Between Wind and Water: Trade-offs of Irrigation and Wind Projects

Steven M. Smith, Daniel Cooley

Abstract: Development of the abundant wind energy across the Great Plains of the United States has been relatively slow. We present a novel factor for the lag: the Ogallala Aquifer. Trade-offs between colocated natural resources are complicated by incongruencies between the scale and technology associated with each. This study considers how irrigation, especially by center pivots, has affected wind power generation. To study the relationship, we combine data on wind projects with center pivot locations derived from a deep learning model using satellite imagery. We find that center pivot fields are 64% less likely to have a wind turbine, and wind projects nearer to center pivots produce 26% less electricity, potentially due to turbine placement that minimizes interference with center pivots or irrigation's microclimate effects on wind. This tension in the food-energy-water nexus can be exacerbated or ameliorated by policy choices.

JEL Codes: O13, Q15, Q42, Q48

Keywords: wind energy, irrigation, colocated resources, deep learning

> The Great Plains has been called the "Saudi Arabia of Wind Energy" because its resources for wind power are so immense, but development of those resources has been slow.
>
> —Ernest Callenbach, in *Encyclopedia of the Great Plains*

MANY HAVE NOTED THE RELATIVE LACK of installed wind generation capacity in the Great Plains of the United States given its abundance of wind energy (e.g., Callenbach 2011; Vokoun 2019). The potential far exceeds the local demand, and

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the expense to move the generated electricity to more populous regions with higher load demands helps explain the slow uptake (Lu et al. 2009). We put forth an additional, novel factor that has not received attention: the presence (and use) of the Ogallala Aquifer. Natural resources are often colocated, and the development and use of each one may be shaped by the other due to the mix of respective technologies, market values, and property rights. The Great Plains is associated with both wind and water, and both have shaped agriculture in the region. The Dust Bowl of the 1930s saw the wind, along with poor farming practices, decimate the region (Hansen and Libecap 2004). The water beneath helped with recovery and protection from later winds; with the advent of center pivot irrigation systems (CPIS) and arrival of rural electrification, the agricultural sector of the region blossomed with its newly irrigated lands (Hornbeck and Keskin 2014; Edwards and Smith 2018). Progress in the power sector means that the wind now offers a rich source of renewable energy, and utility scale projects produced over 330 million megawatt-hours (MWh) in 2020, or 8.4% of US electricity (US EIA 2021). With this growing energy sector, the Great Plains is looked to as a region to invest in, but little attention has been paid to the interactions of wind power and irrigated agriculture.

We assess how the development of water and wind are in conflict with one another given the existing technologies, values, and property rights. Specifically, we explain and quantify how historic irrigation development, with special attention to CPIS, now influences wind turbine siting and electricity production across the Great Plains. This region is of particular interest both because the wind generation potential is massive and because differential access to the Ogallala Aquifer provides quasi-random irrigation development relative to wind resources.

A given plot of land can be endowed with multiple resources such as soil, trees, minerals, wind, and water. This can lead to complementarities for productive activity on the land—good soil and water for irrigation increase agricultural productivity—but colocated resources can also create conflicts where one activity precludes another, such as open-pit mining and agricultural activity. Often a landowner does not face an all-or-nothing trade-off. For instance, oil and gas wells can operate on a portion of a field while agricultural production can continue on most of the remainder (Fitzgerald et al. 2020). The decision to pursue one activity over the other, or the mix of activities, is determined by the owner, who presumably picks the highest valued combination.

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Achieving the right mix of production on a piece of land can rely on contracting between parties with comparative advantages in the different industries (Cheung 1973). Matters are complicated when there is a mismatch of the scales of production and property rights between the resources, introducing externalities and additional transaction costs (Bradshaw and Leonard 2020). These incongruent property right structures between two resources can impede the efficient development of one or both (Libecap and Wiggins 1984; Leonard and Parker 2021). However, wind power generation and farming can generally coexist. Large farmland expanses are conducive to wind project development due to the relative open space for turbines and, when large areas are owned by a single operator, lower transaction costs (Winikoff and Parker 2024). In fact, agricultural land is by far the most common place to find wind turbines, accounting for 93% in the United States (Xiarchos and Sandborn 2017). We hypothesize, however, that irrigation alters joint siting possibilities over the Ogallala Aquifer region, particularly where CPIS are utilized, through multiple channels.

Irrigated land is often more valuable, driving up the compensation necessary to cover a landowner's reservation price for siting a wind turbine on their property. The predictions are further complicated by the ubiquitous CPIS often deployed as the irrigation technology of choice. CPIS are associated with even higher land values (Cooley et al. 2021), and the mechanical workings of CPIS further increase costs due to a nonlinear relationship with the land forced out of (irrigated) production. Simply put, wind turbines will block the circular path of the sprinkler as it inscribes the field, forcing a "slice" to be beyond its reach. While turbines can feasibly be placed in the nonirrigated corners, this spacing constraint may adversely impact the productivity of the wind project by causing deviations from the preferred turbine configuration. Furthermore, cropping patterns and irrigation nearby can alter local wind patterns, affecting turbine output (Vanderwende and Lundquist 2016; Phillips et al. 2022).

In this study, we empirically explore the ways in which development of the aquifer for irrigation—which mostly predates any large-scale wind power development—exerts influence on wind projects. First, we consider how the location and timing of wind projects relate to irrigation at the county level around the Ogallala Aquifer. Second, we drill down to the specific plots using sections (square miles) from the Public Land Survey System (PLSS) as units of analysis to garner insights into the micro-location choices for wind turbines. Third, we consider the wind projects themselves as units of observation to assess whether those located near and around CPIS are more or less productive than their counterparts without CPIS nearby.

In order to conduct these analyses we compile a wide range of data, including output from a machine learning process to locate CPIS across the study region. Using a methodology developed by Cooley et al. (2021), we process satellite images in a manner that identifies the locations of CPIS at 30-meter resolution. Relative to widely available county-level irrigation data, our novel dataset proves essential to our results in at least two ways. First, CPIS have a distinct effect from irrigation by other means, underscoring that the technology in use matters. Second, county-level results on their own would lead to a conclusion that contrasts the section-level analysis, underscoring the importance of the subcounty spatial resolution.

We find that irrigated land helps to explain the smaller and later presence of wind projects in the Great Plains. However, holding irrigation constant, center pivot technology specifically ameliorates a significant portion of the negative relationship between irrigation and wind projects at the county level. Supplementary analysis suggests that this mitigating effect of CPIS on wind project development likely occurs through indirect channels such as policy preferences for smaller setbacks. At the section level, irrigated areas are less likely to have wind turbines, even within small spatial neighborhoods. At this scale, the use of CPIS deters wind development more than other irrigation. Furthermore, the likelihood of turbine placement is reduced by the number of neighboring sections with CPIS, highlighting the disparity of spatial scales between wind projects and irrigated agriculture. Our wind-project-level analysis offers another compelling reason why wind projects avoid placement near CPIS: they produce about 26% less electricity over a year relative to their installed capacity, whether due to layout constraints or microclimate effects stemming from irrigation.

Our research provides insights into the food-energy-water nexus. Rather than focusing on how land-use patterns and irrigation are altered following the development of energy resources (Allred et al. 2015; Hitaj et al. 2020; Fitzgerald and Giberson 2021), our efforts focus on how existing land use and irrigation influence where energy resources are tapped into. Our investigation of the role of irrigation identifies a factor not yet considered in depth as a determinant of siting choices for wind projects and does so at a finer spatial scale than much of the existing economic literature on turbine placement that is limited to larger spatial units like the state or county (e.g., Hitaj 2013; Winikoff and Parker 2024). Given that the nonlinear land use trade-off associated with CPIS is a large factor, our results also speak to the influence of setback policy on wind turbine placement (Winikoff 2022) and energy-resource development more broadly (Ericson et al. 2020).

Furthermore, our findings that wind projects nearer CPIS produce less electricity provides empirical support to related literatures on wind effects. To the extent that the result is driven by layout constraints imposed by the CPIS, the findings provide empirical weight to the largely theoretical literature on optimal wind project layout and wake effects of the wind turbines themselves (Kaffine and Worley 2010; Meyers and Meneveau 2012; González et al. 2014; Stevens et al. 2017).[1] Alternatively, the evidence may be among the first to empirically detect economically significant microclimate effects of irrigation on wind patterns. While scientists have recognized the influence of land use (cropping and irrigation) on temperature and precipitation (Lobell

1. Lundquist et al. (2019) produce empirical evidence of negative downwind wake effects between two wind projects in a case study.

et al. 2008; DeAngelis et al. 2010; Mueller et al. 2016), only recently have economists taken note and connected these effects directly to economic outcomes like crop yields (Braun and Schlenker 2023; Grosset et al. 2023). Less evidence has been compiled on how wind patterns are affected.[2] Exceptions include Vanderwende and Lundquist (2016), who conduct simulations which find that wind speeds—and subsequently wind power production—are influenced by crop choice, and Phillips et al. (2022), who recently report evidence that irrigation reduces upslope winds in the Great Plains.

This study also adds to the literature on the effects of irrigation uptake around the Ogallala (Hornbeck and Keskin 2014) and the externalities of its development (Pfeiffer and Lin 2012; Hornbeck and Keskin 2015; Braun and Schlenker 2023). More generally, our findings contribute to a literature on colocated resources and how the mix of technologies, values, and property rights affects their respective development, inclusive of spatial and cross-sectoral externalities (Libecap and Wiggins 1984; Lewis 2019; Bradshaw and Leonard 2020; Bellanger et al. 2021; Leonard and Parker 2021; Alston and Smith 2022). Finally, the methods deployed also contribute to a burgeoning area of using machine learning to enhance economic research (see Gogas and Papadimitriou 2021).

1. WIND AND IRRIGATION ON THE GREAT PLAINS

The Great Plains region is closely associated with both wind and water. Wind may be most linked with the human-environmental disaster known as the Dust Bowl. The erosion stemming from high winds and poor farming practices (Hansen and Libecap 2004) destroyed farms and uprooted settlement during the 1930s. While erosion control has improved, the high winds remain. Given that power production is a cubic function of wind velocity (Kaffine and Worley 2010), the Plains offer a significant energy resource. Figure 1 shows the wind classes across the continental United States. The central plains, spanning from Canada to Mexico, have higher wind classes than other regions.

Figure 1 also provides the outline of the Ogallala Aquifer. It was widely developed for irrigation shortly after the Dust Bowl when rural electrification, cheaper energy, advances in centrifugal pumps, and center pivot technology came on to the scene in the 1940s. Across the arid western United States, groundwater development accounted for 90% of the growth that occurred in agricultural production after 1940 (Edwards and Smith 2018). For the Ogallala specifically, the value of the underlying water was capitalized into land values at $25 billion (Hornbeck and Keskin 2014). However, under (mostly) open access, the aquifer has experienced widespread depletion (Konikow 2013).

2. Notably, to the extent that wind is affected by land use, relying on its exogeneity to identify causal impacts of those same land use choices on precipitation and temperature is less compelling.

