000]	[0.000]	[0.000]
Mean	7.06	24.48	31.97	37.82
Std.Dev.	2.82	2.82	2.94	23.37
75th-25th Perc. Wind Exp	0.21	0.21	0.21	0.21
Ogallala Counties	232	232	232	232
Outside Ogallala Counties	446	446	446	446
Observations	24,408	24,408	24,408	24,408

Notes: Table shows results for estimating Equation 1 for 678 counties, with centroids within 300km of the centroids of Shelterbelt counties. Dependent variables are June - August averages. Main independent variable is wind exposure (w_i), which measures approximate exposure to winds from afforested areas, interacted by a post-treatment dummy. "75th-25th Perc Wind Exp" shows the difference between the 75th and 25th percentile of the continuous wind exposure measure. Ogallala (Outside Ogallala) is a dummy variable set to 1 for counties over (not over) the Ogallala aquifer. Time-invariant controls, interacted by year, include county-level geospatial and topographic characteristics, baseline erosion, and baseline irrigation. County and state-by-year FE included. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01).

Table S14: Irrigation: Impact of Great Plains Shelterbelt on corn yields, production, and area harvested, using USDA 5-year agricultural census data, 1930 to 1964, by aquifer status

	Dependent variable:		
	Log Production	Log Area	Log Yields
	(1)	(2)	(3)
Wind Exposure:Post 1942	1.854**	1.463*	0.391*
:Ogallala	(0.905)	(0.848)	(0.222)
	[0.042]	[0.085]	[0.080]
Wind Exposure:Post 1942	2.237***	1.982***	0.256
:Outside Ogallala	(0.727)	(0.716)	(0.248)
	[0.003]	[0.006]	[0.304]
75th-25th Perc. Wind Exp	0.22	0.22	0.22
Ogallala Counties	134	134	134
Outside Ogallala Counties	345	345	345
Observations	3,710	3,710	3,710

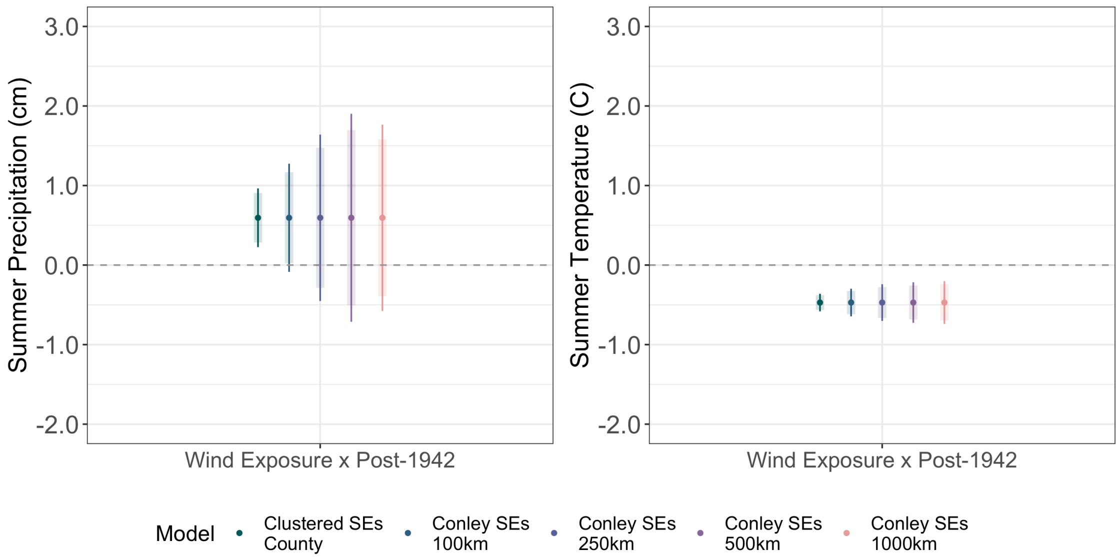
Notes: Table shows results for estimating Equation 1 for 479 counties, with centroids within 300km of the centroids of Shelterbelt counties, dropping directly afforested areas. Dependent variables are from USDA 5-year agricultural census (8 censuses between 1930 and 1964). Main independent variable is wind exposure (w_i), which measures approximate exposure to winds from afforested areas, interacted by a post-treatment dummy. "75th-25th Perc Wind Exp" shows the difference between the 75th and 25th percentile of the continuous wind exposure measure. Ogallala (Outside Ogallala) is a dummy variable set to 1 for counties over (not over) the Ogallala aquifer. Time-invariant controls, interacted by year, include county-level geospatial and topographic characteristics, baseline erosion, and baseline irrigation. County and state-by-year FE included. Standard errors clustered at the county level shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01).

