Spillover Effects of Renewable Energy: Re-examining Wind Turbine Impacts on Crop Yields via U.S. Parcel-level Evidence

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Abstract

As renewable energy development accelerates, wind turbines are increasingly being installed on agricultural land, raising questions about their effects on crop production. This paper investigates the impact of wind turbine installations on agricultural productivity using a high-resolution dataset that combines parcel-level corn yield data with detailed information on wind turbine locations and weather characteristics. Using Difference-in-differences approach to address potential endogeneity, we find that parcels within an 8-kilometer radius of wind turbines experienced, on average, a 1% increase in corn yield after installation. These results suggest that localized microclimatic changes induced by turbines may improve growing conditions. Our findings highlight an overlooked positive externality of renewable energy infrastructure and underscore the importance of incorporating land-use interactions into energy policy and planning.

1 Introduction

The rapid expansion of wind energy across the United States has raised questions about its potential impacts on agricultural production, particularly crop yields. As wind farms increasingly occupy farmland, concerns have emerged regarding the possible effects of wind turbines on the microclimate, soil conditions, and overall productivity of adjacent agricultural areas. While wind energy is championed as a clean and renewable alternative to fossil fuels, the proximity of turbines to crops has prompted debates among farmers, policymakers, and researchers about unintended consequences on crop growth and yield. These concerns are particularly relevant in major agricultural states where wind farms and farmland often coexist, making it crucial to understand the nature and extent of these impacts. A deeper exploration of how wind turbines interact with the surrounding agricultural environment is essential for developing policies that balance the goals of renewable energy expansion with the sustainability and productivity of rural economies.

While previous studies have explored various environmental impacts of wind turbines, including noise, aesthetics, and wildlife disruptions (e.g., Molnarova et al., 2012; Katinas, Marčiukaitis and Tamašauskiene, 2016; Marques et al., 2020), the specific effects on nearby agricultural production are less understood and remain a topic of debate. Kaffine (2019) provide the earliest empirical evidence suggesting that wind farms can alter local microclimates, which may, in turn, affect crop growth conditions such as temperature, wind speed, and humidity levels. However, existing studies, including Kaffine (2019), often rely on aggregated data, potentially overlooking the nuanced, parcel-level variation in crop yield responses to wind turbine installations. These limitations highlight a significant gap in the literature: a lack of fine-grained analyses that can capture the localized and heterogeneous effects of wind turbines on agricultural production. Addressing this gap is critical for developing a more comprehensive understanding of how wind energy infrastructure interacts with agricultural landscapes.

This study examines the impact of wind turbine installations on crop yields using both county-level and parcel-level analyses. We utilize wind turbine data from the U.S. Wind Turbine Database (USWTDB) and combine it with parcel-level crop yield data from Ma et al. (2024) and county-level yield data from the National Agricultural Statistics Service of the United States Department of Agriculture (NASS-USDA). We first replicate county-level analysis result from Kaffine (2019) by measuring the impacts of wind turbine through wind density on corn yield. At the parcel level, we analyze the effects of proximity to wind turbines on corn yield. To address potential endogeneity in wind turbine placement, we adopt a Difference-in-Differences approach by comparing changes in corn yield before and after wind turbine installation, between land located closer to the turbines and land located farther away. This combined approach allows us to provide a more precise evaluation of how wind turbines affect agricultural outcomes.

Given the limitations of prior studies in capturing the localized effects of wind turbines on crop yields, this study aims to provide a more precise evaluation by addressing several key gaps. First, we replicate previous findings using an extended dataset of wind turbine installations that spans a longer time period than those considered in prior studies, incorporating later years during which wind power capacity expanded more intensively. Second, the analysis is further refined by using parcel-level yield data linked to the exact locations of wind turbines, allowing for a more granular evaluation of their effects on agricultural production. By addressing these dimensions, we aim to refine our understanding of how wind turbines influence crop yields and identify specific conditions under which these effects are more pronounced.

We first replicate the impacts of wind turbine installations on corn yield using county-level data following Kaffine (2019). Our results suggest that during 1997–2013, a 100 MW increase in wind capacity is associated with a modest increase in corn yield (0.64%), consitent with the main findings of Kaffine (2019). However, extending the sample to 1997–2023 reveals a reversal: the estimated effect becomes negative (–0.24%). This shift persists across different sets of weather controls, highlighting the sensitivity of county-level estimates to modeling choices. In a subsample focusing on the Midwest states, the positive effect is only observed under specific model specifications and lacks robustness overall.

To better understand the mechanisms behind these aggregate patterns, we complement our analysis with high-resolution parcel-level data. By leveraging parcel-level data and a refined empirical strategy, this study provides new insights into the localized impacts of wind turbine installations on crop yields in the United States. Using yield data from Iowa, we find that the positive effect of proximity to wind turbines on corn yields diminishes with increasing distance and dissipates beyond 8 kilometers, based on a binned regression approach. On average, proximity to a wind turbine is associated with a statistically significant but modest increase of 0.01-0.03% in corn yield per kilometer closer to the nearest turbine. In addition, parcels within an 8-kilometer radius experienced a 0.3% to 2% increase in corn yield after the installation of the wind turbine.These findings are robust across different specifications. *Future work will explore the heterogeneity of wind turbine effects by examining the number of turbines within the defined radius and incorporating wind direction.*

This paper contributes to the literature in the following aspects. First, this study contributes to a growing body of literature on the externalities of renewable energy, and wind energy in particular. Most existing wind turbine externality studies focus on visual disamenities, noise, property values, or health perceptions (reviewed in Saidur et al. (2011) and Sebestyén (2021)) and biodiversity Meng et al. (2025). Our findings introduce empirical evidence that wind turbines generate positive externalities on agricultural production. Furthermore, by leveraging parcel-level data, we refine the spatial understanding of these externalities, offering concrete evidence on how their effects diminish with distance. These findings offer new insights into the agricultural externalities of renewable energy infrastructure and highlight the importance of considering local agricultural outcomes in energy policy evaluations.

Second, this paper contributes to the literature that explores the siting decisions for the wind energy infrastructure. This study provides a novel application of remote sensing data on crop yields to confront the lack of high-quality parcel-level yield data in the U.S. Granular data allows further exploration of the wind turbine crowding effect and long-term learning effect of the siting decisions. In addition, we address a potential endogeneity issue that arises from siting selection bias through difference-in-differences strategies, which strengthens the causal claims that are neglected in previous studies examining the effects of wind development on agriculture.

