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1 Details of Technological Shock

1.1 Pre-existing Technology

Prior to the post-WWII irrigation technology shock, virtually no agricultural land in the Great Plains was irrigated. What little irrigation existed was typically based on surface irrigation from seasonal rivers and streams. As the 1920 Agricultural Census section on irrigation in Kansas put it: "On the High Plains there is ground water, but it occurs at such great depths that the cost of pumping is too great for a large use of water from wells. (p. 179)"

Agriculture west of the 100th meridian (most of the Great Plains), which is typically taken to divide arid from subhumid climates in the western United States, was typically unproductive and highly suceptible to droughts.[1] Subsequent Homestead Acts (of 1904 and 1909) following the original legislation enacted in 1862, revised the law to grant larger landholdings (640 acres, equivalent to a quarter-section in the Public Land Survey System) to farmers settling lands in the Great Plains, where it was recognized that 160 acres was too small to sustain family farms on sub-marginal land where only uproductive dryland farming was possible.

Episodic precipitation often brought bumper crops and waves of settlement, followed by prolonged multi-year droughts which resulted in mass farm failures and mass outmigration. This culminated in the Dust Bowl, the combination of prolonged drought, dust storms, and soil erosion that devastated agriculture in the region between 1930 and 1936 and resulted in mass outmigration to more agriculturally productive regions.[2]

The pre-existing technology for accessing groundwater was the windmill pump, which was typically limited to drawing water from a maximum of 30 feet under the ground. The per-acre foot cost did not justify the windmill's deployment in large-scale crop irrigation. As one scholar puts it: "the average windmill kit a farmer could buy from a local manufacturer cost $75 for an eight-foot mill, $100 for a ten-foot mill, and $135 for a twelve-foot mill. As costs declined, in 1909 a farmer could build his own reservoir and install two twelve-foot windmills with ten-inch pumps for $330...farmers learned regretfully that their costly $330 investment might at best water a total of eight acres...the inherent pumping limits of windmill technology were quickly reached and did little to aid the wheat farmer on his 640-acre section."'[3].

In the 1920s, new and improved pumping technologies emerged, but remained prohibitively expensive to provide large-scale crop irrigation. These included, for example, steam-powered centrifugal pumps. More cost-efficient electric irrigation pumps existed, but farmers typically lacked widespread access to electricity connections. In any case, by the time these technologies became available in the 1920s, farmers in the Great Plains were at the beginning of a 20-year depression in crop prices that made it uneconomical to employ either technology on a large scale for irrigation given their still exorbitant pumping costs.

[1] Seager, Richard, et al. "Whither the 100th meridian? The once and future physical and human geography of America's arid–humid divide. Part I: The story so far." Earth Interactions 22.5 (2018): 1-22.

[2] See e.g. Cook, Benjamin I., Ron L. Miller, and Richard Seager. "Dust and sea surface temperature forcing of the 1930s "Dust Bowl" drought." Geophysical Research Letters 35.8 (2008).; Gregory, James Noble. American exodus: the dust bowl migration and Okie culture in California. Oxford University Press, USA, 1991.

[3] Opie, John. Ogallala: Water for a Dry Land. University of Nebraska Press, 2000, p. 117

1.2 Image of Windmill Pump

FIGURE A1. Image of Windmill Pump

6. A homemade jumbo windmill, ca. 1890s. Many farmers could not afford $300 for a factory-made windmill, so they often worked from rough sketches they made after looking at a neighbor's jumbo. Frequently a windmill was made from scrap wood lying around in the farmyard. Courtesy of the Nebraska Historical Society, W765.32.

Notes: From Opie, John. Ogallala: Water for a Dry Land. University of Nebraska Press, 2000, p. 118. Please note that caption immediately beneath image is from the source cited.

1.3 Post-war Technology Shock

Post-WWII advances in groundwater pumping technology finally made it economical for the typical farmer to irrigate crops on a large scale. Improved petroleum-powered groundwater pumps based on the adaptation of used automobile engines originated in the late 1930s, but did not become widely available until commercialization and mass production, and diffusion through demonstration effects led to widespread uptake in areas overlying the Ogallala aquifer the 1950s. These new pumps were much more efficient in terms of per acre-foot cost than the pre-existing technology: "Compared to earlier operating expenses of about $6.00 per acre-foot, the 1938 irrigator could flood his field for $3.20 to $4.50, including installed well and equipment, interest and depreciation, and fuel and maintenance...Advances in technology would soon give the ordinary farmer access to irrigation, but it would be two more decades before it would be commonplace."[4]

The ability to draw from the Ogallala aquifer on a large scale led to a second problem – how to distribute this water efficiently across a typical 640-acre quarter-section farm. Flood and ditch irrigation systems were both costly to build, in terms of labor and materials, and were also water inefficient as they depended upon immersing fields in water in a context of loamy, permeable soils that are susceptible to rapid dissipation of moisture. A solution arrived in the form of center-pivot irrigation, a system for irrigating large circular fields with a rotating arm affixed with sprinklers. Designed initially to irrigate a 640-acre quarter-section (with a rotating arm about a quarter mile in length), over time center-pivot irrigation systems evolved in scale so that the largest units could irrigate an entire PLSS section (with a rotating arm about a half mile in length).

The main benefit of center-pivot irrigation was that it eliminated the need to build labor-intensive irrigation systems and was much more water efficient, providing water evenly across large circular fields at a rate that could be controlled by the farmer. Center-pivot irrigation was patented in 1952 by its inventor Frank Zybach and spread rapidly across the Great Plains from the 1950s and 1960s onward. The patent for center-pivot irrigation was purchased by Valmont in 1954, which played a major role in the commercialization, mass production and diffusion of the new technology across the Great Plains. In the state of Nebraska, much of which intersects with the Ogallala aquifer, a team of researchers utilizing manual counting of circular fields from Landsat satellite imagery found that the number of center-pivot irrigation systems in the state increased rapidly, from over 4000 in 1973 (when satellite images are first available) to nearly 10,000 in 1976.[5]

The spread of center-pivot irrigation supplied by petroluem-powered deepwell pumps transformed the Great Plains, resulting in the signature irrigated crop circles that are visible from space as well as the quasi-industrial revolution in agriculture that made the Great Plains one of the most agriculturally productive regions in the world. As one observer in the 1970s put it: "What is being observed is perhaps the most significant mechanical innovation in agriculture since the replacement of draft animals by the tractor."[6]

[4] Opie, John. Ogallala: Water for a Dry Land. University of Nebraska Press, 2000, p. 132

[5] Splinter, William E. "Center-pivot irrigation." Scientific American 234.6 (1976): 90-99.