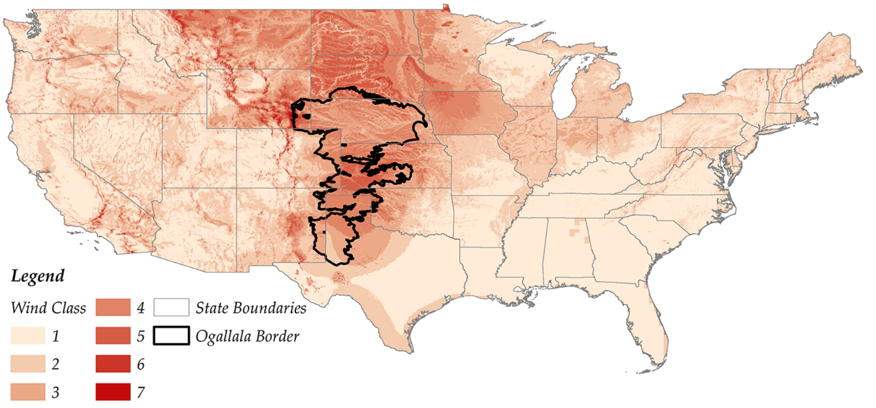

Figure 1. Wind power class and the Ogallala Aquifer. This figure shows the wind power classes (1–7) across the United States and the extent of the Ogallala Aquifer. Wind power class is from the National Renewable Energy Laboratory (NREL 2015), and darker shades indicate higher wind classes. The Ogallala Aquifer border is from USGS (2003).

In table 1, we show that irrigated cropland across the Ogallala states remains more valuable than nonirrigated cropland today.[3] The more arid states have larger price premiums for irrigated lands. On average, irrigated land is worth $2,360 more per acre than nonirrigated cropland, a 128% premium. These premiums are not strictly causal, as more productive land is more likely to warrant irrigation investment.

Also shown in table 1, much of the irrigation is done by sprinkler. In total, 76% of the irrigated land is by sprinkler across these states, although shares are higher in the states most over the Ogallala.[4] Gravity, or flood irrigation, makes up the majority of the remaining share with micro (drip) irrigation comprising just under 2%. The final columns of table 1 estimate the nominal premium of center pivot irrigated cropland over cropland deploying other types of irrigation technologies. It decomposes the overall irrigation premium based on the share of sprinkler acreage in each state and the estimate from Cooley et al. (2021) that sprinkler technology has a 63% premium of land value over nonsprinkler technology in the Ogallala region. The bottom line is that sprinkler irrigated cropland is estimated to be around $1,080 more valuable per acre than other irrigated land in the region.

3. The USDA report on cropland value by irrigated status is only reported down to the state level (USDA NASS 2021), meaning that counties beyond the Ogallala region are contributing to the figures. Furthermore, data for Iowa, Oklahoma, and South Dakota, all in our sample, were not reported.

4. These figures are also only available at the state level. Additionally, it is possible that "sprinklers" include technology other than CPIS, such as side rollers, but we expect that share to be relatively small.

Table 1. Cropland Values and Irrigation in the Ogallala States

	Cropland Values per Acre (2021 $)			Irrigation Premium		Irrigated Acres by Technology (1,000s)				Estimated Irrigation Premium by Technology		
	All ($)	Irrigated ($)	Nonirrigated ($)	Level ($)	%	Sprinkler	Micro	Gravity	% Sprinkler	Sprinkler ($)	Gravity ($)	Sprinkler Premium ($)
Colorado	2,240	5,400	1,400	4,000	286	1,426	4	1,099	56	4,820	2,940	1,880
Kansas	2,370	3,700	2,250	1,450	64	2,310	28	66	96	1,470	900	570
Nebraska	4,960	6,530	3,990	2,540	64	7,003	59	661	91	2,640	1,610	1,030
New Mexico	1,660	4,550	485	4,065	838	396	20	266	58	4,860	2,970	1,890
Texas	2,150	2,540	2,090	450	22	3,267	271	769	76	500	300	200
Wyoming	1,600	2,550	890	1,660	187	473	0	1,562	23	2,370	1,450	920
Average	2,500	4,210	1,850	2,360	94					2,780	1,700	1,080
Total						14,875	383	4,422	76			

Note. Cropland values in 2021 come from USDA NASS (2021); irrigated acreage by technology is as of 2018 and comes from USDA NASS (2019a). The excess value of sprinkler irrigated land over gravity irrigated land is taken to be 63% from Cooley et al. (2021), and level values are calculated such that the acre-weighted average by technology would equal the total irrigated premium in each state, ignoring the small share of micro/drip irrigated acreage.

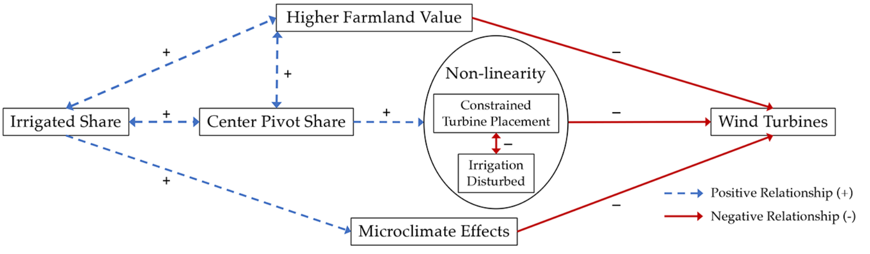

Figure 2. Linkages of irrigation to wind turbine placement, section-level aggregation. This figure is akin to a directed acyclic graph representing potential channels through which irrigation and center pivots may relate to turbine siting decisions observed at the field level. all else equal.

At the field level, this extant irrigation development stands to affect wind generation capacity through at least three channels, all mapped in figure 2. First, given that irrigated land is more valuable, the reservation price for a landowner to agree to a turbine to be sited on their irrigated cropland will be higher than on other farmland, dissuading placement there, all else equal. CPIS specifically drives up the reservation price per acre further. Second, CPIS also creates nonlinear acreage effects owing to the circular geometry of the technology. This creates a trade-off in which the wind project can disturb more irrigated land or accept a more constrained area to place turbines, that is, in the "corners." Third, irrigation influences microclimates, creating cooling effects (Lobell et al. 2008), altering precipitation (DeAngelis et al. 2010), and reducing upslope winds in the region (Phillips et al. 2022). All of these channels suggest that installation of wind generation capacity on irrigated land, particularly where CPIS is used, is less likely to be observed.

Because wind projects' spatial scales are well beyond the typical field size, aggregating up these potential channels to larger units is warranted but less straightforward and yielding more ambiguities (shown in fig. A1; figs. A1–A5, D1–D3, E1–E3 are available online). It remains that higher irrigation shares will mean higher farmland values, and the microclimate effects will persist and be even more pronounced at larger geographies due to nonlinear aggregate effects and spatial spillovers. The complications emerge more so through indirect effects. For instance, the presence of irrigation and CPIS may alter the agricultural sector's structure (e.g., total farmland, cropland, average farm size, and tenancy) both within farms and on nearby lands via general equilibrium effects. More farmland is attractive for turbines, but more cropland, all else equal, is itself less attractive given that turbines would displace crop production.[5] The presence of larger farms reduces the number of parties the wind project needs to negotiate

5. Across the United States, 54% of turbines are on rangeland and 39% on cropland (Xiarchos and Sandborn 2017).

with, lowering transaction costs (Winikoff and Parker 2024).[6] Whether or not higher tenancy is good or bad for turbines is ambiguous, as the landowner may be more likely to accept turbines, experiencing none of the negative externalities themselves, or be more sensitive to disturbing their current farm tenants.[7] More importantly for the net ambiguities, we lack research on how irrigation affects these farm characteristics.

Irrigation can also affect local policy preferences. Most pertinent to our setting is that many counties adopt setback requirements for wind turbines. These setbacks can deter wind projects, but the magnitudes of setbacks are also associated with local factors such as farm sizes (Winikoff 2022). We expand on the potential connection to setback policy here because it also serves as a useful tool to illustrate the additional trade-offs emanating from the circular geometry of CPIS.

Setbacks exist for both property lines and structures, and they are often a function of the turbine height. Given current turbine technology, this has led to setbacks between zero and 2,000 feet, averaging around 500 feet (Winikoff 2022).[8] In figure 3, we provide an illustration of how the presence of CPIS would interact with setbacks for a single turbine. At initially small property setbacks, there is no effect on the center pivot (left panel) because the turbine can remain beyond its reach, allowing irrigation to proceed unencumbered. As the setback increases and compels the turbine to be sited within the circle, its presence forces a “slice” of land out of irrigation beyond the actual turbine footprint owing to the inability for the center pivot to complete the circle. This slice continues to grow until the setback forces the turbine sufficiently close to the center to preclude the center pivot from reaching about a quarter of the once irrigated circle.

In figure 4*A*, we illustrate the nonlinear effect setbacks would have on a 160-acre field with a CPIS, assuming a 0.1 acre wind turbine pad is required.[9] The turbine remains beyond the center pivot until around 350 feet. By 390 feet the slice is already 1.4 acres, or 14 times the turbine pad size itself. A little over 4 acres are lost by 1,000 feet and the effect begins to quickly increase. At 1,250 feet the slice is about 18 acres (14% of the irrigated field) and grows to 30 acres by 1,285 feet. Using the cropland values from table 1, we can estimate the value of the land forced out of center pivot irrigation; at 1,000 feet the excess premium of reduced irrigation is $11,400 if switched to dry land crops and $19,010 if no production occurs in the slice.[10] With a 1,285 foot

6. This would also influence plot-level decisions, targeting those owned by a larger, willing landowner, but we lack plot-level information of ownership patterns to test and control for this.

7. Aesthetics and low frequency noise have been linked to lower levels of well-being and higher incidence of suicide (Krekel and Zerrahn 2017; Zou 2017).

8. See fig. A2 for the full distribution of our subsample.

9. Farm operators we visited stated that they could get CPIS within 40 feet of a turbine, which would be at a minimum equivalent to a 3,200 square foot pad, which is approximately equal to the 0.07 acres estimated to be taken up by a turbine pad in the report by Denholm et al. (2009).

10. See tables A3, A4 for scaling by percentage and land values.

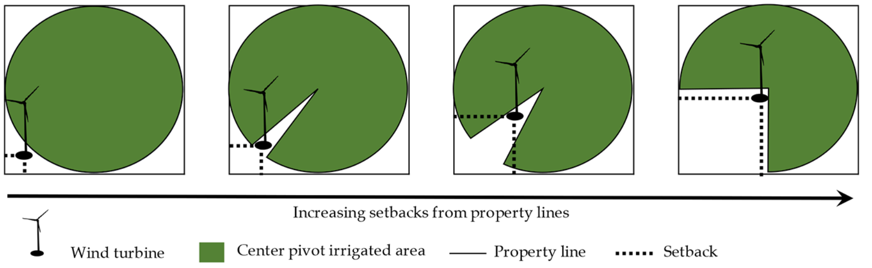

Figure 3. Property line setbacks and center pivots. This figure depicts the conceptual effect of setbacks from property lines for wind turbines on the area a center pivot can service within a square section.

setback, those values would balloon to $83,910 and $139,850, respectively. The effect of setbacks is muted with the less-common 640-acre section served by a single center pivot, as shown in figure 4*B*.