This paper is structured as follows. Section 2 provides a background on the potential impacts of wind turbine installations on corn yields. Section 3 presents the empirical models employed to estimate these impacts, detailing the identification strategy and econometric approach. Section 4 describes the data sources and key variables used in the analysis. Section 5 discusses the results, highlighting the main findings and their implications for understanding the relationship between wind turbines and crop yields. Finally, Section 6 concludes the paper by summarizing the key insights and discussing the limitations of the study.

2 Background

2.1 Wind turbines impact

As the energy transition accelerates, the rapid expansion of wind energy infrastructure raises important questions about the broader consequences of such installations. A significant strand of research on initial externalities of renewable energy literature has focused on the emission savings from wind and solar technologies and whether these benefits justify policy support. For instance, Yang et al. (2022) and Calel et al. (2025) find that carbon emissions can increase following investments in wind infrastructure or carbon offset programs. Similarly, Cullen (2013) suggests that the emissions reductions from wind power only outweigh the cost of renewable energy subsidies when the estimated social costs of pollution are high.

Beyond emissions, researchers have investigated how wind energy infrastructure interacts with local economic and social outcomes. Studies have explored its effects on local property tax (Kahn, 2013), school funding (Brunner, Hoen and Hyman, 2022), and property values (Brunner et al., 2024; Heintzelman and Tuttle, 2012; Gibbons, 2015; Hoen et al., 2015). These findings suggest that wind energy development can reshape communities in varies ways.

One important dimension of this transformation involves the agricultural sector. Wind turbines are increasingly being installed in agricultural regions, transforming rural landscapes in various ways. In fact, more than 90 percent of wind turbines are sited on agricultural land; in the Midwest specifically, a majority of this land was previously used for commodity crops (Maguire et al., 2024). The growth in wind energy projects is often concentrated in areas with high wind speeds and flat terrains, which are typically found in agricultural zones such as the Midwest and Great Plains of the United States (Slattery, Lantz and Johnson, 2011; Lu et al., 2023). These areas offer ideal conditions for wind energy production and simultaneously present unique challenges and opportunities for agricultural producers.

Among the potential benefits, wind energy can provide farmers with supplemental income. Survey data show that 3.5% of agricultural operators received some form of energy payments; producers in wind-producing counties received on average $17,000 ($2022) annually from 2011-2020 (Winikoff and Maguire, 2024). Regarding property values, the evidence remains mixed. For example, Sampson, Perry and Taylor (2020) finds no significant impact of wind turbines on agricultural land values while Mei et al. (2024) show positive effect on land transaction prices.

On the other hand, there are costs and concerns associated with hosting wind infrastructure. While landowners receive lease payments, turbines can interfere with farming logistics, such as field operations, irrigation systems, and road access (Lal, 2004). Long-term concerns include potential effects on land value and agricultural productivity. Some farmers adapt their practices to accommodate turbines, while others report issues such as soil compaction, crop damage from construction, and even aesthetic disruption of the landscape (Pedersen and Persson Waye, 2004).

2.2 Microclimate alterations induced by wind turbines

Wind turbines can induce localized microclimatic changes that may affect agricultural conditions. The most notable change is the creation of a wake effect, where airflow is altered due to the rotating blades, resulting in increased turbulence and modified wind patterns (Zhou et al., 2012). This wake effect can lead to changes in air temperature, particularly at night when turbulence causes warmer air from higher altitudes to mix with cooler air near the ground, potentially increasing nighttime temperatures (Rajewski et al., 2014). This phenomenon may influence frost events, dew formation, and other microclimatic conditions crucial for crop growth.

Additionally, changes in humidity and wind speed due to turbine-induced turbulence can affect evapotranspiration rates and soil moisture levels, which are critical for crop water availability (Baidya Roy, Pacala and Walko, 2004). Some studies suggest that these changes can either positively or negatively impact crop yields depending on local climate conditions and crop types (Armstrong et al., 2014). For example, in arid regions, reduced wind speed might lower the rate of evaporation, potentially benefiting crops by conserving soil moisture. However, in more humid climates, altered wind patterns could lead to increased humidity levels, creating conditions conducive to certain plant diseases.

2.3 Corn yield variability: factors and drivers

The United States is the world's leading producer, consumer, and exporter of corn. Corn ranks as the top agricultural commodity in the U.S. by production volume, with an average yield of 10-15 billion bushels annually over the past decade (Janzen, 2025). Around 90 million acres of corn are planted each year, predominantly in the Heartland region, which is also the focus of our study. In 2023, U.S. crop cash receipts for corn reached almost

$80 billion, accounting for approximately a third of total cash crop receipts[1]. Given the critical role corn plays in fuel, feed, food production, and trade, understanding how its production responds to external factors is essential.

Corn yield is influenced by a complex interplay of stochastic environmental, genetic, and management factors. Environmental stressors such as extreme temperatures, drought, excessive rainfall, and soil quality are among the most significant determinants of corn yield variability (Lobell and Burney, 2021). High temperatures during critical growth periods, such as pollination, can significantly reduce yields, while water stress can impair photosynthesis and nutrient uptake (Hatfield et al., 2011). Additionally, ozone levels and other pollutants can affect corn yields by damaging leaf tissue and reducing photosynthetic efficiency (Ainsworth, 2017).

Management practices, including fertilization, irrigation, pest control, and planting density, also play a crucial role in mitigating or exacerbating yield variability (Cassman, 1999). For instance, precision agriculture techniques that optimize input use based on soil and weather conditions can help reduce the risk of crop failure and increase yields. Understanding these factors is essential for identifying how new variables, such as wind turbine installations, might interact with existing conditions to influence yield outcomes.

2.4 Wind turbine impacts on crop growth: mechanisms and evidence

Existing literature indicates several mechanisms by which wind turbine installations may affect crop growth, although the magnitude and direction of these impacts can vary widely. The most direct impact stems from the wake effect, which can reduce wind speeds at the ground level and potentially influence plant transpiration rates and local soil moisture dynamics (Fitch et al., 2012). Changes in microclimate conditions induced by wind turbines, such as altered air temperature and humidity, can have complex effects on crop physiology. For instance, slight increases in nighttime temperatures might extend the

[1] As shown in Farming and Farm Income statistics by the ERS USDA. https://www.ers.usda.gov/data-products/ag-and-food-statistics-charting-the-essentials/farming-and-farm-income.

growing season in some climates, but could also increase respiration rates, reducing net photosynthesis and yield (Zhou et al., 2012).