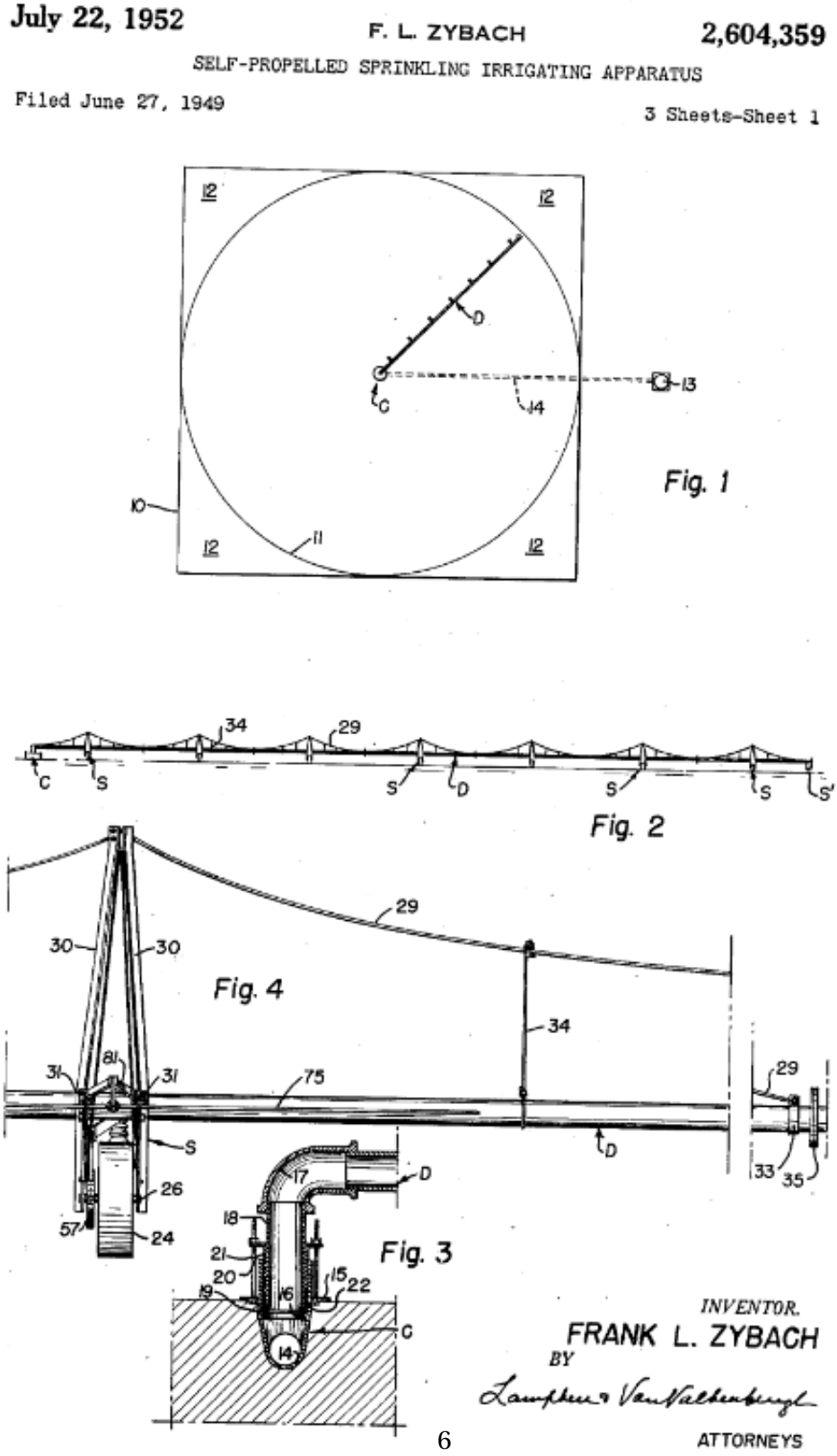
[6] Splinter, William E. "Center-pivot irrigation." Scientific American 234.6 (1976): 90.

FIGURE A2. Image of Petroleum-powered Pumps

9. A typical modern pumping system in southwestern Kansas. *Top*: Centrifugal pump using a rebuilt V-8 automobile engine fueled by natural gas, serving water to an open ditch for flood irrigation. *Bottom*: One of Keith Allen's commercial large-scale pumps and natural-gas engines used to flood his alternative-crop fields. Photos taken in 1988 by the author.

Notes: From Opie, John. Ogallala: Water for a Dry Land. University of Nebraska Press, 2000, p. 135. . Please note that caption immediately beneath image is from the source cited.

FIGURE A3. Image of 1952 Center-pivor Irrigation Patent



Notes: From patent for "Self-propelled Sprinkler Apparatus" (https://patents.google.com/patent/US2604359A/en).

2 Computer Vision Estimates of Center-pivot Irrigation

2.1 Processing Satellite Imagery in Google Earth Engine

Our goal is to count the area-normalized number of center-pivot irrigation systems in operation in all counties in the Great Plains states in each year between 1985 and 2000 (Landsat 5 satellite imagery becomes available from 1984 onwards). We exclude Texas, which does not use the Public Land Survey System (PLSS) from this exercise as well as Montana and North Dakota, which do not intersect with the Ogallala aquifer and are not a part of our empirical strategy. Our focus is therefore on measuring the density of center-pivot irrigation technology adoption for all counties in Oklahoma, New Mexico, Kansas, Colorado, Nebraska, Wyoming, and South Dakota between 1985 and 2000.

For each state-year, we compute a state-wide raster layer comprised of the normalized difference vegetation index (NDVI), which highlights areas of greenery and cropping. The NDVI is defined as (NIR - R) / (NIR + R), where NIR is Near Infrared surface reflectance values and R is Red surface reflectance values. In the case of Landsat 5, this is (Band 5 – Band 4) / (Band 5 + Band 4). We compute this index for each pixel by taking pixel-level median values computed from all cloud-free images of a given pixel taken between July and August in a given year. Some pixels are missing due to cloud cover. Computing and processing this satellite imagery required us to process and analyze terabytes of satellite imagery. All computations were performed on the cloud in Google Earth Engine (code available on request).

We clip these state-year raster files to the extent of individual PLSS sections, rescaling each to a 70×70 pixel image. Given Landsat 5 resolution (each pixel is 30 square meters) this is approximately the typical size in satellite imagery of a PLSS section, which is about 1 mile on a side (with deviation). Shapefiles of PLSS sections are obtained from the Bureau of Land Management. As part of our data pre-processing before we feed images to a convolutional neural network, we also re-scale the NDVI index to a measure that ranges between 0 (minimum possible value) and 1 (maximum possible value).

There are a total of $\approx 621{,}000$ PLSS sections in each of 16 years for which we have imagery or nearly 10 million images which we wish to make predictions about the number of center-pivot irrigation systems contained therein. Once we have these predictions, it is possible to aggregate up to the county level by counting all the center-pivot irrigation systems in PLSS sections contained within a county, and normalizing by total land area to get a measure of the number of center-pivots per 1000 square kilometers.

2.2 Ground Truth Annotations from the Nebraska Center-pivot Inventory

Manually counting center-pivot irrigation systems in nearly 10 million PLSS sections is beyond human ability. As a result, we turn to tools from computer vision to automate this process. We train a convolutional neural network (CNN) that takes as input the 70×70 pixel image of a PLSS section and as output makes a prediction of the number of center-pivot irrigation systems contained therein. CNNs are supervised learning algorithms and require labeled training data where the labels represent “ground truth" estimates of the count of center-pivot irrigation

systems in an image.

To obtain ground-truth labels, we utilize a geo-coded inventory of center-pivot irrigation systems that was compiled though hand counting of crop circles in Landsat satellite imagery by a team of researchers for the state of Nebraska.[7] The inventory consists of a spreadsheet of every center-pivot irrigation system observed manually in Landsat satellite imagery for each year between 1972 and 1987 with longitude and latitude coordinates.