Even without setbacks, siting turbines in the corners of center pivot fields can induce costs on wind projects. This is because there are important downwind interactions among wind turbines, and specific wind project layouts, which may be impeded by the CPIS, can produce more electricity (Kaffine and Worley 2010; Meyers and Meneveau 2012; Stevens et al. 2017). While each wind- and land-scape is distinct, a general rule of thumb is that turbines should be around 8–10 rotor diameters apart in the downwind direction and half that in the crosswind direction (Pao and Johnson 2009).

Figure 5 summarizes the trade-offs CPIS can create. Figure 5*A* shows a simple 10-turbine project across a landscape with 160-acre plots where the wind is predominantly

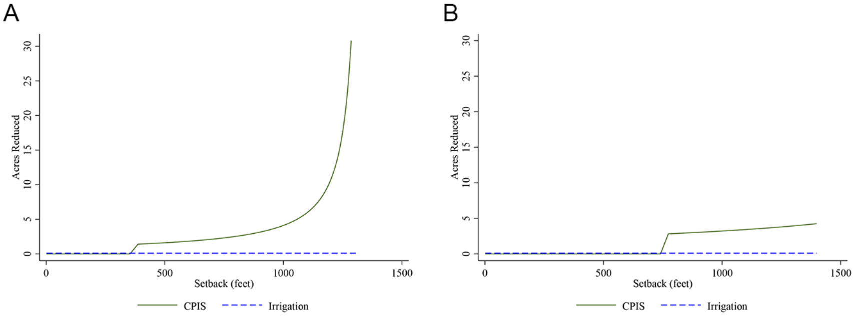

Figure 4. Setback influence on a wind turbine's effect on irrigated land. This figure shows the acres of the irrigated field that would be taken out of production to accommodate a wind turbine across a range of property line setback distances in a landscape of quarter-sized (160 acre) CPIS (*panel A*) and section-sized (640 acre) CPIS (*panel B*).

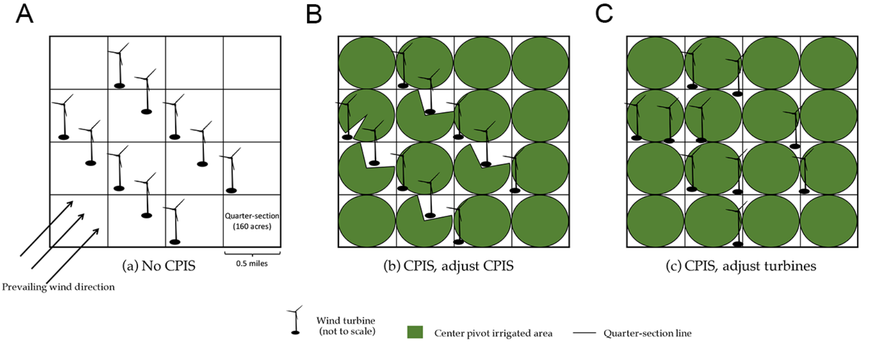

Figure 5. Irrigation-wind project trade-offs. This figure shows the ideal placement of 10 turbines of average diameter size (300 feet) according to general rules of thumb (Pao and Johnson 2009) and trade-offs when CPIS are present.

out of the southwest. The spacing is scaled to the wind turbines in the sample having an average rotor diameter of around 300 feet. In figure 5*B*, we populate the landscape with CPIS and maintain the optimal spacing of the turbines. This layout causes large slices to be made inaccessible for many of the CPIS, incurring the large reservation costs akin to the setbacks above. Instead, the wind project could opt to stay in the corners, leading the turbine placement to be altered, as in figure 5C.[11] Although reducing the royalty payments that would be required, this layout will potentially reduce the amount of electricity produced by the wind project. Either way, the net revenues stand to be reduced by the presence of CPIS.

Rarely will the landscape be fully populated by CPIS as is shown in figure 5. However, given that wind projects' footprints extend across multiple farms (roughly 8.5 farms based on averages in the sample), coordination across landowners is necessary. This has its own transaction costs independent of irrigation, but the opportunity cost of the land needed for the entire project is notably subject to the irrigation status of neighboring sections. Additionally, nearby irrigation may adversely alter microclimates. All else equal, more plots nearby that have CPIS will dissuade wind turbine placement on a given field whether or not it has a center pivot.

The notion that irrigation, or at least the Ogallala Aquifer, is negatively correlated with installed wind generation capacity can be seen in figure 6.[12] Because the geological

11. In fig. A5 we provide zoomed-in satellite images in the region showing actual examples of wind project patterns relative to cropland and CPIS. We also provide similar images from Illinois to contrast patterns among cropland predominantly not irrigated.

12. Following Hornbeck and Keskin (2014), we limit the geography to counties within 100 km, or about 62 miles, of the Ogallala. We show below that this maintains reasonable overlap of covariates whereas counties beyond increasingly have distinct characteristics. We also show that results are not qualitatively sensitive to this sample choice.

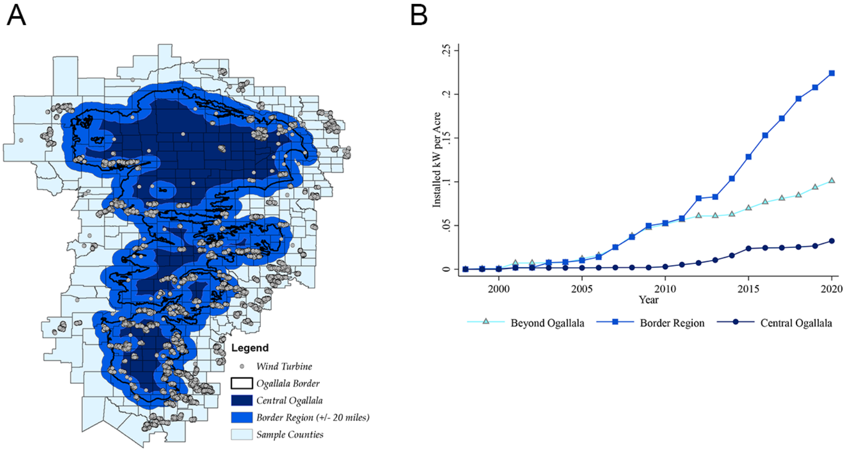

Figure 6. Installed wind generation capacity in the Ogallala region. This figure depicts the location and timing of wind turbines and extent of the Ogallala Aquifer. Panel *A* provides a spatial overview for the counties within 62 miles (100 km) of the Ogallala border. The border is shown along with a plus or minus 20 mile (32 km) buffer around that border. Turbine locations are from Hoen et al. (2018), and the Ogallala border is from USGS (2003). Panel *B* provides the temporal variation of when wind generation capacity, scaled by area, was installed in the three delineated regions.

extent of the aquifer does not begin to account for the variation in saturation or water depth, we have created a buffer zone around the border where wind resources may be similar to what we call the central Ogallala, but where worse water access has not allowed for as much irrigation development.[13] First, we note that the central Ogallala has notably fewer wind turbines by number and capacity per acre. What wind generation capacity development has occurred over and around the Ogallala tends to be within 20 miles of the edge, where irrigation uptake has likely been lower. Second, seen in figure 6*B*, what installed wind capacity has developed over the central Ogallala did not begin until after 2010, whereas the surrounding development began closer to 2000.

2. DATA AND RESOURCE COLOCATION

2.1. Data

For wind project turbine siting locations and characteristics—the primary outcomes—we use the US Wind Turbine Database produced by USGS (Hoen et al. 2018). We are primarily concerned with turbine location, year installed, capacity, height, and rotor

13. The size of this buffer, 64 km or 40 miles, is arbitrary and for descriptive purposes only, although in table 2 we confirm that the buffer does have similar wind resources and less irrigation uptake.

swept area. We have also gathered annual electricity production by the wind projects for 11 years (2010 through 2020) from the Energy Information Administration (EIA 2021). To account for the general quality of the wind resources at a location, we utilize the wind power class from the National Renewable Energy Laboratory (NREL 2015), which categorizes discrete classes (1–7).

For county-level analysis, based on 2010 county borders (Minnesota Population Center 2011), we rely on censuses of agriculture and irrigation conducted by the US Department of Agriculture for farm and irrigation data, digitized by Haines et al. (2018). We utilize the 2007 census to provide a snapshot close to, but before, when wind projects began appearing widely in the area. The primary variables from this source are farm, crop, and irrigated acres, all of which are expressed as a share of a county's total acreage.

We also conduct analyses at the section level, which are the first divisions of the national Public Land Survey System and are typically 640 acres (1 square mile) (Bureau of Land Management 2020). Notably, the national PLSS grid does not extend into Texas, meaning that Texas is not included in the section-level analysis. For this finer scale, we draw on CropScape data from USDA NASS (2019b) to calculate cropland. We use land coverage in 2008 as this is the first year the CropScape data covered the entirety of our sample region. Unfortunately, CropScape does not distinguish between irrigated and nonirrigated cropland. To get some traction on irrigation at the section level, we draw on MIrAD data that derive irrigation at the 250 m resolution by taking county-level USDA irrigated acreage in 2007 and assigning spatial locations based on spikes in the Normalized Difference Vegetation Index across different crops (Pervez and Brown 2010). This down sampling creates some measurement errors and is at a coarser spatial aggregation than our other data sources at this level.[14]

The locations of CPIS specifically are not uniformly available across administrative units. The USDA census reported sprinkler-irrigated acreage at the county level in their 1959 and 1969 reports, but not since. To overcome this, we adapt a deep learning model developed in Saraiva et al. (2020) to identify CPIS from satellite imagery and deploy it across the Ogallala region (see Cooley et al. 2021). The modified U-Net model was trained with Landsat satellite imagery pulled from Google Earth Engine and a hand-coded key of CPIS in Nebraska taken from 2005 aerial imagery to identify the presence of CPIS at the 30 m × 30 m level. To develop the model, we divided Nebraska into 13 nonoverlapping regions from which nine were randomly selected for training, two for validation, and two for testing. Training occurred using a 25-gigabyte share of a P-100 GPU on Google Colab Pro, processing 40 epochs in less than six hours.

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14. For a square mile, MIrAD 250 m resolution data will have around 40 cells compared to 2,900 cells for 30 m resolution data like CropScape and our own CPIS data.