While some studies suggest that the overall impact of wind turbines on crop yields may be minor or highly localized, others highlight significant changes in crop growth patterns, especially for wind-sensitive crops like corn (Kaffine, 2019). The effect may depend on several factors, including the density and configuration of the turbines, the local topography, and prevailing climate conditions (Armstrong et al., 2014). Given these mixed findings, further empirical research is needed to clarify the specific conditions under which wind turbines impact crop growth and to identify any potential mitigation strategies.

3 Empirical Model

3.1 County-level empirical model

In this section, we construct an empirical model to investigate the impacts of wind energy infrastructure on agricultural productivity at the county level, while rigorously accounting for a range of environmental factors. Counties are indexed by i, states by s, and years by t. The estimating equation is presented as follows:

$$Y_{it} = \alpha W_{it} + \mathbf{X}_{it}\beta + \gamma_i + \mu_{(s)t} + \varepsilon_{it} \tag{1}$$

where Y_{it} represents log crop yield, the primary outcome of interest. The main explanatory variable, W_{it}, captures wind turbine density, defined as the total nameplate capacity of wind turbines relative to the total land area within a county. This variable allows for a nuanced examination of how the spatial concentration of wind energy infrastructure might influence agricultural productivity, potentially through mechanisms such as microclimate alterations, land use changes, or disturbances in agricultural practices due to the presence of wind turbines.

The control variables, represented by the vector $\mathbf{X}_{it}$, include a comprehensive set of climatic factors well-established in the literature as critical determinants of crop yields. Specifically, we incorporate growing degree days between 8 and 32 degrees Celsius ($\mathrm{GDD}_{8,32}$) and its square term, capturing the non-linear effects of temperature within the optimal range for crop growth. This approach follows seminal works such as Schlenker and Roberts (2009), who emphasize the importance of temperature within specific thresholds on crop yields. Additionally, the model includes the square root of growing degree days above 34 degrees Celsius (GDD_{34+}), reflecting the detrimental impact of extreme heat on crops, as highlighted by Deschênes and Greenstone (2007). Total precipitation and its square term are also included to account for the influence of rainfall variability, which is crucial given the reliance of agriculture on water availability, as supported by studies like Lobell and Burney (2021). These controls are incorporated to ensure that the estimated effect of wind turbine density on crop yields is not confounded by these essential environmental factors.

To control for unobserved heterogeneity across counties and over time, we include county fixed effects (γ_i) and state-year fixed effects ($\mu_{(s)t}$) in the model. The county fixed effects account for time-invariant characteristics unique to each county, such as soil quality, topography, and long-standing agricultural practices, which might influence crop yields. On the other hand, the state-year fixed effects account for unobserved factors that vary over time within each state but are common to all counties in that state. This controls for policy changes, regional economic conditions, and weather shocks that may differ across states but follow similar trends within a state in a given year. By including these fixed effects, the model aims to provide a more accurate estimation of the relationship between wind turbine density and crop yields, mitigating potential biases from omitted variable confounding. The error term, ε_{it}, captures unobserved factors that might influence crop yields but are not explicitly included in the model. In our baseline analysis, we cluster standard errors at the county level.

3.2 Parcel-level empirical model

Estimating the effects of wind turbines on crop yields at the county level, while useful for comparison with existing studies, suffers from several significant drawbacks. One primary issue is the potential for aggregation bias, where the variability in proximity to wind turbines within a county is lost when averaging yields across the entire county. This can obscure localized effects that are critical to understanding the true impact of wind turbines. Additionally, counties often cover large geographic areas with varying microclimates, soil qualities, and agricultural practices, leading to heterogeneous effects that are difficult to capture in a county-level analysis. Such an approach also assumes that the influence of wind turbines is uniformly distributed across the county, which is rarely the case. This can result in biased or misleading conclusions about the relationship between wind turbines and crop yields, particularly when wind turbines are clustered in specific parts of a county. Finally, county-level analyses are less sensitive to the specific distances between farmland parcels and wind turbines, a factor that could be critical in determining the magnitude of any observed effects.

To address these limitations, we propose a parcel-level model that estimates the effects of proximity to wind turbines on crop yields. The estimation equation is

$$Y_{jt} = \alpha Post * WindTurbine_{jt} + \mathbf{X}_{ct}\beta + \gamma_j + \mu_{(c)t} + \varepsilon_{jt}. \tag{2}$$

In this model, j indexes individual farmland parcels, and t indexes years. The dependent variable, Y_{jt}, represents the crop yield for parcel j in year t. The key explanatory variable, $Post * WindTurbine_{jt}$, measures indicates whether there is a wind turbine within 8 kilometers of parcel j. This variable allows us to precisely assess how proximity to wind turbines affects crop yields, capturing the potential for localized effects that are lost in broader, county-level analyses.

Parcel fixed effects, denoted by γ_j, are included to control for time-invariant characteristics of each parcel that could influence crop yields, such as soil quality, topography, and historical land use. By accounting for these unobserved factors, the model helps isolate the effect of proximity to wind turbines from other parcel-specific attributes that do not vary over time. Additionally, year fixed effects or county-year fixed effects, represented by $\mu_{(c)t}$, are incorporated to control for temporal shocks that could affect all parcels equally within the broader state or county, such as annual variations in weather patterns, macroeconomic conditions, or changes in agricultural policies. When we use a year level fixed effect, we also control for precipitation and degree days at the county level. In our analysis, we account for spatial and temporal correlations in the error structure by clustering standard errors at the county level, which helps to ensure that our estimates are robust to potential misspecification of the error structure.

4 Data and Variables

The main datasets consist of three parts. First, to estimate the effect of wind turbine establishment on crop yield, we collect wind turbine establishment statistics from the U.S. Wind Turbine Database (USWTDB). Next, we utilize county-level and remote-sensing corn yield data from NASS-USDA and Ma et al. (2024). Third, we collect climate condition variables from the PRISM Climate Group. The following describe each datasets.