Since geo-coding was performed by hand, there is some noise in the recorded coordinates (i.e. when coordinates are overlaid with accurately geo-referenced satellite imagery, they do not exactly correspond to center-pivot irrigation systems). This makes certain approaches to counting, for instance those based on dot-annotated density maps,[8] difficult to implement. However, it is possible to obtain highly accurate estimates of the number of center-pivot irrigation systems contained within aggregated spatial units, in our case PLSS sections.

A typical PLSS section contains between 0 and 4 center-pivot irrigation systems in predictable arrangements (see Figure A4 below). We use three years of ground truth annotations (1985-1987) overlapping with our years of interest to label the count of center-pivot irrigation systems in clipped satellite images of all PLSS sections in Nebraska, which comprises our training dataset (N≈220,000). We use a 80:20 training/testing split, stratified by county-year, where 80 percent of the data is used for traning and validation of the CNN model and 20 percent of the data is used to test the model's out-of-sample predictive performance. That is, we randomly sample 20% of all county-year pairs in Nebraska for the years 1985-1987 and allocate all images of PLSS sections taken in each of these county-year pairs to the test set and allocate the remaining images to the training set. There are 93 counties in Nebraska observed over three years or 279 county-year pairs; of these, 223 were allocated to the training set and 56 to the test set. This stratified construction of a test set permits us to measure the predictive of the algorithm at two levels: at the PLSS section and at the county-year level.

2.3 Model Architecture, Training, and Testing Accuracy

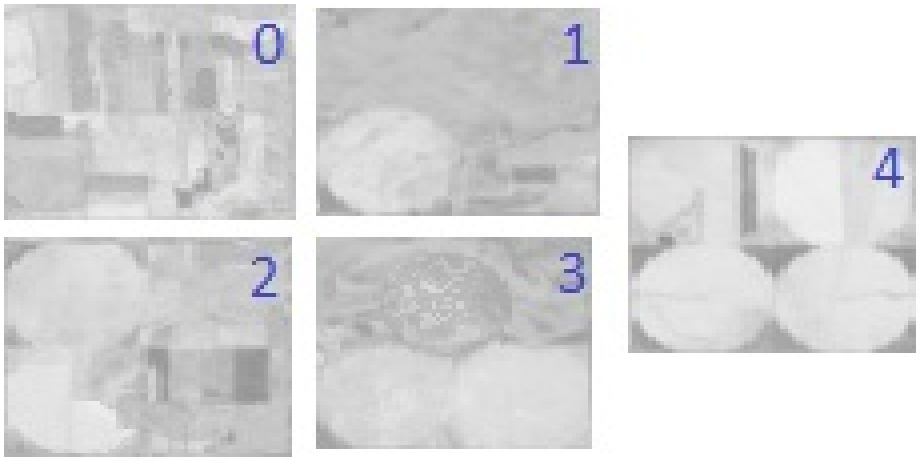
We utilize a modified version of the VGG16 network architecture to design our convolutional neural network.[9] We modify it in the following ways. First, we modify the input dimensions of the model so that it takes as input the $70 \times 70 \times 1$ dimension image (i.e. a 70 by 70 pixel image in a single color channel) of a PLSS section. Second, we replace the softmax activation layer with a linear activation layer so that as output the model make a continous regression estimate of the number of center-pivots in the image. Third, since we have a relatively focused task, we replace the two 4096 neuron dense layers at the bottom of the standard VGG16 network architecture with a much smaller single 128 neuron dense layer. This convolutional neural network model has a total of 14,975,937 trainable parameters.

[7] Carlson, Marvin P. "The Nebraska Center-Pivot Inventory: An example of operational satellite remote sensing on a long-term basis." Photogramm. Eng. Remote Sens 55 (1989): 587-590.

[8] Arteta, Carlos, Victor Lempitsky, and Andrew Zisserman. "Counting in the wild." European conference on computer vision. Springer, Cham, 2016.

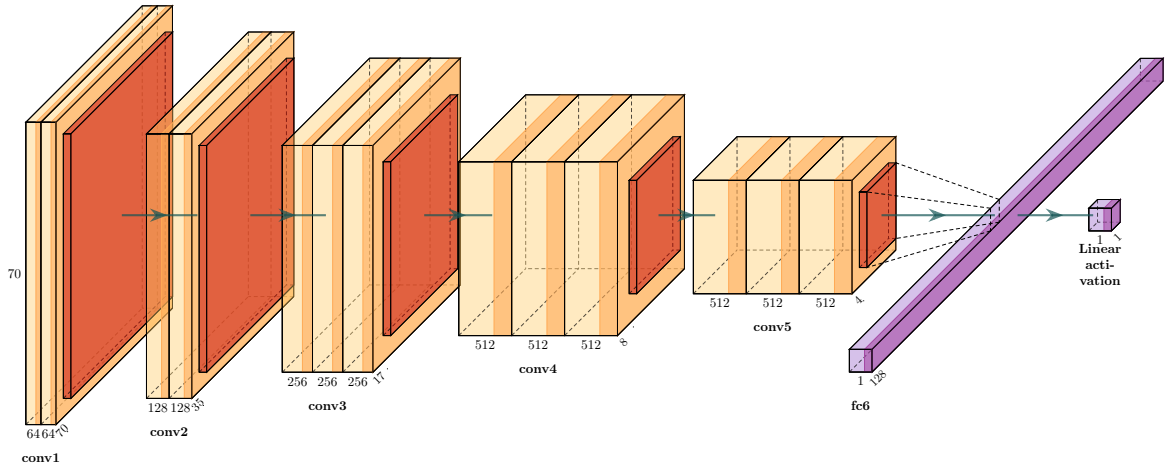
[9] Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." arXiv preprint arXiv:1409.1556 (2014).

FIGURE A4. Example of Labeled Training Data



Notes: Images represent examples of Landsat 5 satellite imagery (NDVI index) of PLSS sections from Nebraska with “ground truth" labels corresponding to the number of center-pivot irrigation systems in the image according to the Nebraska center-pivot inventory.

FIGURE A5. Visualization of CNN architecture



Notes: Image represents layers of convolutional neural network which takes as input a 70 by 70 pixel image of a PLSS section in a single channel and as output makes a linear regression estimate of the number of center-pivot irrigation systems in the image. Our approach treats counting center-pivot irrigation systems as a regression problem, requiring as labels only the total number of objects per training image.

Our general approach is in the spirit of “learning to count" objects in images with deep neural networks without object localization, in which counting is treated as a regression problem, requiring as labels only the total number of objects per training image. Similar approaches have

been taken to counting objects ranging from fruits and leaves to animals in imagery.[10] While there may be some degree of idisyncratic error in the predictions in the case of individual PLSS sections, as we aggregate to the county-year level, much of this prediction error 'cancels out' (in the sense that the variance of the sum of at least partially uncorrelated random variables is less than the sum of their variances). This is also why we opt for a linear activation layer that makes a continuous estimate of the number of center-pivots in supplied images rather than softmax classification of the image into whole integer categories. Numerical over- and under-predictions relative to an integer-valued target label contain useful information about classification ambiguity that improves overall predictive power when we aggregate up to the county-year level.