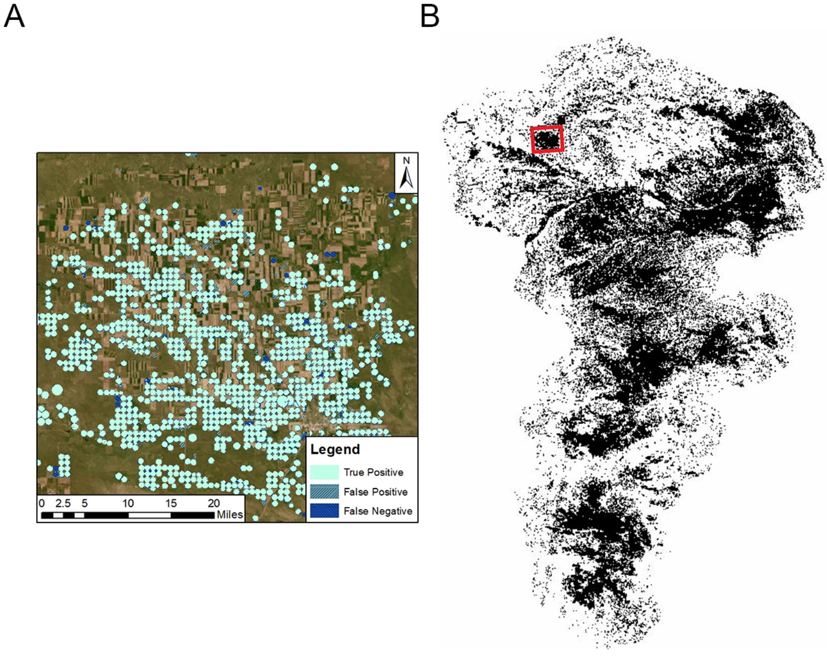

Figure 7. Machine learning output. This figure depicts the machine learning output at two scales. *A*, Predicted CPIS versus ground truth. *B*, Predicted CPIS in the Ogallala region. Panel *A* provides a close up of western Nebraska where ground truth is available. Panel *B* provides the model output for the entire Ogallala Aquifer region with black pixels representing predicted locations of CPIS.

An example image is provided in figure 7*A*, showing both the model predictions and the ground truth for a portion of Nebraska. The model has an accuracy rating—the rate of correctly identified pixels—of 98% in the test images. Additionally, the model achieved a specificity rating of 99% and a recall rating of 88%. Specificity measures how well the model categorizes negative (non-CPIS) pixels while recall measures how well the model categorizes positive (CPIS) pixels. In other words, we are slightly more likely to miss a CPIS pixel than to mislabel a non-CPIS pixel as one. The recall rate is pulled down by the difficulty the model has when interpreting the precise location of the borders of CPIS where the inscribed circular patterns meet the surrounding land but usually captures the presence, if not the exact extent, of CPIS.[15] Finally, we procured Landsat images of the entire Ogallala region from 2008—aligning with the earliest

15. The lower recall rate means that when we aggregate the raster up to the county, PLSS section, and wind project levels we are likely to slightly understate the center pivot share and overstate distances from the edge of a center pivot.

CropScape data available across the entire region—and used the model to detect CPIS throughout. The visual of the model output is provided in figure 7*B*.

We collect additional controls for topography, soil quality, surface water, weather, population, and transmission lines (USGS 1996, 2014; PRISM Climate Group 2004; USDA NRCS 2006; US Census Bureau 2012; US DHS 2017), constructing appropriate measures for each spatial unit of observation: 2010 counties (Minnesota Population Center 2011); PLSS sections (Bureau of Land Management 2020); and wind project footprints, delineated by the smallest convex hull containing all of a project's turbines. Below we provide county-level summary statistics, but we also provide more complete explanations and summary statistics for each unit of observation in tables B1–B3 (tables B1–B3, C1–C9, D1–D7, E1–E7 are available online).

2.2. Resource Colocation

Table 2 provides descriptive evidence that the Ogallala Aquifer region has more wind than the surrounding counties but also more irrigation development and less installed wind generation capacity. Column 1 provides the averages for the entire sample (counties with borders within 100 km of the Ogallala). Column 2 considers only counties with more than 50% over the aquifer while columns 3 and 4 further break that subsample into portions over the central aquifer (20 miles within the border) and counties on the outer ring. Column 5 summarizes the counties beyond the Ogallala Aquifer, and column 6 provides the additional counties that are within the Ogallala Aquifer states but farther than 100 km from the aquifer boundary. Once again, we emphasize that these spatial zones are somewhat arbitrary and for illustrative purposes only; the formal analysis does not rely on these zones other than defining the sample.[16]

First we note that the average wind power class across the Ogallala counties is 3.73, or about 12% higher than counties beyond the aquifer. Still, anything above 3 is considered to be a commercially viable wind resource for power production. Notably, counties beyond the main sample have an average wind power class closer to 2. Maximum wind power class is more similar across the sample but, once again, lower beyond.[17] Second, as expected, irrigation—measured as the share of all county acres irrigated—is much larger across the Ogallala region, at 0.171 compared to just 0.0242 beyond. These general patterns hold when looking at the center pivot share from our deep learning

16. We do show that our main county-level results are robust to the inclusion of all counties in the Ogallala states and to smaller subsamples such as only counties above the Ogallala Aquifer and the exclusion of Texas, which is not included in the PLSS section-level analysis.

17. Using the share of county c overlying the Ogallala Aquifer (OG_c) and the nested share over the central Ogallala ($CentOG_c$) as the main control variables, we also provide regression results from a framework akin to the analysis in Hornbeck and Keskin (2014). Details and results are in table C1 and show that many of the distinctions are statistically significant, even when accounting for covariates.

Table 2. Descriptive Statistics for County Data

	Main Sample (1)	Ogallala (2)	Central Ogallala (3)	Ogallala Ring (4)	Beyond Ogallala (5)	Beyond Sample (6)
Ogallala share	.434	.923	.999	.856	.0566	. . .
Central Ogallala share	.213	.490	.895	.140	.0000200	. . .
Average wind class (1–7)	3.498	3.730	3.613	3.831	3.319	2.097
Max wind class (1–7)	4.964	4.857	4.872	4.844	5.046	3.530
Center pivot share	.0677	.134	.171	.103	.0164	. . .
Irrigated share	.0901	.171	.237	.114	.0242	.0111
Cropland share	.446	.522	.524	.522	.387	.306
Farmland share	.880	.934	.933	.936	.838	.694
Wind capacity installed (kW) per acre	.179	.144	.0618	.216	.207	.114
First turbine year	2010.5	2011.9	2013.7	2011.0	2009.4	2010.6
Average turbine year	2012.9	2014.0	2014.2	2013.9	2012.2	2013.8
Transmission lines (miles/mile^2)	.213	.177	.188	.167	.242	.263
Population density (people/mile^2)	43.42	13.89	11.91	15.60	66.17	92.51
Average elevation (ft)	2,671.0	2,903.2	2,916.9	2,891.3	2,492.1	1,959.1

SD of elevation (ft)	201.6	143.8	124.3	160.7	246.1	266.3
Average soil class (1–8)	3.888	3.846	3.963	3.744	3.921	3.871
Large stream access	.730	.653	.640	.665	.790	.801
Average temperature (°F)	53.42	52.78	51.38	53.99	53.92	56.90
Average precipitation (inches)	23.61	21.90	21.86	21.93	24.92	33.48
Property line setback (ft)	542.4	559.0	623.7	468.8	523.6	475.9
Structure setback (ft)	1,336.3	1,529.4	1,635.1	1,382.3	1,117.0	1,259.1
Counties	386	168	78	90	218	428
Counties for setback data	126	67	39	28	59	85

Note. Column 1 includes the main sample of counties, defined as any with its border within 100 km of the Ogallala Aquifer. Column 2 reports the means for subsample with at least 50% overlying the Ogallala. Column 3 reports the means for the subsample with 50% overlying the central Ogallala (32 km/20 miles inside the Ogallala boundary). Column 4 is the subsample remaining from col. 2 not in col. 3. Column 5 reports the means for counties within 100 km of the Ogallala but with less than 50% overlying the aquifer. Column 6 reports the means for counties in Colorado, Iowa, Kansas, Nebraska, New Mexico, Oklahoma, Texas, and Wyoming that are beyond 100 km from the Ogallala border. ". . ." indicates missing data. Setback data are limited to sample overlap with Winikoff (2022).

model as well.[18] Furthermore, in the central aquifer, irrigated acreage shares are nearly twice that of the counties nearer the edge, confirming that this central region has been developed more for irrigation. We highlight this because, third, the installed wind capacity, while lower across the Ogallala on the whole compared to neighboring counties, is only 0.0618 kilowatts (kW) per acre in the central portion compared to 0.216 kW in the outer ring, more similar to counties completely beyond the Ogallala borders (0.207 kW per acre). In other words, the Ogallala region does not systematically have fewer wind turbine installations until reaching the central Ogallala, where wind availability is similar but irrigation uptake is greater.

Although we emphasize the distinct levels of irrigation development as a crucial explanation to the lower installed wind capacity, there are other differences as well. In general, the whole study sample also has lower populations and fewer transmission lines. Not only is this true of the whole region, but the Ogallala counties have just 0.177 miles of transmission lines per square mile in the county compared to 0.242 miles in the counties immediately surrounding. The population density is just 13.89 per square mile across the Ogallala counties, but 66.17 per square mile beyond the Ogallala. In other words, these factors—lower local demand and higher costs to export electricity—help to explain the lower and delayed installed wind capacity in this region. Hence, we wish to look more directly at the association of irrigation development and turbine siting, controlling for these other factors in a regression framework.

3. COUNTY-LEVEL ANALYSIS

3.1. County-Level Empirical Strategy

To look at the role of irrigation and center pivots in influencing wind projects more directly, we begin by estimating the following equation:

$$\text{turb}_{csj} = \beta_1 \text{irr}_c + \beta_2 \text{CPIS}_c + \beta_3 \text{farm}_c + \beta_4 \text{crop}_c + \boldsymbol{\omega}' \boldsymbol{W}_c + \boldsymbol{\lambda}' \boldsymbol{X}_c + \delta_s + \epsilon_{cj}, \quad (1)$$

where turb_{csj} is the turbine activity in county c of state s and spatial region j. We measure turbine activity in two ways. First, we measure total kW capacity of wind power generation installed per acre as of 2020. Because a large number of counties have zero wind projects (57%), we estimate that outcome with a Tobit model. Second, we consider the year of the first turbine in the county in an ordinary least squares (OLS) regression.[19] The main variables of interest are irr_c (irrigated share) and CPIS_c (center pivot share), which we include separately and together in different specifications to assess the distinction between the two measures of irrigation. When both measures are included, we interpret the coefficient on center pivot share as an interaction effect since

18. It is worth highlighting that the ratio of center pivot irrigation to total irrigation for the entire sample is 0.75(= 0.0677/0.0901), which aligns quite close to the 76% of irrigated acreage served by sprinklers across the sample states based on USDA numbers reported in table 1. In other words, our model detecting CPIS appears accurate, on average.

19. An alternative duration (Cox) model specification yields qualitatively similar results.

center pivot share is nested within irrigated share. We also control for the share of the county in farmland (farm_c) and cropland (crop_c). In addition, we include $\boldsymbol{W}_c$ to account for the quality of the underlying wind resources, including both the county spatial average wind power class and the county maximum wind power class.