4.1 Agricultural yields data and measures

County-Level Corn Yield Data from NASS-USDA This study employs county-level corn yield data from the National Agricultural Statistics Service of the United States Department of Agriculture (NASS-USDA), a key source of agricultural statistics in the U.S. Corn yields are calculated as the total corn production, measured in bushels, divided by the harvested area in acres for each county. Thus, the yields are expressed in bushels per acre, which serves as the measure of corn productivity. Recent studies have utilized NASS-USDA data to explore various dimensions of agricultural production and its sensitivity to environmental and economic conditions, such as Burke and Emerick (2016) and

Schlenker and Roberts (2009). These studies underscore the robustness and suitability of the NASS-USDA dataset for analyzing the effects of environmental factors on crop production.

Parcel-Level Corn Yield Estimates from Remote Sensing Data The main variables of interest, corn and soybean crop yields, are derived from the 30-meter crop yield dataset developed by Ma et al. (2024). This dataset employs a machine learning method called Quantile loss Domain Adversarial Neural Networks (QDANN) to map yields at a subfield level using satellite remote sensing data, specifically Landsat imagery, in conjunction with Gridmet weather data. The dataset spans eight U.S. states—Illinois, Indiana, Iowa, Minnesota, Missouri, Ohio, South Dakota, and Wisconsin— covering the period from 2008 to 2022.

To integrate this data into our study, we calculate average yields at the level of the Common Land Unit (CLU), an individual contiguous parcel of agricultural land defined by the USDA Farm Service Agency (FSA). The CLU boundaries are stable and capture farm records consistently across time, making them ideal for our analysis. By merging the remote sensing yield estimates with CLU parcels, we can assess wind turbine impacts on crop yields at a granular level, offering a significant improvement over county-level data aggregation.

The parcel-level data enables us to compute average crop yields within each CLU polygon. To do this, we first overlay the yield raster data onto the CLU shapefile and apply a zonal statistics method to calculate the mean yield for each polygon in ArcGIS Pro. This transformation of high-resolution raster data into CLU-specific averages allows for detailed analysis of environmental and man-made influences on crop yields, particularly the localized effects of wind turbines.

Compared to county-level yield data from NASS-USDA, our approach offers two key advantages. First, it provides finer spatial resolution, enabling us to detect smaller-scale variations in yields that would be obscured at the county level. Second, it allows for more precise matching of yield data with control variables such as weather and soil characteristics, thereby improving the accuracy of our analysis on the impact of wind turbines on agricultural production.

Figure 1 presents the spatial and temporal distribution of corn yields across the United States and within Iowa. Between 2008 and 2022, national corn yield trends closely mirror those observed in Iowa. Additionally, the Iowa yield map reveals notable variation in yield levels across counties using the parcel-level data.

4.2 Wind turbine data and measures

This study utilizes data on wind turbine locations from the U.S. Wind Turbine Database (USWTDB), an authoritative and comprehensive resource maintained by the U.S. Geological Survey (USGS), the American Wind Energy Association (AWEA), and the Lawrence Berkeley National Laboratory (LBNL) (USGS, 2024). The USWTDB provides detailed information on the geographic coordinates, height, capacity, and commissioning date of over 70,000 wind turbines across the United States. This dataset, updated regularly, is widely recognized for its precision and reliability in capturing the spatial distribution and characteristics of wind energy infrastructure.

The primary purpose of using the USWTDB in this analysis is to quantify the distance between farmland parcels and their nearest wind turbines. This distance measure is critical for evaluating how proximity to wind turbines influences agricultural yields, particularly corn yields. To achieve this, we calculate the shortest distance from each farmland parcel boundary to the nearest wind turbine location recorded in the USWTDB. This calculation serves as a proxy for the potential exposure of farmland to the localized microclimatic changes induced by wind turbine operations, such as alterations in temperature, wind patterns, and humidity levels, which can significantly impact crop growth conditions. With this data, we can capture the potential heterogeneity in yield impacts due to varying distances from wind turbines, offering insights into the spatial extent of wind turbine effects on agricultural landscapes.

Figure 2 summarizes the spatial and temporal distribution of wind energy facilities across the United States and Midwest states. Between 2008 and 2022, national wind energy capacity increased more than sixfold. Turbine installations are concentrated in regions with higher wind speed potential. The map highlights a recent acceleration in wind energy development, especially in the central U.S. where wind resources are most abundant.

4.3 Climate data and variables

The weather data employed in this study are sourced from the PRISM Climate Group, which provides high-resolution (4km x 4km) raster data on temperature and precipitation for the United States. This dataset spans from 1980 to 2023 and contains critical monthly degree days that help quantify the effects of temperature on crop growth. Our analysis relies on temperature data to compute growing degree days and precipitation data to compute total rainfall during growing season for each grid cell. These PRISM grids are subsequently matched with the Common Land Unit (CLU) data, allowing us to integrate weather variables at the parcel level.

To capture the influence of temperature on crop yields, we focus on two specific Growing Degree Day (GDD) measures. The first, GDD8,32, represents the degree days where temperatures fall between 8°C (46°F) and 32°C (90°F), a range conducive to corn growth. The second measure, GDD34+, quantifies the degree days where temperatures exceed 34°C (93°F), a threshold where heat stress can adversely affect crop development. Growing degree days are well-established in agricultural literature as essential indicators for tracking crop development (e.g., Schlenker and Roberts (2009), Lobell and Burney (2021), Burke, Hsiang and Miguel (2015)). While moderate GDD values accelerate crop growth, excessive heat, as captured by GDD34+, can reduce yield potential, particularly for heat-sensitive crops like corn (Ma et al., 2024).

In addition to temperature, we incorporate total precipitation as a key variable in our analysis, as water availability is crucial for crop growth through its role in photosynthesis and nutrient uptake. Precipitation data are extensively used in yield studies to account for water stress effects (e.g., Schlenker and Roberts (2009), Deschênes and Greenstone (2007)). The combination of temperature and precipitation data allows for a more comprehensive understanding of the climatic factors affecting crop yields (Ma et al., 2024). Temperature and precipitation variables are calculated based on data from April to September, aligning with the corn growing season in the Midwest.

Weather variables are calculated at both county and parcel levels to ensure a robust analysis. County-level weather variables are derived by aggregating the PRISM data over all grid cells within a county, averaging the monthly degree day and precipitation values. This provides a consistent measure of weather conditions across counties. Parcel-level weather variables are calculated by matching each CLU parcel with the nearest PRISM grid cells. This fine-scale approach allows us to match weather data precisely with crop yields, offering a more granular view of how wind turbines affect local weather patterns. These detailed weather variables provide a solid foundation for controlling broad weather pattens that impact crop production while parsing out how wind turbines affect local climate.