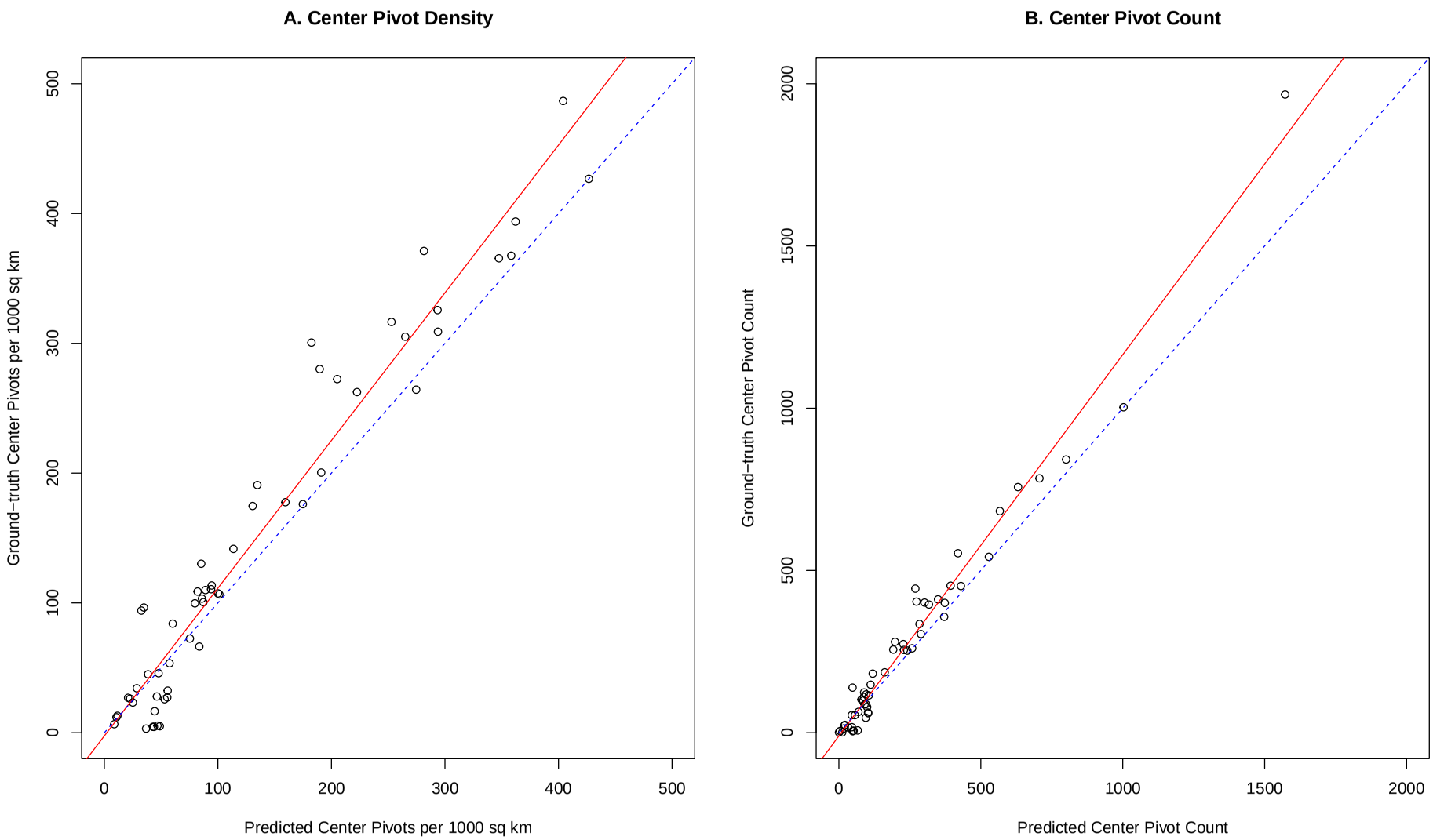
In terms of a loss function, we minimize the mean squared error (MSE) of predictions. The model was trained on the Nebraska training data for a total of 10 epochs using a the Root Mean Squared Propagation (RMSprop) optimizer and a learning rate of 1e-4. Training was implemented in the *keras* package in R which uses TensorFlow in Python as a backend. In test data for the state of Nebraska 1985-87, when "ground truth" labels were regressed on predicted counts in PLSS sections in Nebraska, the coefficient on the predicted count variable was 0.98 and the R^2 was 0.73. This implies a high level of accuracy at the PLSS section level. But accuracy is even better when counts are aggregated to the county-year level and the idiosyncratic prediction error in PLSS section counts cancel each other out as we aggregate to higher levels.

Using the trained model, we can make predictions for a massive number of PLSS sections (approximately 10 million) across all of the Great Plains states for each year between 1985 and 2000. We then aggregate up to the county level and divide by total county land area (omitting PLSS sections missing predictions due to cloud cover) to get a panel dataset on center-pivot irrigation density (center-pivots/1000 sq kilometers) at the county-year level. We achieve near-human predictive accuracy at this level. When we regress ground-truth measures (based on manual counts from the Nebraska center-pivot inventory) of center-pivot irrigation density for the 56 county-year pairs in Nebraska that were allocated to the test set to our computer vision estimates of center-pivot irigation density, the coefficient on the predicted density variable is 1.1 and and the R^2 is 0.94. The accuracy of our computer vision estimates is even higher (R^2 = 0.98) when we predict total center-pivots (see Figure A6).

Below we provide images of predicted center-pivot irrigation counts at the PLSS section and county level for Oklahoma, New Mexico, Kansas, Colorado, Nebraska, Wyoming, and South Dakota between 1985 and 2000. Figure A7 provides a map of counties shaded by the quartile of center-pivots per 1000 square kilometers averaged between 1985 and 2000. As the map illustrates, center-pivot irrigation was overwhelmingly concentrated within the boundaries of the Ogallala aquifer.

[10] Rahnemoonfar, Maryam, and Clay Sheppard. "Deep count: fruit counting based on deep simulated learning." Sensors 17.4 (2017): 905; Hoekendijk, Jeroen, et al. "Counting using deep learning regression gives value to ecological surveys." Nature scientific reports 11.1 (2021): 1-12.