S.8 Spatial correlation

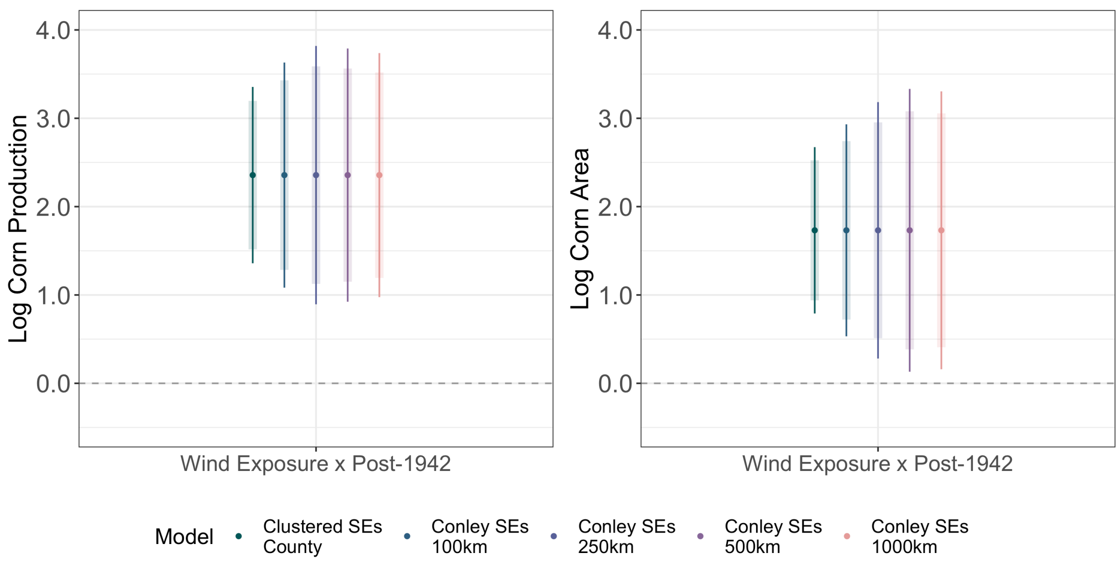
We implement Conley standard errors to address potential concerns about spatial correlation influencing statistical inference. We show that even using a conservative, large distance cutoff (1000km), and a range of distance cutoffs, most of our main estimates remain statistically significant despite slightly less precise estimation (Figure S21).

Figure S21: Robustness to Conley standard errors

Panel A: Climate outcomes



Panel B: Economic outcomes



Notes: Figures plot coefficient estimates and 95%(thin line) and 90% (thick line) confidence intervals using for climate outcomes (Panel A) and economic outcomes (Panel B). In the first version of each regression, we show our main results without controls (Equation 1), using clustered standard errors at the county level. We then repeat the same regression using Conley standard errors are various distance cutoffs.

S.9 Hyperlocal, 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 (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 S.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 25km radius of each station. We then estimate a version of our main difference-in-differences Equation 1.

$$y_{st} = \beta_{LOC}(AA_s \times P_t) + \xi_t + \rho_s + \epsilon_{st} \tag{7}$$

where y_{st} is the outcome of interest at the station-year level, AA_s is the area afforested within 25km 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 S15 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.

Table S15: Impact of Great Plains Shelterbelt on Jun-Aug station climate, 1930 to 1965

	Dependent variable:			
	Precipitation (cm)	Mean Temp (C)	Max Temp (C)	Degree Days (29C)
	(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: Table shows results for estimating a version of Equation 1 with a continuous treatment variable for tree planting (from 2019). 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. Standard errors clustered at the station level shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01).