5 Results

Our main analysis is in two parts. First, we conduct county analysis of the wind farm effect by replicating Kaffine (2019). Next, we identify the effective buffer range within which wind turbines influence corn yields, using a bin analysis approach. We then estimate the average treatment effect using Difference-in-Differences approach to account for potential endogeneity.

5.1 County Analysis

In our county-level analysis, we replicate the approach of Kaffine (2019) by estimating the effect of wind turbines on corn yield, using wind density as a proxy variable. Our main specification follows a fixed effects framework, controlling for both county fixed effects and state-by-year fixed effects. To assess the robustness of the model, we compare results across alternative sets of control variables and different time periods. The results are summarized in Table 2.

In Table 2, columns (1)–(3) use weather control variables consistent with Kaffine (2019), while columns (4)–(6) incorporate weather controls following Schlenker and Roberts (2009) and others. Using the same time span as in Kaffine (2019) (1997–2013), we find that a 100 MW increase in wind capacity is associated with a 0.64% increase in corn yield.[2] However, when we extend the sample period to 1997–2023, the estimated effect turns negative, with a 0.24% decrease in corn yield for the same increase in wind capacity. This reversal in sign persists even when applying the control variables suggested by Schlenker and Roberts (2009), suggesting that the county-level estimates are sensitive to specification choices and may lack robustness.

We further restrict the analysis to the Midwestern region. Table 3 presents estimates based on a sample limited to eight Midwestern states. In column (1), a 100 MW increase in wind capacity is associated with a 0.56% increase in corn yield. However, this effect is not statistically significant when using alternative model specifications or control sets, indicating limited robustness within the regional subsample as well.

[2]Given an average county size of 800 square miles, a 1% increase in log yields for a 100 MW wind farm corresponds to a coefficient of 0.08, since $0.08 \times \frac{100}{800} = 0.01$.

5.2 CLU Analysis

5.2.1 Bin analysis

To examine how wind turbine proximity affects crop yields, we regress the logarithm of corn yield on distance bins defined at 1 km intervals using data from Iowa. Importantly, we exclude parcels where turbines are installed directly on the land, as these areas may be subject to unique disruptions—such as land use conflicts or construction disturbances—that differ from effects on surrounding parcels.

Figure 3 reveals a declining trend in yield effects as distance from wind turbine increases. Specifically, the effect is positive and statistically significant within 2-8 kilometers, but becomes negligible beyond that range. We adopt a 8-kilometer buffer zone as the preferred treatment group for further analysis.

5.2.2 Difference-in-differences

In Table 5 we present our main results from the difference-in-difference analysis. We examine three different control groups: parcels within 20 kilometers of a wind turbine (columns 1-3), parcels within 15 kilometers of a wind turbine (columns 4-6), and finally, parcels within 10 kilometers of a wind turbine but not-yet-treated (columns 7-9). We explore effects using different fixed effects and controlling for county-level weather patterns. Using our 20 kilometer buffer zone, we find that after wind turbine installation, corn fields within 8 kilometers experience a 0.7-0.8% increase in yields. (Our model with county-year fixed effects find a positive but insignificant effect on crop yields.) Using our 15 kilometer buffer, we see yield increases ranging from 0.4-1.2%. When limiting our sample to fields within 10 kilometers, we see the largest effects of yield increases from 0.5-2.2%. We conclude that wind turbines lead to statistically significant yield increases for corn.

5.2.3 Mechanisms

To investigate the pathways through which wind turbine impact agricultural production, we investigate how wind turbines impact local weather patterns. We see evidence that wind turbines decrease precipitation levels by 3%. We see that the probability of extreme rainfall above the 95th percentile decreases by 7.5 percentage points. The probability of rainfall occurring below the lowest 5th percentile (a drought event) declines by 2.2 percentage points. This suggests that wind turbines make the local climate more mild and mitigate extreme precipitation events.

6 Conclusion

While the advent of renewable energy technologies has been celebrated for their ability to mitigate the negative externalities of fossil fuels, it is crucial to understand the broader impacts of these technologies on the environments in which they are deployed. As renewable energy development continues to accelerate globally, a comprehensive evaluation of both the positive and negative externalities is essential for informed policy-making. In the case of wind power, its unique characteristic of being spatially dispersed and often co-located with agricultural land makes it particularly important to assess its localized effects, especially on crop production. In this paper, we investigate a previously underexplored aspect of wind energy development—the impact of wind turbines on crop yields at the parcel level.

Our findings indicate that the estimated effects of wind turbines based on county-level analysis are not robust across different model specifications or subsamples, likely due to aggregation bias that masks localized impacts on crop yields. Leveraging a rich dataset that integrates parcel-level crop yield data with detailed information on wind turbine locations and characteristics, we provide evidence that supports and extends previous studies, while addressing concerns about endogeneity. Our analysis shows that proximity to wind turbines is associated with higher corn yields suggesting that microclimatic changes induced by turbines, such as shifts in temperature, wind flow, and humidity, may enhance growing conditions. This positive effect is especially pronounced for parcels located within an 8-kilometer radius, underscoring the importance of local-level analysis in capturing spatial spillovers.

These findings highlight the need for further investigation into the underlying mechanisms, particularly the potential role of altered wind patterns and microclimatic conditions. Overall, the results emphasize the importance of accounting for both the direct and indirect effects of renewable energy infrastructure on surrounding land use. As renewable energy expansion continues, policymakers should carefully consider these potential trade-offs, especially in regions where agriculture remains a key component of the local economy.