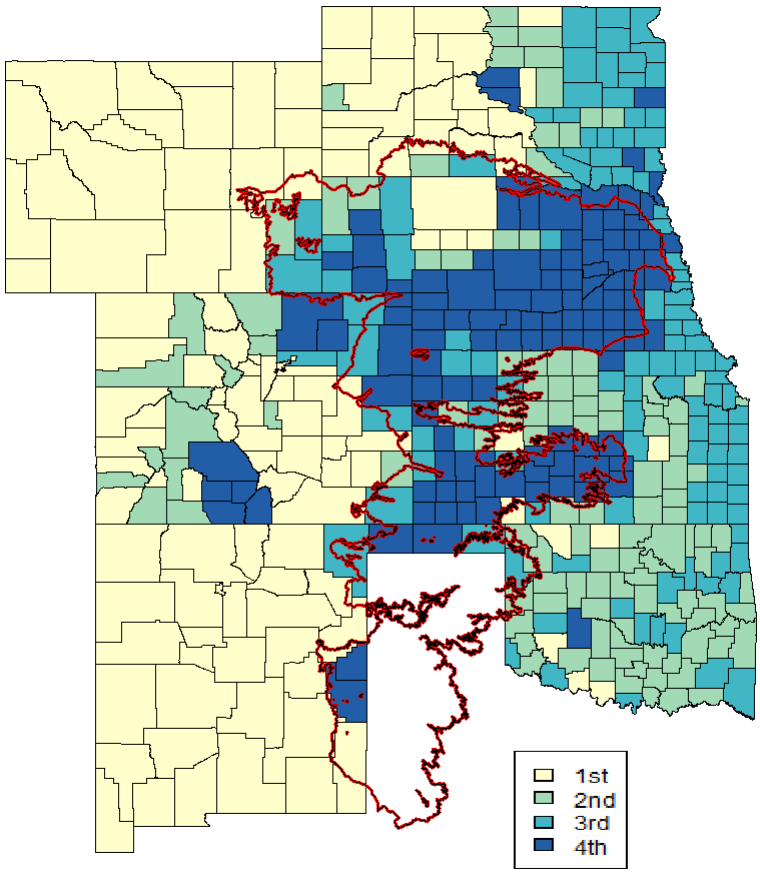
FIGURE A6. Accuracy of Computer Vision Estimates of Technology Adoption at County Level



Notes: Points represent test-set county-year observations from Nebraska for which we can compare “ground truth" estimates of center-pivot irrigation (based on manual counts from the Nebraska center-pivot inventory) against computer vision estimates of technology adoption. Estimates contructed by using trained CNN to count the number of center-pivots in every PLSS section image in a given county-year and then aggregating these counts to the county level. Red line represents fitted regression line. Dashed blue line represents x=y diagonal. Adjusted R^2 in panel A (where the measure is center-pivots per 1000 sq km) is 0.94. Adjusted R^2 in panel B (where the measure is total center-pivot count) is 0.98.

2.4 State-by-State Center-pivot Counts

FIGURE A7. County Estimates Across Great plains



Notes: Map depicts county-level quartile of center-pivots per 1000 sq km averaged between 1985-2000. Note that Texas is excluded because it does not use the PLSS system. Red polygon is Ogallala aquifer boundary.

3 Notes on GIS Analysis

3.1 Source of Shapefiles

To measure county boundaries, we utilize shapefiles published by the IPUMS National Historical Geographical Information System (NHGIS).[11] NHGIS provides decennial shapefiles of county boundaries. These files contain polygons representing county boundaries at 10-year intervals corresponding to population censuses.

To measure the boundaries of the Ogallala aquifer, we utilize a shapefile produced by the US Geological Survey.[12]. This shapefile contains a polygon representing the boundaries of the Ogallala aquifer, as synthesized from a range of historical and local geological surveys.[13]

3.2 Software and Packages Used in GIS Analysis

All GIS and spatial analyses are performed in the R programming language. The *rgdal* package is used to load, store, and project shapefiles into a coordinate reference system (WGS84 is used throughout).

The package *rgeos*, which provides an R interface to GEOS (an open-source C package for analyzing spatial geometries), is used to perform spatial operations, including computation of county centroids and the intersection county and aquifer boundaries in order to compute the degree to which a county overlaps with the Ogallala aquifer.

The packages *geosphere* is used to measure spatial distances and areas. This package is used to compute the geodesic distance of county centroids from the Ogallala aquifer boundary in each state as well as to compute the share of each county's surface area that overlies the Ogallala aquifer.

3.3 Defining Stable County Boundaries

To identify counties that possessed "stable" boundaries between 1920 and 2000, we compute polygons representing the union and intersection of the boundary of a given county (identified by name and ICPSR code) in 1920 and in 2000. If the county exists in both years and the intersection is at least 99 percent of the union in terms of land area, it is considered to have stable boundaries over this time period (and not if either condition is not satisfied).

[11] https://www.nhgis.org/

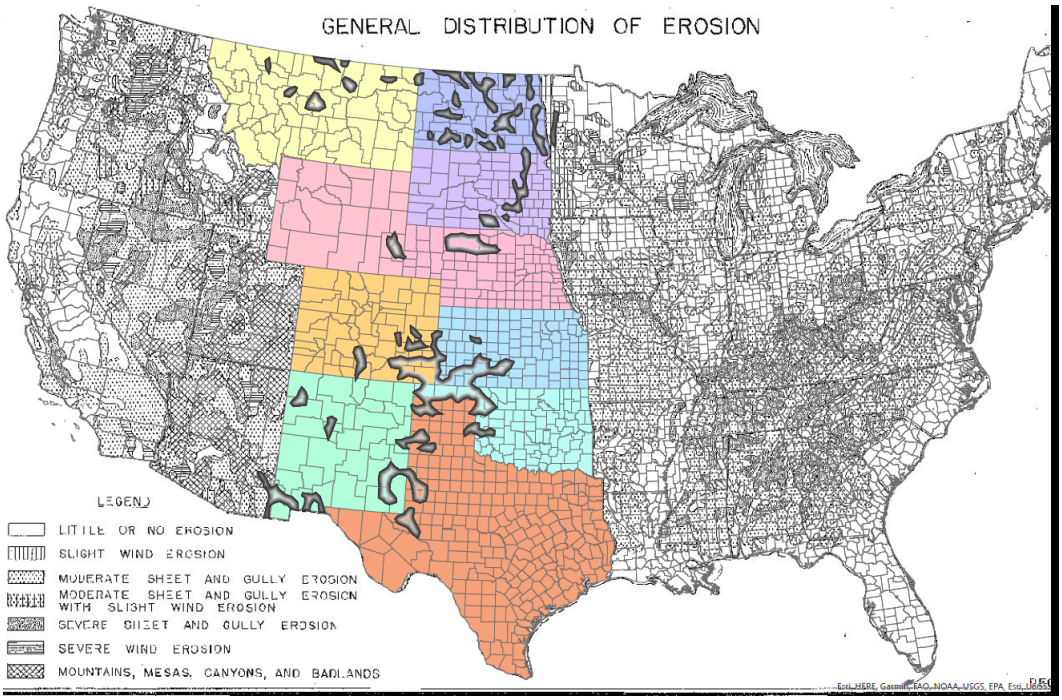
[12] Qi, Sharon. Digital Map of Aquifer Boundary for the High Plains Aquifer in Parts of Colorado, Kansas, Nebraska, New Mexico, Oklahoma, South Dakota, Texas, and Wyoming. No. 543. US Geological Survey, 2010

[13] For details, see: https://water.usgs.gov/GIS/metadata/usgswrd/XML/ds543.xml

4 Additional Data Description

4.1 Soil Conservation Service Map

FIGURE A8. Exposure to Dust Bowl Computed from Soil Erosion Map



Notes: Map represents Soil Conservation Service's estimates of areas exposed to different degrees of soil erosion by 1937. Exposure to the Dust Bowl is defined as the share of county land exposed to severe wind erosion based on geo-referenced map. This map was geo-referenced in ArcGIS and polygons were manually constructed to represent areas of "severe wind erosion" in the Great Plains states. The measure of exposure to the Dust Bowl is the share of county land that was exposed to severe wind erosion according to this measure. For comparable analyses, see: Hornbeck, Richard. "The enduring impact of the American Dust Bowl: Short-and long-run adjustments to environmental catastrophe." American Economic Review 102.4 (2012): 1477-1507. Source: National Archives.