S.10 Synthetic difference-in-differences

To address possible concerns with the parallel trends assumption, we repeat our difference-in-differences with binary treatment variables 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

$$(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \arg\min \{ \sum_{i=1}^{N} \sum_{t=1}^{U} (y_{it} - \mu - \alpha_i - \beta_t - (T_i \times P_t)\tau)^2 \hat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid} \}. \quad (8)$$

The difference between Equation 8 and the standard two-way fixed effects regression described in Equation 5 is only the addition of the unit and time weights ($\hat{\omega}^{sdid}$ and $\hat{\lambda}^{sdid}$) (Arkhangelsky et al. 2021).

Appendix Table S16 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 S17 presents results for corn yields, which are slightly lower in magnitude, but generally in line with our main results. Appendix Figures S22 and S23 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.

Table S16: Synthetic Difference-in-Differences: Impact of Great Plains Shelterbelt on Jun-Aug county climate, 1930 to 1965

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

Notes: Table shows results for estimating Equation 8. Dependent variables are June - August averages. Main independent variables are Shelterbelt treatment groups shown in Figure 6. Standard errors shown in parentheses and calculated using the "jacknife" standard error estimator described in Section IV of Arkhangelsky et al. (2021); p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01).

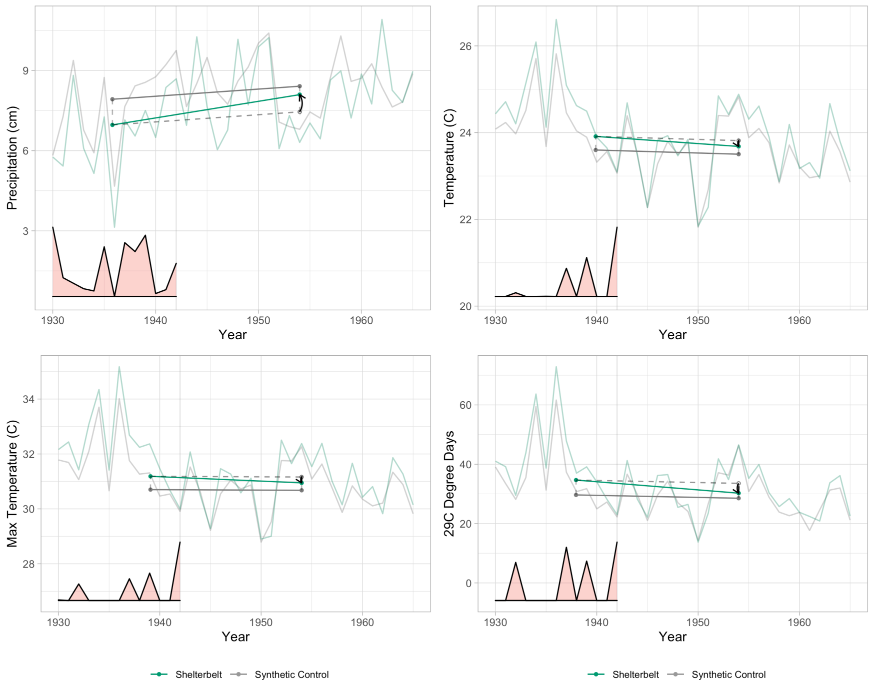
Table S17: Synthetic Difference-in-Differences: Impact of Great Plains Shelterbelt on corn yields, 1930 to 1965