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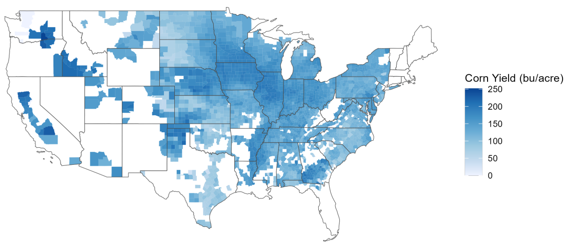
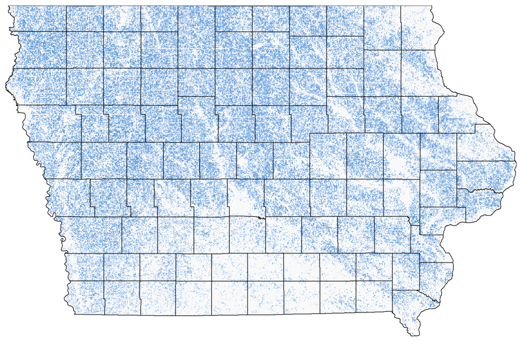
Figures

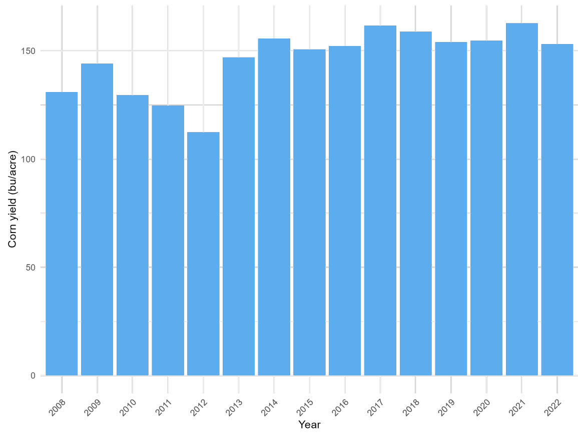
Figure 1: National and Iowa corn yield



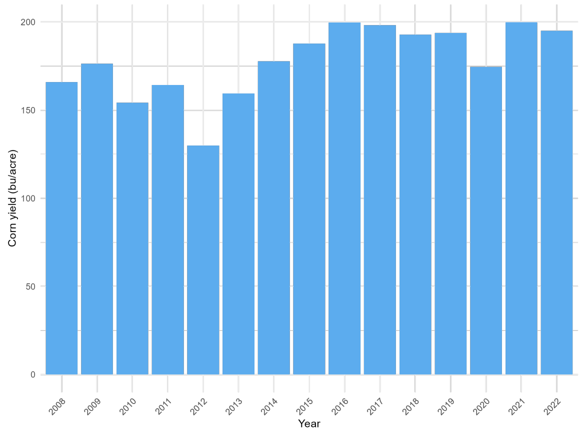
(a) Average national corn yield



(b) Average Iowa corn yield



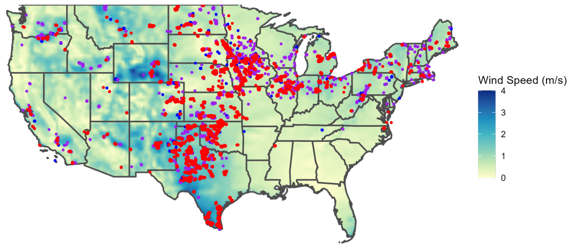
(c) National corn yield by year



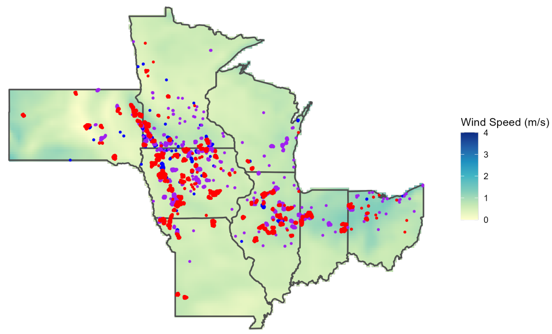
(d) Iowa corn yield by year

Note: This figure illustrates spatial and temporal information of the corn yield data used in our analysis. Panel (a) and (b) portray the average corn yield across 2008-2022. Panel (c) and (d) show the average corn yield from 2008 to 2022 at the national level and in Iowa.

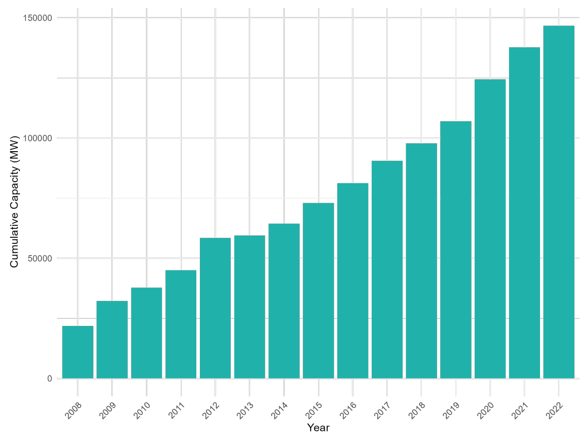
Figure 2: National and eight Midwest states wind turbine distribution