The term $\boldsymbol{X}_c$ includes additional covariates: transmission line density, population density, elevation, elevation variation, soil class, presence of large streams, average temperature, average precipitation, and county centroid latitude and longitude. To account for state-level policies that influence investment in renewable energy, we include state fixed effects (δ_s). Finally, we cluster standard errors by spatial region j. This follows the approach put forth by Bester et al. (2011) to address inference of spatially and temporally dependent data and recently deployed in similar contexts by Bazzi et al. (2020) and Leonard and Smith (2021). Specifically, we construct an arbitrary grid of 93 mile (150 km) by 93 mile squares and use the counties' centroids to assign spatial regions. To cover our sample, this yields 60 regions.[20]

3.2. County-Level Results

Results from estimating equation (1), provided in table 3, indicate that irrigation is associated with less and later wind power development, and center pivot irrigation mitigates the effect at the county level. Looking at column 1, we find that increasing the county irrigated share reduces the installed kilowatt capacity per acre. For some sense of scale we decompose the effect on the latent variable into the effects on the observed variable and scale it to a one-standard-deviation increase in a county's share irrigated (0.134).[21] The one-standard-deviation increase of share irrigated reduces the probability of any wind capacity installed by 7 percentage points, or 16% of the underlying probability. Conditional on having some wind generation capacity, the same one standard deviation in irrigated share reduces the expected capacity per acre by 0.0489 kW, or 28% of the average kW per acre in the sample. Furthermore, from column 4, we also see that a one standard deviation in the share of irrigated acres delays the first turbine by an average of 1.27 years. We emphasize that these results are conditional on wind power class, which hastens and increases installed wind generation capacity.

For additional context, we consider the relative scale of the irrigation effect compared to the estimated effect of transmission line infrastructure, one of the dominant explanations for the relatively slow development.[22] The estimated effect on installed wind capacity of a one-standard-deviation increase of irrigation share is equivalent to

20. Results are robust to spatial heteroskedasticity and autocorrelation consistent (HAC) standard errors as well (Conley 2008; Hsiang 2010).

21. We report the three average marginal effects ($\partial \Pr(y > 0)/\partial x$, $\partial E[y|y > 0]/\partial x$, and $\partial E[y]/\partial x$) for the two irrigation measures in table C2.

22. We caution that these estimated effects are not causal, particularly for the transmission line density as these data are a snapshot from 2020 and thus likely include lines constructed for the wind projects.

Table 3. Installed Wind Generation Capacity and Irrigated Land, Counties

	Wind Capacity per Acre			First Turbine Year		
	(1)	(2)	(3)	(4)	(5)	(6)
Irrigated share	−.916***		−2.296***	9.440*		10.17
	(.349)		(.679)	(5.119)		(8.231)
Center pivot share		−.570	2.178**		8.356	−1.001
		(.594)	(.947)		(6.494)	(9.788)
Average wind	.285***	.277***	.265***	−.878	−.876	−.876
	(.0908)	(.0893)	(.0900)	(1.029)	(1.042)	(1.033)
Max wind	.108*	.122**	.107*	−3.137***	−2.965***	−3.138***
	(.0568)	(.0612)	(.0577)	(.488)	(.473)	(.491)
Transmission line density	1.227***	1.268***	1.188***	−8.391*	−8.094*	−8.392*
	(.387)	(.380)	(.388)	(4.332)	(4.375)	(4.333)
Observations	371	384	371	161	166	161
Adjusted/pseudo R-squared	.251	.240	.259	.368	.339	.363
Mean dependent variable	.175	.180	.175	2010.1	2009.9	2010.1
Censored observations	210	218	210			
Farm/cropland	x	x	x	x	x	x
Geographic controls	x	x	x	x	x	x
Spatial fixed effect	State	State	State	State	State	State
Total no. fixed effects	9	9	9	9	9	9
Standard error clusters (93 miles^2)	60	60	60	48	48	48
Model	Tobit	Tobit	Tobit	OLS	OLS	OLS

Note. This table presents the results of estimating eq. (1). Measures are at the county level for counties within 62 miles of the Ogallala. Columns 1–3 measure wind power development by the installed kW in 2020 per county acre. Columns 4–6 measure wind power development timing by the first turbine year for the counties with some capacity installed. Column 1 controls for irrigation share as the total irrigated land in 2007 divided by county acres. Column 2 measures center pivot share as measured by our machine learning process in 2008 and divided by county area. Column 3 uses both in which the center pivot share is interpreted as an additional effect to irrigated share. Columns 4–6 are analogous. The geographic controls included in the regressions are average elevation, standard deviation of elevation, soil class, presence of large streams, average temperature and precipitation, population density, and county centroid latitude and longitude. The farm/cropland controls are the shares of the county area in farmland and cropland. Robust standard errors, clustered by arbitrary spatial neighborhoods (93 miles squared), in parentheses.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

60% of the effect of a one-standard-deviation decrease in transmission line density. For timing, the one-standard-deviation increase of irrigation share is equivalent to 91% of the delay associated with a one-standard-deviation decrease in transmission density. In other words, irrigation is not an alternative explanation, but it is a sizable additional explanation, particularly for variation within the Great Plains.

Looking at columns 2 and 5, where we measure irrigation by CPIS only, the estimated effects are smaller and less precise. Turning to column 3, the center pivot share coefficient, which we interpret as an interaction term of irrigation by CPIS in this specification, is statistically distinct and reduces the lion's share of irrigation's negative effect. This aligns with the smaller, noisier effect of CPIS in column 2: without controlling for non-center-pivot-irrigated acreage, the coefficient on center pivot share is averaging the larger negative effect of irrigation on wind generation capacity with the smaller negative effect of CPIS. The distinction in timing of the first turbine (col. 6) is less pronounced.

These results stand up to a battery of robustness checks (see app. C; apps. A–E are available online).[23] Our findings are consistent with irrigated land driving up opportunity costs but seemingly inconsistent with our theory that those issues are accentuated, both in value per acre and scale of affected acreage, by CPIS. Accordingly, we consider indirect effects that CPIS could have at the county level that we identify in figure A1: (1) setback policy, (2) farm structure, and (3) microclimates. Here we summarize the findings of these auxiliary analyses, leaving the details to appendix C.

Drawing on county-level wind turbine setback data from Winikoff (2022), we find evidence that property line setbacks are considerably smaller in counties with larger center pivot shares (see table C7). A one-standard-deviation increase in center pivot share reduces property setbacks by 273 feet, or 50% of the average setback in the sample, while irrigation share on its own has no statistically significant relationship. This is consistent with center pivot dense counties choosing policy that is cognizant of the nonlinear land effects on center pivot fields, maintaining the ability to place turbines in the corners, which also reduces constraints at all potential sites across the county. Additional regression specifications confirm that larger setbacks are deterrents to wind projects and that the smaller negative effects of CPIS in our main results could be consistent with an omitted-variable bias that CPIS indirectly benefits wind turbine installation at the county level through advocacy for smaller setbacks.[24]

23. Results are robust to a Cox-duration model (table C3), OLS model for installed capacity and spatial standard errors (table C4), sample restrictions (table C5), and the inclusion or exclusion of various covariates (table C6).

24. Winikoff's (2022) efforts to gather setback data covered the north central portion of the United States, meaning overlap with our sample draws from Colorado, Iowa, Kansas, Nebraska, and Wyoming, leaving only one-third of the observations from our main sample.

Second, we consider how irrigation and CPIS influence farm characteristics, like farmland value, farm sizes, and land use choices, that then may influence turbine installation decisions. These exercises are presented in detail in tables C8 and C9 but overall do not generate much insight. It is true that irrigation and CPIS do covary with many of the farm characteristics: farmland and crop production values are greater with irrigation, especially center pivot irrigation; tenancy rates increase no matter the irrigation technology used; and, for center pivots specifically, associated farm shares and crop shares are higher. No pattern is found with average farm size, but the rate of change since 1959 indicates that farm size did increase more where center pivot expansion was greater. More importantly, as covariates in the main estimating equation of total wind capacity installed per acre, the coefficients on these farm characteristics are not statistically significant while the coefficients on irrigation share and center pivot share remain robust. In other words, collectively these associations between farm characteristics and irrigation do not explain away the irrigation and CPIS effects on installed wind capacity at the county level.

The third indirect channel we highlight is microclimate effects on wind due to irrigation. While the wind power class data we utilize do show that installed wind capacity is sensitive to the quality of the underlying resource, these constructed data on power class likely average over any "micro" effects produced by irrigation. With little research or data on wind effects specifically, directly probing this mechanism here at the county scale is beyond the scope of this study. However, our wind project results below do yield indirect evidence that this channel is likely relevant.

4. SECTION-LEVEL ANALYSIS

4.1. Section-Level Empirical Strategy

Our second empirical objective is to characterize the relationship between the presence of irrigation and center pivots with turbine siting decisions at a finer spatial resolution by using the first division sections of the Public Land Survey System (one square mile). For this endeavor we estimate the following equation:

$$\mathbf{1}[\text{turb}_{irc}] = \mathbf{f}(\text{CPIS}_i) + \mathbf{g}(\text{irr}_i) + \boldsymbol{\gamma}'\boldsymbol{CS}_i + \boldsymbol{\omega}'\boldsymbol{W}_i + \boldsymbol{\lambda}'\boldsymbol{X}_i + \kappa_r + \varepsilon_{ic}. \quad (2)$$

The outcome is an indicator variable equal to one if a wind turbine is present on section i in county c and spatial region r as of 2020. The variables of interest are CPIS_i, which is the share of section i that is irrigated by a center pivot, and irr_i, which is the share of the section irrigated by any means. For our main analysis, we specify $\mathbf{f}(\text{CPIS}_i)$ as γ_1 CPIS_i, meaning we control for the share of center pivot irrigation on section i linearly. Similarly, we begin by specifying $\mathbf{g}(\text{irr}_i) = \gamma_2\text{irr}_i$. This specification mirrors the approach taken at the county level where we try both metrics as alternative measures of irrigation independently and also include both in a single regression. When both are included, we interpret γ_1 as the additive effect of center pivot irrigation beyond irrigation generally, and $\gamma_1 + \gamma_2$ provides the total effect of center pivot irrigation relative to nonirrigated land. While a useful exercise, recall that the underlying irrigation data are far coarser spatially and less precise than our CPIS data (62,500 square meters vs. 900 square meters). To be cognizant of this coarseness, in many specifications we utilize a simpler indicator function for $g(\cdot)$ set equal to one if 0.05 or more of the section is irrigated.[25]

At this spatial resolution, we control for the share of the section that is cropland, with trees, and "developed" as classified by the CropScape data ($\mathbf{CS}_i$). Like the county-level regressions, we also control for the quality of the wind resource with a function of average wind and maximum wind power class ($\boldsymbol{W}_i$), and a similar set of geographic covariates ($\boldsymbol{X}_i$), including latitude and longitude, elevation (mean and standard deviation), distance to nearest stream, average temperature and precipitation, and distance to transmission lines.

In addition, we utilize a series of spatial fixed effects that progressively get smaller for κ_r to address policies and local features we do not directly measure. We begin with state fixed effects, moving to county fixed effects (our preferred specification), followed by township fixed effects. Townships are the preceding division in the PLSS and consist of 36 sections in a 6 mile by 6 mile area. We further divide the townships into thirds, fourths, and ninths for even finer scale spatial fixed effects. At that smallest fixed effect (one-ninth of a township), there are but four observations within each spatial unit to generate the identifying variation. Across our main specifications, standard errors are clustered at the county level.