4.2 Descriptive Statistics

TABLE A1. Decadal Averages of Major Variables in Full Sample

	Presidential Vote Share	Senatorial Vote Share	Gubernatorial Vote Share	Irrigation Farmland %	Farm Value $1000s	Farms Density #/1000 Acres	Agricultural Employment %	Population Density People/1000 Acres	Urbanization Urban %	Religiosity Members per Capita
FUL SAMPLE										
1920s	0.53	0.47	0.41	1.77	244.16	3.04	–	32.84	13.94	0.34
1930s	0.28	0.36	0.34	1.69	215.55	3.24	51.12	37.23	17.36	0.34
1940s	0.41	0.39	0.38	0.81	184.28	2.71	46.53	38.25	20.62	–
1950s	0.60	0.42	0.36	2.72	–	2.02	36.87	41.63	27.81	0.49
1960s	0.51	0.51	0.42	4.02	868.52	1.52	26.80	48.60	32.58	–
1970s	0.60	0.49	0.43	5.51	1530.75	1.28	18.95	54.68	35.27	0.34
1980s	0.63	0.53	0.51	5.60	1249.43	1.27	16.02	64.84	36.33	0.39
1990s	0.60	0.60	0.56	6.17	917.60	1.20	12.65	79.25	36.19	0.37
200 KM SAMPLE										
1920s	0.59	0.53	0.46	1.06	300.52	2.35	–	24.26	12.18	0.32
1930s	0.33	0.43	0.41	1.23	266.54	2.56	50.56	28.12	16.06	0.34
1940s	0.47	0.47	0.47	0.60	217.50	2.18	46.75	27.31	18.97	–
1950s	0.64	0.49	0.44	2.98	–	1.76	39.26	29.52	25.20	0.49
1960s	0.56	0.56	0.47	4.97	960.81	1.36	30.40	33.92	29.85	–
1970s	0.62	0.53	0.46	7.01	1687.97	1.15	22.84	36.53	31.87	0.37
1980s	0.67	0.57	0.54	7.23	1356.80	1.06	20.00	40.80	33.32	0.43
1990s	0.64	0.63	0.58	8.02	1001.27	0.95	15.67	45.33	33.27	0.40
100 KM SAMPLE										
1920s	0.59	0.52	0.46	0.71	300.42	2.26	–	22.60	11.09	0.32
1930s	0.32	0.42	0.40	0.95	274.98	2.47	51.88	26.29	15.30	0.35
1940s	0.47	0.46	0.47	0.47	212.60	2.10	47.83	25.34	18.19	–
1950s	0.64	0.49	0.43	3.52	–	1.73	39.89	27.37	24.35	0.49
1960s	0.56	0.56	0.47	6.18	957.43	1.35	31.43	31.58	29.26	–
1970s	0.63	0.53	0.46	8.87	1700.78	1.15	24.11	33.22	31.28	0.39
1980s	0.68	0.57	0.55	9.00	1347.11	1.06	21.35	36.25	32.17	0.46
1990s	0.66	0.64	0.59	10.08	1013.83	0.93	16.75	39.86	32.29	0.42

Notes: Data represent decadal averages for full sample of data (all counties with stable boundaries between 1920 and 2000 in Texas, Oklahoma, New Mexico, Kansas, Colorado, Nebraska, South Dakota, Wyoming). Vote share variables are the Republican party's county-level share of the two-party vote in presidential, senatorial, or gubernatorial elections. Irrigation is average percentage of farmland that is irrigated as computed from agricultural censuses conducted in 1920, 1925, 1930, 1935, 1940, 1945, 1950, 1954, 1959, 1964, 1969, 1974, 1978, 1982, 1987, 1992, and 1997. Farm value is inflation-adjusted average market value of farm land, machinery and buildings in 2016 dollars (source: agricultural censuses). Farm density is the number of farms per 1000 acres of county land (source: agricultural censuses). Population density is the number of people per 1000 acres of county land (source: decennial population censuses). Urbanization is the percentage of the county population living in census-defined urban areas (source: decennial population censuses). Agricultural employment is the percentage of workforce employed in agriculture (source: decennial population censuses). Religiosity is church membership per capita (data from the US Census of Religion Bodies conducted in 1926, 1936; the survey of Churches and Church Membership conducted by the National Council of Churches in 1952, 1971, 1980 and 1990.

5 Full Tables for Selected Tables and Figures in Main Paper

5.1 Full Results for Table 1 in Main Paper

TABLE A2. Impact of Technological Shock on Conservative Voting: Panel A (Full Sample)

	Republican Share of Two-party Vote											
	Baseline			Reweighted			Time-interacted Covariates			Pure Treatment/Control		
	President	Senator	Governor	President	Senator	Governor	President	Senator	Governor	President	Senator	Governor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Aquifer	0.007	0.003	0.012	0.005	0.001	0.013	0.013	0.009	0.010	0.005	0.007	0.015
	(0.015)	(0.013)	(0.012)	(0.020)	(0.017)	(0.020)	(0.013)	(0.014)	(0.012)	(0.018)	(0.010)	(0.009)
Aquifer×Post-shock	0.117***	0.103***	0.086***	0.115***	0.104***	0.079**	0.087***	0.073***	0.058***	0.122***	0.100***	0.088***
	(0.022)	(0.022)	(0.015)	(0.031)	(0.028)	(0.027)	(0.018)	(0.019)	(0.014)	(0.022)	(0.020)	(0.012)
Erosion							−0.003	−0.0001	−0.001			
							(0.010)	(0.006)	(0.010)			
Erosion×Post-shock							0.015	0.025	0.028			
							(0.021)	(0.018)	(0.018)			
New Deal							−0.00005**	−0.00003	−0.00000			
							(0.00002)	(0.00003)	(0.00003)			
New Deal×Post-shock							0.0001***	0.0001**	0.00004			
							(0.00003)	(0.00003)	(0.00003)			
Residential stability							0.105**	0.132**	0.099			
							(0.048)	(0.055)	(0.057)			
Residential stability×Post-shock							−0.003	−0.102	−0.066			
							(0.069)	(0.070)	(0.068)			
Droughts							−0.009	0.013	0.020			
							(0.060)	(0.037)	(0.042)			
Droughts×Post-shock							−0.034	−0.114	−0.038			
							(0.137)	(0.122)	(0.114)			
White							0.209***	0.077***	0.105***			
							(0.050)	(0.024)	(0.022)			
White×Post-shock							−0.021	0.083	0.075			
							(0.108)	(0.080)	(0.074)			
WW2							0.00000	0.00000	0.00000			
							(0.00000)	(0.00000)	(0.00000)			
WW2×Post-shock							0.00000	0.00000	0.00000			
							(0.00000)	(0.00001)	(0.00000)			
Observations	1,350	1,350	1,350	1,350	1,350	1,350	1,336	1,336	1,336	1,072	1,072	1,072
Adjusted R^2	0.774	0.857	0.815	0.710	0.809	0.773	0.785	0.862	0.821	0.765	0.855	0.816

Notes: Unit of analysis is county-period average (pre-period is 1920-1940 and post-period is 1980-2000). Republican Vote is the Republican party's share of the two-party vote in presidential, senatorial, or gubernatorial elections, depending on specification. Aquifer is a cross-sectional measure of the share of county land overlying Ogallala aquifer. Post-shock is a time dummy variable taking a value of one for the post-shock period and zero otherwise. Control variables are per capita New Deal spending and share of county land exposed to severe wind erosion during the Dust Bowl, interacted with time. Analysis estimated by OLS. Standard errors adjusted for clustering by county and state-period reported in parentheses: *p<0.1; **p<0.05; ***p<0.01. Conley standard errors adjusted for serial correlation and spatial correlation within a 200km radius of county centroids reported in brackets.