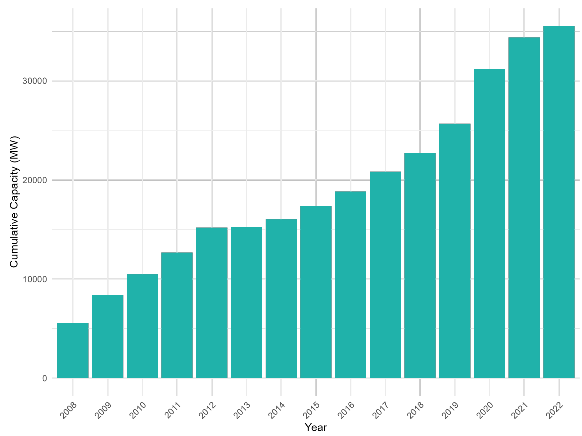
(a) National wind turbine distribution



(b) Midwest wind turbine distribution



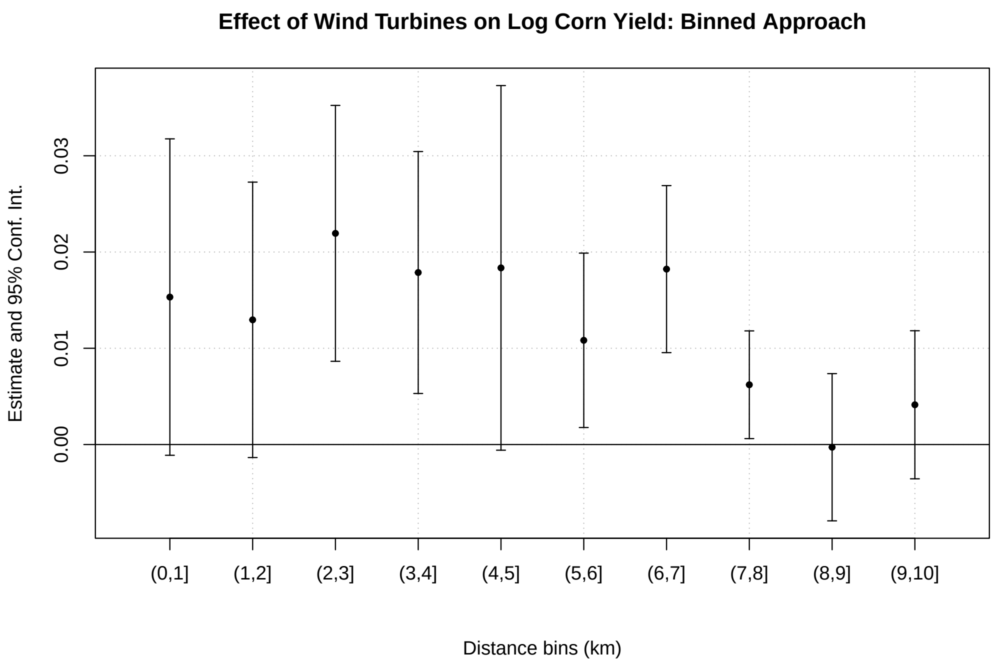
(c) National wind capacity



(d) Midwest wind capacity

Note: This figure presents spatial and temporal information on wind energy facilities across the United States. Panels (a) and (b) display the spatial distribution of wind turbines, grouped by construction year. The background shading represents the average wind speed intensity from 2008 to 2022. Blue dots indicate turbines constructed before 2008, purple dots show the wind turbine installed between 2008-2013, while red dots represent those installed after 2013. Panels (c) and (d) illustrate the cumulative wind energy capacity at the national and Midwest levels, respectively.

Figure 3: Effect of wind turbine on log corn yield for fields within 1 km buffer zones around the wind turbine.



Note: This model includes field level and year fixed effects as well as weather controls. The control group for this model are fields within 15 kilometers of a wind turbine.

Tables

Table 1: Summary statistics for corn fields within 15 kilometers of a wind turbine in Iowa.

Statistic	N	Mean	St. Dev.	Min	Max
Parcel-level variables					
Corn yield (bushel/acre)	5,080,295	180.253	31.904	27.449	342.520
Post Turbine x 0-8 km	5,080,295	0.482	0.500	0	1
Area	5,080,295	0.00001	0.00001	0.00000	0.0005
Average wind speed	5,080,295	0.978	0.177	0.520	1.563
Precipitation	5,080,295	0.651	0.186	0.248	1.543
Degree days (8-32C)	5,080,295	19.166	1.455	13.586	24.872
Extreme degree days (34C+)	5,080,295	0.503	1.232	0.000	17.150
County-level variables					
Wind turbine growth rate	5,080,295	6.407	3.259	0.000	11.241
Precipitation	5,080,295	25.982	7.165	6.414	55.756
Degree days (8-32C)	5,080,295	2,961.574	254.693	2,085.667	3,685.464
Extreme degree days (34C+)	5,080,295	27.757	22.244	0.106	159.061

Notes: This table summarizes key statistics for parcels included in the main sample that are located within 15 kilometers of a wind turbine in Iowa from 2008-2023. Corn yield data are derived from remotely sensed measurements provided by Ma et al. (2024) and aggregated annually at the common land unit level. Information on wind turbines is sourced from the U.S. Wind Turbine Database, while weather data are obtained from the PRISM Climate Group dataset.

Table 2: Wind turbine effect on county-level corn yield (All counties)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Log of yield (Bushel/acre)					
Wind density	0.051*	0.004	-0.019*	0.047*	0.014	-0.015
	(0.022)	(0.026)	(0.010)	(0.022)	(0.026)	(0.010)
County FE	✓	✓	✓	✓	✓	✓
State-year FE	✓	✓	✓	✓	✓	✓
Same controls with Kaffine (2019)	✓	✓	✓			
Different set of controls				✓	✓	✓
Year range	1997-2013	2014-2023	1997-2023	1997-2013	2014-2023	1997-2023
F-stat	94.03	22.36	93.44	265.0	89.43	278.0
R^2	0.803	0.846	0.818	0.813	0.856	0.827
Observations	31,246	13,117	45,919	31,246	13,117	45,919

Notes: This table presents regression results examining the relationship between wind turbine density and corn yields, where the dependent variable in all columns is the natural logarithm of yield (measured in bushels per acre). All specifications employ a two-way fixed effects (TWFE) model with county fixed effects and state-by-year fixed effects. Columns (1)–(3) include the same set of control variables used in Kaffine (2019), while Columns (4)–(6) use an alternative set of controls. Columns (1) and (4) restrict the sample to the pre-2014 period (1997–2013), Columns (2) and (5) cover the post-2014 period (2014–2023), and Columns (3) and (6) use the full sample from 1997 to 2023. Standard errors, clustered at the county level, are reported in parentheses. Statistical significance is denoted as follows: ***p<0.01, **p<0.05, *p<0.1.

Table 3: Wind turbine effect on county-level corn yield (Midwestern counties)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Log of yield (Bushel/acre)							
Wind density	0.045*	0.007	-0.011	-0.022	0.025	0.001	0.002	-0.004
	(0.022)	(0.022)	(0.008)	(0.013)	(0.017)	(0.020)	(0.008)	(0.013)
County FE	✓	✓	✓	✓	✓	✓	✓	✓
State-year FE	✓	✓	✓	✓	✓	✓	✓	✓
Same controls with Kaffine (2019)	✓	✓	✓	✓				
Different set of controls					✓	✓	✓	✓
Year range	1997-2013	2014-2023	1997-2023	2008-2022	1997-2013	2014-2023	1997-2023	2008-2022
F-stat	47.78	22.81	55.86	35.51	171.3	72.03	197.9	151.0
R^2	0.805	0.826	0.828	0.817	0.837	0.846	0.856	0.860
Observations	10,047	4,688	15,250	8,112	10,047	4,688	15,250	8,112

Notes: This table reports regression results estimating the effects of wind turbine density on corn yields with a focus on Midwestern counties. The dependent variable in all columns is the natural logarithm of yield, measured in bushels per acre. All regressions employ a two-way fixed effects (TWFE) specification that includes county fixed effects and state-by-year fixed effects. Columns (1)–(4) use the control variables from Kaffine (2019), while Columns (5)–(8) use an alternative set of controls. The time period varies by column, as indicated in the row labeled "Year range." Standard errors clustered at the county level are reported in parentheses. Statistical significance is denoted as follows: ***p<0.01, **p<0.05, *p<0.1.