4.2. Section-Level Results

Results provided in table 4 show that irrigation is a strong deterrent to wind turbine siting at the section level and that CPIS specifically strongly drives the result. These estimates of equation (2) all include county-level fixed effects. Looking at column 1, a section completely irrigated is estimated to reduce the likelihood of a turbine being sited there by 1.66 percentage points. When irrigation is captured by CPIS only in column 2, the effect is larger, reducing the likelihood by 2.24 percentage points. Because no 640-acre section is completely irrigated by CPIS, we consider the effect of an average center pivot section—which has a mean share of 0.19 or roughly one complete quarter section. This average center pivot section reduces the chance of a wind turbine by 33% $([(0.0224 \times 0.19)/0.0129] \times 100)$. When we introduce both irrigated share and center pivot share in column 3, we see that irrigated land alone does not have a statistically significant effect. In contrast, the additional effect of irrigation by a center pivot is statistically distinct (from irrigation alone and from zero) and about four times the magnitude of the irrigation point estimate. These general results hold in columns 4

25. This 0.05 share roughly aligns with two cells of the 42 per square mile having irrigation and also corresponds to the area a center pivot would irrigate if operating on one-quarter of a quarter section.

Table 4. Wind Turbines and Irrigation, PLSS Sections

	1[Turbine]					
	(1)	(2)	(3)	(4)	(5)	(6)
Irrigated share	−.0166**		−.00573	−1.246**		−.360
	(.00773)		(.00733)	(.494)		(.588)
Center pivot share		−.0224***	−.0191***		−1.648***	−1.436***
		(.00770)	(.00725)		(.365)	(.427)
Cropland share	.0109**	.0111**	.0121**	.317*	.342*	.384**
	(.00464)	(.00453)	(.00481)	(.166)	(.176)	(.169)
Average wind	.0112***	.0111***	.0112***	1.272***	1.268***	1.268***
	(.00248)	(.00249)	(.00249)	(.225)	(.224)	(.225)
Max wind	.00497***	.00503***	.00500***	.389**	.392**	.393**
	(.00169)	(.00169)	(.00169)	(.188)	(.189)	(.189)
Observations	275,303	275,283	275,282	131,451	131,441	131,441
Adjusted/pseudo *R*-squared	.073	.073	.073	.337	.339	.339
Mean dependent variable	.0129	.0129	.0129	.0270	.0270	.0270
MEM of irrigation share				−.0272		−.0078
MEM of center pivot share					−.0358	−.0312
Geographic controls	x	x	x	x	x	x
Forest/developed share	x	x	x	x	x	x
Spatial fixed effect	County	County	County	County	County	County
Total no. fixed effects	303	303	303	113	113	113
SE clusters, counties	303	303	303	113	113	113
Model	OLS	OLS	OLS	Logit	Logit	Logit

Note. This table presents the results of estimating eq. (2) with a linear specification for irrigation and center pivot share. Measures are at the PLSS section level for those within 62 miles of the Ogallala, excluding Texas, which is not part of the PLSS. The outcome variable is an indicator equal to one if the section has a wind turbine on it by 2020. Column 1 reports results deploying irrigation share calculated from MIrAD as of 2007 as the main independent variable, col. 2 reports results deploying center pivot share calculated from our machine process in 2008, and col. 3 reports results including both in which the center pivot share is interpreted as an additional effect to irrigated share. Columns 4–6 are analogous but from logit estimates. All columns use county fixed effects. The geographic controls included are average elevation, standard deviation of elevation, soil class, distance to large streams, average temperature and precipitation, centroid latitude and longitude, and distance to a transmission line. Forest/developed shares are those land type shares from CropScape data. MEM is the marginal effect at the mean. Robust standard errors, clustered at the county level, in parentheses.

* $p < .1$.
** $p < .05$.
*** $p < .01$.

through 6 where we repeat the exercise with a logit model.[26] Additionally, we note that cropland, our best proxy for farmland at this scale, generally makes wind turbine siting more likely. Finally, higher wind power classes, even here based on within-county variation, make wind turbine siting more likely on a section.

Figure 8 shows that this result is generally robust across alternative spatial fixed effects. The plot provides point estimates arising from specifications like that in column 3 of table 4, but the CPIS estimate is shown as the total effect ($\gamma_1 + \gamma_2$).[27] The estimated CPIS effect is always larger than the irrigation by other means effect across spatial fixed effects. Furthermore, aside from the state-level fixed effects, the total CPIS effect is always statistically distinct from zero. That said, the magnitude does diminish once we consider only variation within townships, but we also note that the underlying variation for turbine placement within those areas is much smaller as many units that size do not have wind turbines on any sections.[28] Additionally, within township thirds and township ninths, irrigation by non-CPIS means does have a statistically significant reduction in turbine siting and the additional CPIS effect, though more negative, is not statistically distinct. Evidence below suggests that these smaller effects in small neighborhoods are driven by the need to place turbines throughout the landscape and a CPIS nearby can negatively affect the odds for all sections in the neighborhood to receive a turbine.

These results, that CPIS deters placement of turbines on sections and more so than irrigation by other means, are robust to alternative specifications. This includes irrigation as an indicator function and alternative standard error clustering (table D2), the logit model with various spatial fixed effects (table D3), turbine count rather than an indicator (table D4), and restricting the sample to only sections above the Ogallala Aquifer (table D5).

Additionally, when we specify $\mathbf{f}(\mathrm{CPIS}_i)$ as a flexible semi-parametric model where we include five indicator functions that capture how many equivalent quarter sections are inscribed by a center pivot on the section, we find that most of the effect arises with just a single quarter-section center pivot.[29] Even having less than one full quarter section irrigated by CPIS immediately reduces the odds of a wind turbine placed on the section. The effect of having one full quarter under center pivot irrigation is larger and statistically distinct: a one-quarter section center pivot reduces the odds of wind turbine

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26. The number of observations is reduced because the logit model excludes spatial units, counties in this case, with no variation in the outcome.

27. See table D1, for tabular results and additional specifications with irrigation and CPIS only.

28. For example, after accounting for county-level fixed effects, 131,451 observations offer within-county variation of the outcome variable, or roughly half the sample. With township fixed effects, only 15,679 sections provide meaningful variation in turbine siting.

29. See figs. D1–D3, table D6, and surrounding discussion in app. D for full details.

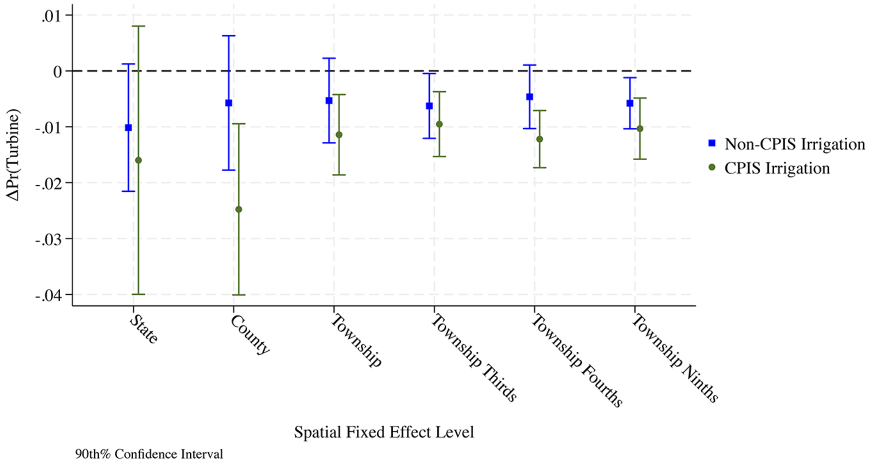

Figure 8. Estimated effects of irrigation on turbine siting. This figure plots the coefficient estimates and 90th percentile confidence intervals for the effect non-center pivot and center pivot irrigation shares of a section. Coefficients are from estimating equation (2) with increasingly smaller spatial fixed effects. The tabular version of the results is available in table D1, panel C. Confidence intervals are based on robust standard errors clustered at the county level.

by 58% ((0.00744/0.0129) × 100), nearly twice the effect implied by the linear estimates. Once two quarters are fully serviced by CPIS, the predicted reduction in turbine placement is 1.08 percentage points, or 84% of the underlying probability. Although the point estimates continue to grow in magnitude for sections with three and four quarters serviced by CPIS, they are not statistically distinct from the effect of having just one complete quarter with a center pivot.

It remains that even nearby CPIS may be sufficient to dissuade wind turbine placement, particularly given the scale of wind projects and desire to coordinate across the landscape. In figure 9, we show that neighboring sections' center pivot use does influence wind turbine siting, and we see that the magnitude of the effect is conditional on a section's own center pivot use.[30] Two general trends are worth attention. First, sections with a center pivot are generally less likely to have a turbine than their non-CPIS counterparts regardless of neighbors' center pivot statuses.[31] However, once surrounded by

30. We define a center pivot section as one with at least a 0.05 center pivot share (equivalent to one-fourth of a quarter-section circle) and consider the number of neighboring sections, potentially eight in the typical PLSS grid, that have center pivots by this definition. Full details are provided in app. D, and tabular results are provided in table D7 for the coefficients shown (cols. 8 and 9) as well as alternative specifications that capture nearby CPIS activity differently.

31. The gap is statistically distinct for CPIS sections vs. non-CPIS sections for neighbor counts of 3, 4, 5, and 7.

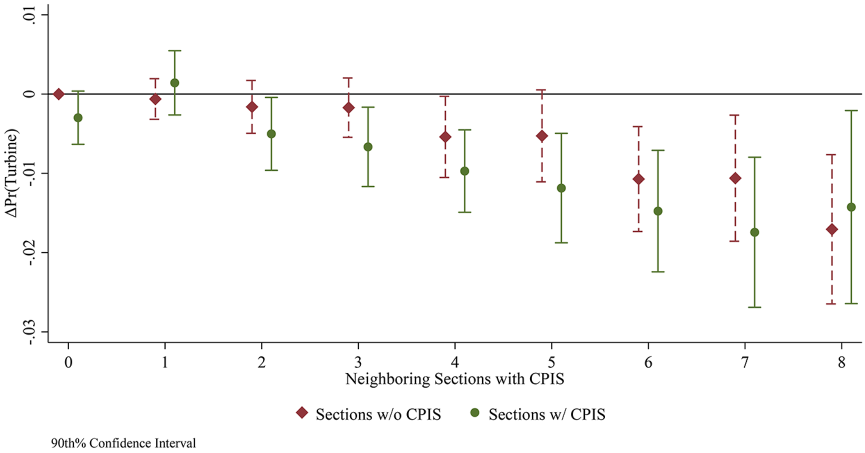

Figure 9. Estimated effects of neighbors' CPIS on turbine siting. This figure plots the coefficient estimates and 90th percentile confidence intervals for the effect of the number of neighboring sections with CPIS on the probability the section has a wind turbine. Coefficients are from estimating equation (2) with county fixed effects. The tabular version of the results is available in table D7, columns 8 and 9. The reference group is sections with center pivot shares of less than 0.05 and zero neighbors with CPIS. Confidence intervals are based on robust standard errors clustered at the county level.

eight neighbors, the section's odds of a turbine are severely and similarly reduced no matter its own CPIS status. Second, as more neighboring sections have CPIS, the odds of a turbine on section *i* generally decline. For center pivot sections, the neighbor effect first emerges with two CPIS neighbors and generally grows from there. Seldom does a single additional neighbor have a statistically distinct effect, but having four neighbors is distinct from having two or six.[32] Beyond six neighboring CPIS, additional neighbors do not have a statistically distinct effect. For non-CPIS sections it is not until four neighboring sections have CPIS that the impact is statistically distinguishable from zero. The effect grows statistically larger going from five to six neighboring CPIS, but further distinctions beyond that are not detected.