TABLE A3. Impact of Technological Shock on Conservative Voting: Panel B (200km sample)

	Republican Share of Two-party Vote											
	Baseline			Reweighted			Time-interacted Covariates			Pure Treatment/Control		
	President	Senator	Governor	President	Senator	Governor	President	Senator	Governor	President	Senator	Governor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Aquifer	0.006	0.007	0.014	0.001	0.004	0.011	0.014	0.013	0.012	0.003	0.010	0.018
	(0.019)	(0.015)	(0.015)	(0.021)	(0.017)	(0.018)	(0.016)	(0.016)	(0.015)	(0.023)	(0.013)	(0.014)
Aquifer×Post-shock	0.097***	0.078***	0.064***	0.091***	0.073**	0.058**	0.072***	0.056**	0.047**	0.108***	0.081***	0.067***
	(0.024)	(0.021)	(0.017)	(0.030)	(0.026)	(0.023)	(0.020)	(0.020)	(0.017)	(0.025)	(0.020)	(0.014)
Erosion							−0.007	−0.007	−0.007			
							(0.012)	(0.011)	(0.011)			
Erosion×Post-shock							0.015	0.030	0.030			
							(0.018)	(0.017)	(0.018)			
New Deal							−0.00002	−0.00001	0.00003*			
							(0.00002)	(0.00003)	(0.00002)			
New Deal×Post-shock							0.0001**	0.0001	0.00001			
							(0.00003)	(0.00004)	(0.00004)			
Residential stability							0.081	0.079	0.047			
							(0.058)	(0.063)	(0.069)			
Residential stability×Post-shock							−0.061	−0.104	−0.097			
							(0.087)	(0.085)	(0.096)			
Droughts							−0.009	0.012	0.005			
							(0.078)	(0.047)	(0.058)			
Droughts×Post-shock							−0.056	−0.152	−0.065			
							(0.133)	(0.127)	(0.130)			
White							0.198**	0.085	0.102			
							(0.079)	(0.068)	(0.064)			
White×Post-shock							0.361***	0.371***	0.386***			
							(0.083)	(0.079)	(0.082)			
WW2							0.00000	0.00000	0.00000			
							(0.00000)	(0.00000)	(0.00000)			
WW2×Post-shock							−0.00000	0.00000	0.00000			
							(0.00001)	(0.00000)	(0.00001)			
Observations	826	826	826	826	826	826	826	826	826	548	548	548
Adjusted R^2	0.788	0.861	0.806	0.701	0.793	0.732	0.803	0.870	0.817	0.780	0.859	0.807

Notes: Unit of analysis is county-period average (pre-period is 1920-1940 and post-period is 1980-2000). Republican Vote is the Republican party's share of the two-party vote in presidential, senatorial, or gubernatorial elections, depending on specification. Aquifer is a cross-sectional measure of the share of county land overlying Ogallala aquifer. Post-shock is a time dummy variable taking a value of one for the post-shock period and zero otherwise. Control variables are per capita New Deal spending and share of county land exposed to severe wind erosion during the Dust Bowl, interacted with time. Analysis estimated by OLS. Standard errors adjusted for clustering by county and state-period reported in parentheses: *p<0.1; **p<0.05; ***p<0.01. Conley standard errors adjusted for serial correlation and spatial correlation within a 200km radius of county centroids reported in brackets.

TABLE A4. Impact of Technological Shock on Conservative Voting: Panel C (100km sample)

	Republican Share of Two-party Vote											
	Baseline			Reweighted			Time-interacted Covariates			Pure Treatment/Control		
	President	Senator	Governor	President	Senator	Governor	President	Senator	Governor	President	Senator	Governor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Aquifer	0.017	0.019	0.024	0.014	0.016	0.023	0.019	0.017	0.017	0.015	0.022	0.029
	(0.019)	(0.014)	(0.016)	(0.018)	(0.015)	(0.016)	(0.016)	(0.015)	(0.015)	(0.024)	(0.014)	(0.016)
Aquifer×Post-shock	0.072**	0.055**	0.042**	0.070**	0.053**	0.042*	0.055**	0.041**	0.032*	0.082**	0.057**	0.042**
	(0.025)	(0.021)	(0.018)	(0.027)	(0.023)	(0.020)	(0.020)	(0.019)	(0.018)	(0.029)	(0.023)	(0.017)
Erosion							−0.005	−0.006	−0.007			
							(0.012)	(0.013)	(0.012)			
Erosion×Post-shock							0.021	0.036*	0.037*			
							(0.017)	(0.019)	(0.020)			
New Deal							−0.00001	0.00001	0.00005*			
							(0.00002)	(0.00004)	(0.00002)			
New Deal×Post-shock							0.0001*	0.00002	−0.00001			
							(0.00003)	(0.00005)	(0.00004)			
Residential stability							0.060	0.049	0.023			
							(0.047)	(0.047)	(0.055)			
Residential stability×Post-shock							−0.037	−0.081	−0.078			
							(0.068)	(0.072)	(0.084)			
Droughts							0.028	0.032	0.022			
							(0.081)	(0.050)	(0.068)			
Droughts×Post-shock							−0.013	−0.100	−0.041			
							(0.124)	(0.140)	(0.143)			
White							0.211***	0.145**	0.120**			
							(0.067)	(0.065)	(0.050)			
White×Post-shock							0.435***	0.377***	0.379***			
							(0.078)	(0.075)	(0.074)			
WW2							−0.00001	−0.00001	−0.00001			
							(0.00001)	(0.00001)	(0.00001)			
WW2×Post-shoc							0.00001	0.00001	0.00001			
							(0.00001)	(0.00001)	(0.00001)			
Observations	562	562	562	562	562	562	562	562	562	284	284	284
Adjusted R^2	0.821	0.880	0.829	0.789	0.858	0.802	0.841	0.891	0.843	0.819	0.884	0.839

Notes: Unit of analysis is county-period average (pre-period is 1920-1940 and post-period is 1980-2000). Republican Vote is the Republican party's share of the two-party vote in presidential, senatorial, or gubernatorial elections, depending on specification. Aquifer is a cross-sectional measure of the share of county land overlying Ogallala aquifer. Post-shock is a time dummy variable taking a value of one for the post-shock period and zero otherwise. Control variables are per capita New Deal spending and share of county land exposed to severe wind erosion during the Dust Bowl, interacted with time. Analysis estimated by OLS. Standard errors adjusted for clustering by county and state-period reported in parentheses: *p<0.1; **p<0.05; ***p<0.01. Conley standard errors adjusted for serial correlation and spatial correlation within a 200km radius of county centroids reported in brackets.