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

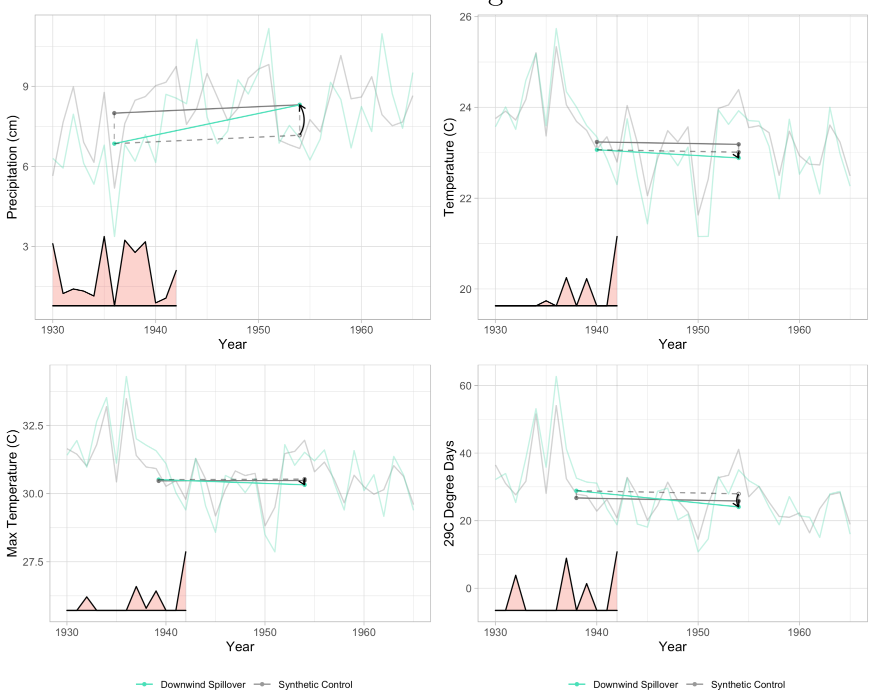
Notes: Table shows results for estimating Equation 8. Main independent variables are Shelterbelt treatment groups shown in Figure 6. Standard errors shown in parentheses and calculated using the "jacknife" standard error estimator described in Section IV of Arkhangelsky et al. (2021); p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01).

Figure S22: Climate synthetic difference-in-differences graphs

Shelterbelt:



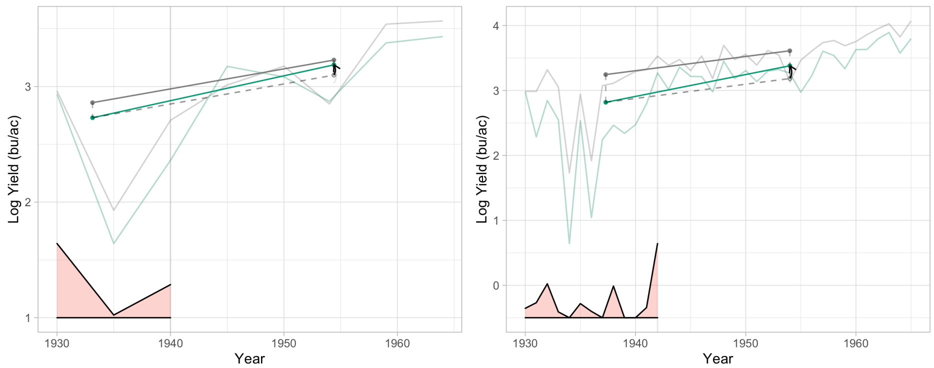
Downwind Neighbors:



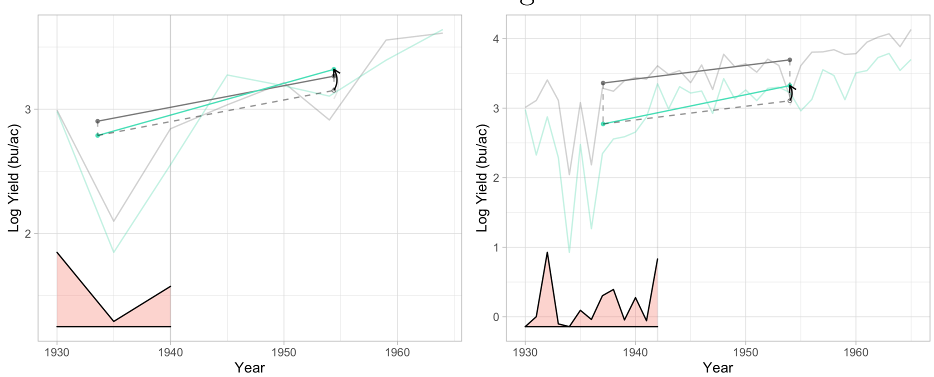
Notes: Figure shows climate synthetic difference-in-differences results graphically. Shelterbelt (top panel) and downwind neighbor (bottom panel) precipitation and temperature trends are plotted along with their respective synthetic controls trends; weights used to average pretreatment time periods are 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 S23: 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.