In sum, irrigation deters wind turbine siting at the section level and mostly where CPIS are deployed. The evidence further indicates that it is not solely the higher opportunity cost of center pivot land on a particular section, but the increased costs at the wind project level due to CPIS in the region, either driving up the aggregate reservation costs, limiting the layout options that would reduce those explicit costs, microclimate

32. Having two neighbors is statistically distinct from one, as is going from five to six neighbors for CPIS sections.

effects, or some combination thereof. While counties with more CPIS have attracted relatively more turbine investment compared to other irrigation, it has occurred away from CPIS sections within those counties—further suggesting that that county-level effect is operating through indirect mechanisms. As initial sites have been developed for wind generation, future development may require that wind projects consider siting closer to the CPIS themselves. The next section considers the trade-offs this presents for electricity production based on what investment has occurred near and around CPIS.

5. WIND PROJECT ANALYSIS

5.1. Wind Project Empirical Strategy

Only a little less than 6% of turbines in the sample are sited on a section with a center pivot. These specific turbines are far more likely to be placed at distances corresponding to "corners" than turbines on other sections.[33] In these instances, it is clear that the layout is affected by the CPIS, but even when not on center pivot sections specifically, wind projects across the Ogallala region remain quite close to CPIS. Over 50% of wind projects in the sample have at least one turbine within a quarter mile of a center pivot. Figure 10 shows the distribution of average turbine-to-center-pivot distance for wind projects in the sample. Forty percent of the wind projects have turbines that are just one to two sections removed from a center pivot on average.

Does avoiding those center pivot sections nearby mean the turbine locations are suboptimal? Does the nearby irrigation affect wind flows? Although we are limited in our ability to parse out the mechanism, we do explore how the proximity of CPIS affects a wind project's ability to convert wind resources into electricity. Our analysis focuses on actual electricity output, holding installed capacity constant, over the period from 2010 to 2020. In other words, the precise reason for departures in production given the installed capacity is not readily identifiable, but we can observe whether there is a detectable effect related to the proximity of CPIS. To do so, we estimate the following equation:

$$\text{CapacityFactor}_{psky} = \mathbf{h}(\text{CPIS}_p) + \theta_2\text{crop}_p + \boldsymbol{\omega}'\boldsymbol{W}_p + \boldsymbol{\lambda}'\boldsymbol{X}_p + \tau_{sy} + \mu_{ky} + \varepsilon_{py}. \quad (3)$$

The outcome metric is the capacity factor in year y for wind project p located in state s and with vintage year k. Capacity factor is the share of the theoretical total electricity production based on the nameplate capacity and running continuously at that capacity over the entire year. For the Ogallala region wind projects, the average annual capacity factor is 0.35, which aligns closely with the average for utility-scaled wind

33. See fig. E1, which plots the density distribution for turbine distances from section centroids across different levels of CPIS presence and surrounding discussion in app. E.

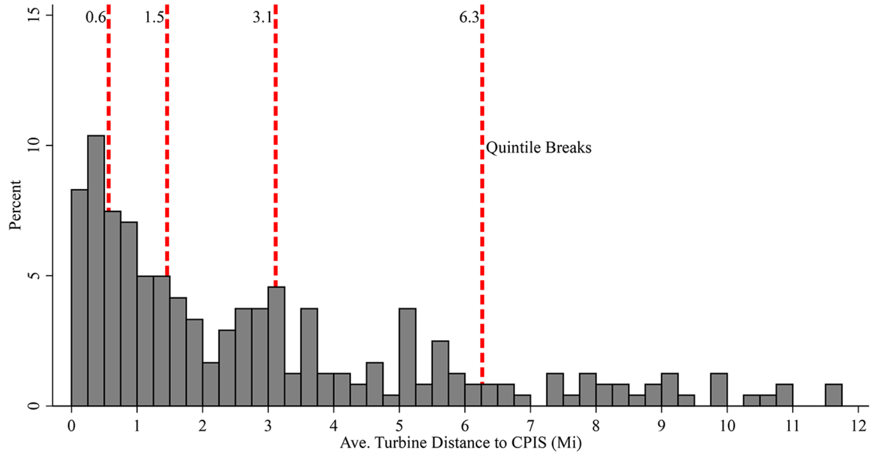

Figure 10. Wind projects' distances from CPIS. This figure plots the distribution for wind projects' distances from CPIS. The variable is the distance of each turbine from its nearest center pivot averaged over the turbines in the wind project; 252 wind projects are shown. To maintain a legible *x*-axis, another 24 projects are excluded that have average distances greater than 12 miles (topping out at 29.6 miles). The dashed lines provide the quintile breaks for the entire sample used in the analysis.

projects across the whole United States.[34] We specify alternative forms of $\mathbf{h}(\mathrm{CPIS}_p)$ to capture a wind project's proximity to CPIS. We prefer a semi-parametric approach that bins the projects by their average turbine distance into quintiles (as shown in fig. 10), omitting the furthest (beyond 6.3 miles) as the reference group. As alternatives, we also consider deciles, bins by miles, indicators whether the wind project is "close" to CPIS (average distance < 1.5 miles) or "closer" to CPIS (average distance < 0.6 miles), and the share of the enlarged wind project's footprint overlapping CPIS.

While our outcome variable provides temporal variation, many of the covariates are cross-sectional. As with the empirical specifications at the other scales, we again control for the share of the wind project that encompasses cropland (crop_p), the wind power class ($\boldsymbol{W}_p$), and the additional covariates ($\boldsymbol{X}_i$), including latitude and longitude, elevation (mean and standard deviation), distance to a stream, and average temperature and precipitation, all calculated for the convex hull of the wind project's turbines. To address the temporal component, we include two sets of fixed effects in our main specification. First, recognizing that wind turbine technology has evolved over the past 20 years, we include a project-vintage-year (k) fixed effect for each year (y). In other

34. See table 6.07.B, Capacity Factors for Utility Scale Generators Primarily Using Non-Fossil Fuels, https://www.eia.gov/electricity/monthly/epm_table_grapher.php?t=epmt_6_07_b.

words, μ_{ky} accounts for the dynamic evolution in power production common to projects of similar vintage across time. Second, we also include τ_{sy} to soak up state s specific production trends in year y that may be related to state-level policy or general weather trends.[35] We conduct robustness checks for the inclusion or exclusion of these fixed effects and other controls and find that the results are quite robust. To account for spatial and temporal correlation, we cluster the standard errors by the same arbitrary 93 mile squared grids as used in the county regressions, noting that these contain around 10 wind projects each.

5.2. Wind Project Results

In figure 11, we show that wind projects nearer CPIS tend to produce less electricity. The graph shows the estimated effect of wind projects' distances from CPIS, binned into quintiles and relative to the fifth quintile from estimating equation (3).[36] Wind projects in the closest quintile, where turbines are within 0.6 miles of a center pivot on average, have capacity factors 0.09 lower than projects in the fifth quintile. Relative to the average capacity factor in the sample of 0.346, this is a substantial reduction of 26%. As projects are further removed from CPIS, performance improves. Those in the second quintile, out to 1.5 miles away on average, have capacity factors only 0.044 lower (13% of the average). Beyond this, performance continues to improve and the third and fourth quintiles do not show any statistical distinctions from the fifth quintile. These general patterns hold for alternative binning of the distances by deciles and by miles (see figs. E2, E3).

We conduct our robustness checks comparing the two closest quintiles to the rest of the sample by creating an indicator variable equal to one if the average distance to CPIS of the turbines in the project is less than 1.5 miles. At that distance, these "close" projects have turbines that are at most one PLSS section removed from a center pivot on average. Shown in table 5, the result for lower capacity factors is robust across covariate selection. The effect ranges between 0.037 and 0.068 lower capacity factors and is always statistically significant. Additional robustness checks are provided in appendix E. The results are robust to looking at the "closer" wind projects (less than 0.6 miles, see table E2). The time period and use of panel data do not drive the result and are supported by cross-sectional versions (table E3) for each year and the overall average. The lower capacity factor is found in every individual year and with statistical significance other than in 2010, when few projects were yet sited close to CPIS. Results are also robust to using spatial HAC standard errors (Conley 2008; Hsiang 2010) (see table E4).

35. County-level fixed effects are not fruitful due to the relatively low number of counties with multiple projects. However, we do include an indicator equal to one for the small number of projects that span two different counties or two different states.

36. For point estimates in tabular form, see table E1. We also provide estimates for the decile version and 10 bins based on miles in that table.

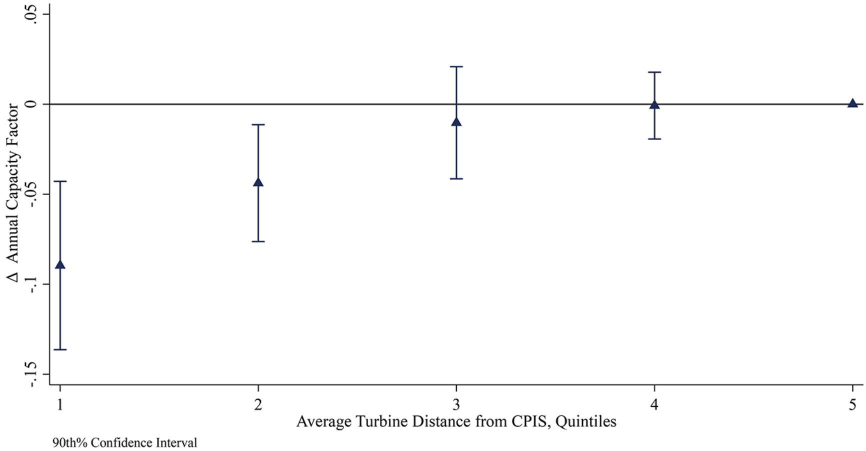

Figure 11. Capacity factor and proximity of wind projects to CPIS. This figure plots the coefficient estimates and 90th percentile confidence intervals for the effect of proximity to CPIS on annual capacity factor. Coefficients are from estimating equation (3) using quintile bins of average turbine-to-center-pivot distance. The reference group is the furthest bin (> 6.3 miles from CPIS). The tabular version of the results is available in table E1, column 1. Confidence intervals are based on robust standard errors clustered at an arbitrary 93 by 93 mile spatial grid.