Table 4: Wind turbine effect on log corn yield: Difference-in-differences

	log corn yield								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post x 0-8 km	0.008***	0.007***	0.003	0.012***	0.012***	0.004**	0.022***	0.021***	0.005*
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.005)	(0.004)	(0.003)
Precipitation (1000)		-0.160			-0.188			-0.355	
		(1.48)			(1.61)			(1.82)	
Precipitation sq (1000)		0.0004			0.0008			0.004	
		(0.024)			(0.026)			(0.030)	
GDD (1000)		-0.115			-0.139			-0.183	
		(0.149)			(0.151)			(0.166)	
GDD sq (1000)		0.00003			0.00003			0.00004	
		(0.00002)			(0.00002)			(0.00003)	
EDD (1000)		-0.411			-0.665			-0.866	
		(0.646)			(0.682)			(0.757)	
EDD sq (1000)		-1.93			1.31			3.35	
		(7.12)			(7.39)			(8.07)	
Observations	6,865,909	6,865,909	6,865,909	5,080,295	5,080,295	5,080,295	3,236,486	3,236,486	3,236,486
Adjusted R^2	0.61762	0.61792	0.66484	0.61615	0.61650	0.66432	0.61344	0.61389	0.66341
F-stat	15.642	11.186	284.56	15.351	10.980	280.09	14.640	10.475	268.74
Mean corn yield	179.57	179.57	179.57	180.25	180.25	180.25	181.24	181.24	181.24
Distance buffer	<20 km	<20 km	<20 km	<15 km	<15 km	<15 km	<10 km	<10 km	<10 km
CLU fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓		✓	✓		✓	✓	
county-year fixed effects			✓			✓			✓

Notes: This table reports regression results estimating the impact of wind turbine installations on log corn yields. All regressions employ a two-way fixed effect Difference-in-Differences specification that includes CLU fixed effects and year or couty-year fixed effects. Standard errors clustered at the CLU level are reported in parentheses. Statistical significance is denoted as follows: ***p<0.01, **p<0.05, *p<0.1.

Table 5: Wind turbine effect on micro-climate: Difference-in-differences

	Precipitation (1)	IHS Precipitation (2)	Extreme Rrain (3)	Drought (4)	GDD (5)	IHS GDD (6)	EDD (7)	IHS EDD (8)
Post x 0-8 km	-0.038***	-0.030***	-0.075***	-0.022*	0.024	0.0008	-0.126	-0.032
	(0.006)	(0.005)	(0.018)	(0.012)	(0.016)	(0.0009)	(0.096)	(0.029)
Observations	6,865,909	6,865,909	3,236,486	3,236,486	5,080,295	5,080,295	3,236,486	3,236,486
Adjusted R^2	0.67443	0.68378	0.13233	0.24784	0.97341	0.97364	0.67338	0.77910
Distance buffer	<15 km	<15 km	<15 km	<15 km	<15 km	<15 km	<15 km	<15 km
County weather	✓	✓	✓	✓	✓	✓	✓	✓
CLU fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table reports regression results estimating the impact of wind turbine installations on micro-climate variables. The dependent variables include either the CLU-level weather indicators in their original form or their inverse hyperbolic sine (IHS) transformation. All regressions employ a two-way fixed effect Difference-in-Differences specification that includes CLU fixed effects and year fixed effects. Standard errors clustered at the CLU level are reported in parentheses. Statistical significance is denoted as follows: ***p<0.01, **p<0.05, *p<0.1.

Appendix

Table 6: Wind density effect on corn yield by different year ranges

Wind turbine effect on corn yield from 1997-2013						
	(1) corn_yield	(2) corn_yield	(3) corn_yield	(4) corn_yield	(5) lcorn_yield	(6) lcorn_yield
Wind Density	31.1088***	6.5556**	6.6280**	11.7301***	0.0513**	0.0807**
	(7.7109)	(2.6947)	(2.7363)	(3.4580)	(0.0209)	(0.0311)
R^2	0.5368	0.5579	0.5588	0.5585	0.5663	0.5665
County FE		✓	✓	✓	✓	✓
State-Year FE	✓	✓	✓	✓	✓	✓
Weather Interact			✓	✓	✓	✓
Trim				✓		✓
Observations	31842	31842	31842	31756	31343	31257
Wind turbine effect on corn yield from 2014-2023						
	(1) corn_yield	(2) corn_yield	(3) corn_yield	(4) corn_yield	(5) lcorn_yield	(6) lcorn_yield
Wind Density	14.5626***	-0.3649	-0.6380	4.7577	-0.0015	0.0451
	(3.7332)	(2.8501)	(2.8699)	(4.3038)	(0.0210)	(0.0345)
R^2	0.5475	0.4008	0.4042	0.4050	0.3785	0.3794
County FE		✓	✓	✓	✓	✓
State-Year FE	✓	✓	✓	✓	✓	✓
Weather Interact	✓	✓	✓	✓	✓	✓
Trim				✓		✓
Observations	14666	14666	14666	14459	14666	14459
Wind turbine effect on corn yield from 1997-2023						
	(1) corn_yield	(2) corn_yield	(3) corn_yield	(4) corn_yield	(5) lcorn_yield	(6) lcorn_yield
Wind Density	16.9385***	0.3602	0.5249	1.7458	-0.0192*	-0.0218
	(4.0624)	(1.3183)	(1.3352)	(2.3960)	(0.0113)	(0.0204)
R^2	0.6120	0.6576	0.6582	0.6576	0.6290	0.6289
County FE		✓	✓	✓	✓	✓
State-Year FE	✓	✓	✓	✓	✓	✓
Weather Interact			✓	✓	✓	✓
Trim				✓		✓
Observations	46508	46508	46508	46274	46009	45775

Notes: Clustered standard errors at the state level in parentheses. WeatherInteract: If not specifies then includes linear and quadratic precipitation and growing degree days; If specifies ✓ then interact the previous terms with an irrigated county dummy as suggested in Kaffine (2019). Statistical significance is denoted as follows: ***p<0.01, **p<0.05, *p<0.1.