For a final robustness check, we measure CPIS presence as a share of the convex hull of the turbines included in the wind project, but to capture the nearby CPIS, we add a 1.5 mile buffer to that area. This technique also allows us to bring in the share of irrigation, no matter the technology, as calculated from the MIrAD data with the same cautions from the section-level analysis pertaining to its spatial coarseness relative to the CPIS data. Presented in table E5, we again find that higher presence of CPIS lowers the capacity factor. Furthermore, the coefficient for irrigation by other means is half the size and statistically indistinguishable from zero. We also note that the CPIS estimate, while statistically distinct from zero, is not statistically distinguishable from other irrigation. To the extent that microclimate effects from irrigation are unrelated to the application technology being used, these results would imply that CPIS reduce capacity factors of wind projects through their influence on project layout and design constraints. However, whether the irrigation technology used influences the microclimate effect of irrigation has not been documented. Alternatively then, the findings here may be among the first evidence that technology utilized does have an influence and further investigation is warranted.

As a small step in that direction, we conduct ancillary analysis to probe for distinct properties of wind projects nearer CPIS. Details are provided in appendix E. As noted previously, turbines are far more likely to be in the corners of sections with CPIS than of those without CPIS, indicating that corners are not preferable locations but that

Table 5. Wind Project Capacity Factor (2010–20) and Distance from CPIS

	Capacity Factor										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1[avg dist < 1.5 miles]	−.0477*	−.0503**	−.0573***	−.0683***	−.0534***	−.0514***	−.0544***	−.0372*	−.0553***	−.0558***	−.0579***
	(.0253)	(.0225)	(.0210)	(.0198)	(.0177)	(.0162)	(.0188)	(.0207)	(.0182)	(.0191)	(.0193)
Observations	2,115	2,115	2,115	2,115	2,115	2,115	2,113	2,113	2,079	2,076	2,076
Adjusted R-squared	.030	.165	.203	.219	.239	.249	.244	.350	.484	.483	.551
Mean dependent variable	.347	.347	.347	.347	.347	.347	.347	.347	.346	.346	.346
Cropland share	x	x	x	x	x	x	x	x	x	x	x
Year fixed effects	x	x	x	x	x	x	x	x	x	x	x
Vintage year fixed effects		x	x	x	x	x	x	x	x	x	x
State fixed effects			x	x	x	x	x	x	x	x	x
Wind measures				x	x	x	x	x	x	x	x
Geographic controls					x	x	x	x	x	x	x
Development and forest shares						x					

State by year fixed effects							x			x	x
State by vintage year fixed effects								x			
Vintage year by year fixed effects									x	x	x
Wind project characteristics											x
Total no. fixed effects	11	33	46	46	46	46	132	111	179	266	266
SE clusters (93 miles^2)	44	44	44	44	44	44	44	44	44	44	44
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS

Note. This table presents the results of estimating eq. (3). Measures are at the wind project level for those with at least two turbines and within 62 miles of the Ogallala. The outcome is the capacity factor based off of annual electricity production and nameplate capacity. The reported coefficient is for an indicator variable equal to one if the wind project's turbine to center pivot distance averages less than 1.5 miles. Columns generally add more covariates as indicated, but we note that not all interacted fixed effects could be included at once due to the sample size. Column 10 is our preferred model. Robust standard errors, clustered by arbitrary spatial neighborhoods (93 miles squared), in parentheses.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

CPIS do compel their use. While placement of wind turbines in suboptimal patterns is the most obvious effect of CPIS, many other decisions are made simultaneously—number of turbines, height, swept area, capacity, and so forth—that can potentially compensate for the placement constraint. At the wind project level, we find some support that those closer to CPIS have fewer and smaller turbines, combining to have smaller aggregate generation capacities. But these results are sensitive to how we determine "closeness," and other wind project characteristic estimates are swamped by imprecision (table E6). The lack of any discernible pattern could be due to the jointness of these choices and that wind projects make different trade-offs. Turbine-level analysis does yield stronger statistical evidence that proximity to CPIS is associated with smaller turbines (see table E7). However, even controlling for these ex ante wind project choices does not account for the lower capacity factor of wind projects nearer CPIS ex post (col. 11 of table 5). There remains something about wind projects closer to CPIS that we are unable to explicitly measure and that contributes to lower capacity factors, giving credence to the notion that microclimate impacts of irrigation on the wind resource could be a relevant factor.

6. DISCUSSION

More irrigation in an area tends to reduce and delay installed wind generation capacity and lower electricity output. Using the semi-parametric regression results (col. 2, table D6) to predict the number of sections with turbines having removed all irrigation, we find that 472 additional sections would have turbines, or a 13% increase in the study region. This abstracts from capital constraints and general equilibrium effects among other things, meaning it is an upper bound that almost certainly overstates a true counterfactual. Furthermore, the thought exercise is extreme, removing all CPIS off of 50,000 sections in the region to net 472 more with wind turbines. If we instead consider targeting 472 sections to remove their CPIS and install wind turbines, we would reduce water withdrawals by an estimated 74,000 to 295,000 acre-feet, depending on how many quarter-section CPIS those sections operate.[37] This is between 0.8% and 3.3% of estimated annual withdrawals from the Ogallala.[38]

Beyond the effect on installed wind capacity, we can consider an alternative counterfactual in which the total installed capacity remains the same and we instead approximate

37. Determining the specific 472 sections to target is a complicated matter. The empirical model itself contains a lot of noise, and sections with the predicted highest probability are not necessarily those that are closest to the margin in practice. Furthermore, policies could target those closest to the margin, sections more ideal for wind projects or sections with higher water use, depending on the policy's goals.

38. Because most states do not collect or report on field-level water use, these numbers are based on Cooley et al. (2021) that apply the Kansas average of 161 acre-feet per year per center pivot across the Ogallala region. This likely underestimates use in drier, hotter regions and overestimates use in relatively wetter, cooler regions.

how much more electricity would be produced if we "moved" the existing wind projects to the third quintile distance from CPIS (3.1 miles away). We calculate that production would have been 5.9 million MWh higher in 2020. For context, this amounts to 5% of annual production for wind projects in the sample in 2020 and roughly 1.7% of all wind project production in the United States.[39] This lower capacity factor compounds the fact that wind turbines closer to CPIS also tend to have lower nameplate capacities.

Between the higher lost value of crop production and the lower electricity production, it is not clear which side of the market, those with the wind turbines or those with land, drives the equilibrium we observe. One expert in securing land rights for energy projects stated that their clients generally ask to avoid center pivot locations, explaining that corner placement can limit the height and size of the turbines to meet setback rules. This is consistent with our finding that turbines of smaller stature are associated with closeness to CPIS. We spoke to an engineer on a wind project in western Kansas, who reported not having an issue. In the data, this project, in fact, does not exhibit a lower capacity factor.[40] However, it is notable that the largest landowner involved in that project told the wind company not to worry about placing turbines within center pivot circles, reckoning that "with two turbines the most I lose is half a circle and the revenue from two turbines makes up for the smaller profit after switching to dry-land cropping."[41] In other words, the layout can be improved if the lost irrigation can be compensated for, but the potential for this will depend on the wind rents available to the landowner and the differential value between irrigated and nonirrigated agriculture in the specific region.

Finally, the results also speak to the importance of considering local farming practices in policy debates related to wind projects. For instance, the effect of setbacks is likely to be more severe in areas with CPIS in a nonlinear fashion that may quickly dissuade wind projects altogether. However, given that the Ogallala Aquifer is commonly characterized by overdraft due to its common-pool nature, efforts and policies could target more effective investment in wind generation capacity that also decreases aquifer use to create win-wins.

7. CONCLUSION

In addition to the relatively low local load demand and expense of constructing transmission lines, we have identified another factor that helps explain the slower development

39. Back-of-the-envelope calculations utilize estimates in col. 1 of table E1. The predicted capacity factor based on the estimates is converted to implied annual production and then compared to predictions having changed all wind projects in the first two quintile bins to the third quintile bin. The total US percentage is based on the EIA estimate of 338 million MWh from wind in 2020 (US EIA 2021).

40. This was assessed by looking at the residual capacity factor after controlling for the other covariates besides CPIS proximity.

41. Confidential conversation during interviews.

of the wind resources across the Great Plains: irrigation. Furthermore, irrigation technology in place matters. At the county level, irrigation by center pivot technology ameliorates the negative effect, likely through indirect channels such as smaller setbacks. At the section level, however, wind turbines are far less likely to be placed on sections with CPIS or sections surrounded by CPIS compared to nonirrigated or even flood irrigated land. Furthermore, the evidence suggests that wind projects nearer to CPIS produce less electricity on average. In other words, CPIS make siting turbines costlier, either in terms of lost food production or reduced electricity output. This means that future development of wind projects in the Great Plains may face increased costs and challenges given that the choice non-CPIS areas have already been developed.

Our findings invite additional research. For instance, while we present suggestive evidence for mechanisms that CPIS have a smaller effect than other irrigation at the county level, it is not conclusive, and more probing of these and other channels is warranted. We also do not identify a clear mechanism to explain our robust result that wind projects nearer to CPIS tend to produce less electricity. While our estimates are of a similar magnitude to the effect switching crops has on wind project output due to aerodynamic effects (e.g., 14% found by Vanderwende and Lundquist [2016]), little evidence as to irrigation's effect on wind patterns has been compiled (see Phillips et al. [2022] for a recent exception). Evidence here is among the first to suggest that there may be meaningful economic effects, but the lower electricity production may also stem from turbine placement constraints. A better understanding could emerge through more structural engineering models and simulations of wind projects. We also limited the scope of our study to how the preexisting use of water affects the development of wind projects, and we did not begin to address how wind projects subsequently affect land and water use. Finally, we have also focused on a particular pair of colocated resources in a certain region, meaning insights from other settings and resources are needed to better assess the generalizability of the findings.

Still, our results underscore how use of one natural resource at a given location and scale can shape and constrain the development of another resource at the same location. More nuanced is that the constraint is shaped by the technology in place. Given the potential trade-offs, an important question is which use of the land is more valuable; is society better off with a center pivot field or its conversion to better accommodate wind turbines? Nothing in this analysis spoke to this; rather it identified that trade-offs are present. Additional research is needed to assess whether the deterred investment in wind power is suboptimal, especially considering external effects, positive and negative, of wind projects.

On a larger spatial scale, it is not necessary to consider a dichotomous choice between CPIS and wind projects, and more effective contracting between parties could bring about the right spatial distribution and mix of both (Cheung 1973). Indeed, given the externalities of the shared Ogallala (Pfeiffer and Lin 2012) and resulting depletion (Konikow 2013), it seems likely that there are potential win-wins for irrigation and wind projects. Subsidizing alternative irrigation technology that is less physically constraining for turbines or using turbines and their associated royalty payments to help subsidize landowners to fallow fields could at once reduce the overuse of the aquifer and underuse of the wind. Thoughtful attention to policy and technological change could reduce the tension between wind and water on the Great Plains and elsewhere.

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