5.2 Table Version of Figure 6 in Main Paper

TABLE A5. Pre- and Post-technological Shock Trends

	Dependent variable:			
	President (Republican share)	Senator (Republican share)	Governor (Republican share)	Irrigation (% Farmland)
Aquifer×1910s	0.010	0.005	−0.004	−1.230
	(0.014)	(0.014)	(0.014)	(1.673)
Aquifer×1920s	0.037***	0.011	−0.008	−0.060
	(0.008)	(0.015)	(0.014)	(1.314)
Aquifer×1940s	0.032***	0.002	−0.014	0.488
	(0.009)	(0.013)	(0.011)	(1.316)
Aquifer×1950s	0.049***	0.022	−0.014	6.286***
	(0.012)	(0.014)	(0.012)	(1.847)
Aquifer×1960s	0.070***	0.046***	0.015	11.279***
	(0.015)	(0.016)	(0.015)	(2.154)
Aquifer×1970s	0.048***	0.042***	0.015	15.658***
	(0.012)	(0.015)	(0.019)	(1.844)
Aquifer×1980s	0.082***	0.055***	0.034*	14.991***
	(0.014)	(0.016)	(0.019)	(1.765)
Aquifer×1990s	0.107***	0.068***	0.042**	16.338***
	(0.016)	(0.016)	(0.017)	(1.811)
State-year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Sample	100-km	100-km	100-km	100-km
Observations	6,438	8,824	10,122	5,050
Adjusted R^2	0.920	0.885	0.910	0.720

Notes: Unit of analysis is county-year (election year in the case of electoral outcomes and agricultural census year in the case of irrigation). Coefficients represent decadal relationship between aquifer coverage and outcome relative to relationship existing in 1930s (which is left out as reference category). Analysis estimated by OLS. Standard errors adjusted for clustering by county and state-year reported in parentheses.

5.3 Table Version of Figure 7 in Main Paper

TABLE A6. Potential Channels (Table Version of Figure 7 in Main Paper)

	Dependent variable:									
	Machinery Per Farm $	Log Average Farm Value	Farms per 1000 Acre	Agricultural Employment %	Crop Production Per Farm $	Livestock Per Farm	Population Density	Urbanization Rate	Religosity	White Share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Aquifer×1910s	−8,673.277	−0.131	−0.292		−4,824.334***	30.183	0.454	−0.171		
	(8,819.765)	(0.253)	(0.183)	(0.000)	(1,747.929)	(26.842)	(2.746)	(1.072)	(0.000)	(0.000)
Aquifer×1920s	−6,792.439	0.036	−0.108		6,917.297***	10.752	−0.186	0.824	−0.014	
	(6,777.719)	(0.158)	(0.139)	(0.000)	(2,296.122)	(13.972)	(2.103)	(1.043)	(0.032)	(0.000)
Aquifer×1940s	−1,904.120	−0.095**	0.133	−0.703*	3,973.136	11.021	0.461	−1.307***		−0.003
	(6,351.129)	(0.042)	(0.157)	(0.369)	(5,558.204)	(12.080)	(1.078)	(0.375)	(0.000)	(0.005)
Aquifer×1950s		0.289***	0.451***	−0.787**	50,348.110***	17.000	0.698**	1.594	−0.006	−0.002
	(0.000)	(0.070)	(0.154)	(0.273)	(12,926.990)	(13.130)	(0.236)	(1.022)	(0.025)	(0.006)
Aquifer×1960s	32,850.730***	0.318***	0.715***	1.375*	52,584.400***	31.829**	−1.956	0.095		0.002
	(6,649.863)	(0.070)	(0.152)	(0.613)	(15,773.530)	(14.943)	(2.786)	(1.827)	(0.000)	(0.007)
Aquifer×1970s	85,493.670***	0.223***	0.823***	0.217	120,115.200***	60.808***	−5.212	2.402	0.017	0.009
	(11,841.440)	(0.068)	(0.172)	(0.776)	(24,484.850)	(17.162)	(5.342)	(2.114)	(0.027)	(0.009)
Aquifer×1980s	65,625.160***	0.179*	0.866***	0.322	72,368.160***	88.997***	−8.307	5.186*	0.043	−0.010
	(8,630.330)	(0.099)	(0.188)	(1.024)	(13,605.250)	(18.453)	(6.728)	(2.326)	(0.031)	(0.009)
Aquifer×1990s	62,659.690***	0.133	0.917***	0.823	80,350.130***	135.978***	−15.492	6.276**	0.027	−0.022
	(8,324.530)	(0.087)	(0.202)	(1.238)	(15,153.900)	(23.251)	(9.349)	(2.509)	(0.030)	(0.013)
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	100-km	100-km	100-km	100-km	100-km	100-km	100-km	100-km	100-km	100-km
Observations	3,644	3,926	4,769	2,248	4,142	4,657	2,800	2,796	1,672	2,248
Adjusted R^2	0.842	0.959	0.587	0.468	0.507	0.287	0.004	0.089	0.333	0.406

Notes: Unit of analysis is county-year (agricultural, population or religious census year depending on outcome). Note that 1930s left out as reference category. Machinery is market value of machinery. Average farm value is market value of farm land and buildings. Farm density is the number of farms per 1000 acres of county land. Agricultural employment is the percentage of workforce employed in farms. Crop production per farm is total value of crop production divided by number of farms. Livestock is total number of cattle and pigs divided by number of farms. All dolar amounts adjusted for inflation to 2016 dollars. Population density is the number of people per 1000 acres of county land. Urbanization is the percentage of the county population living in census-defined urban areas. Religiosity is church membership per capita. Data from the US Census of Religion Bodies conducted in 1926, 1936; the survey of Churches and Church Membership conducted by the National Council of Churches in 1952, 1971, 1980 and 1990. White Share is white share of population. Analysis estimated by OLS. Standard errors adjusted for clustering by county and state-year.

6 Additional Results

6.1 Main Results with County Fixed Effects

TABLE A7. Impact of Technological Shock on Conservative Voting (County Fixed Effects)

	Republican Share of Two-party Vote								
	Baseline			Time-interacted Covariates			Pure Treatment/Control		
	President	Senator	Governor	President	Senator	Governor	President	Senator	Governor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Full Sample									
Aquifer×Post-shock	0.117***	0.103***	0.086***	0.087***	0.073***	0.058***	0.122***	0.100***	0.088***
	(0.013)	(0.017)	(0.012)	(0.012)	(0.015)	(0.012)	(0.013)	(0.015)	(0.013)
Observations	1,350	1,350	1,350	1,336	1,336	1,336	1,072	1,072	1,072
Adjusted R^2	0.850	0.897	0.871	0.852	0.901	0.873	0.849	0.900	0.880
Panel B: 200km Sample									
Aquifer×Post-shock	0.097***	0.078***	0.064***	0.072***	0.056***	0.047***	0.108***	0.081***	0.067***
	(0.012)	(0.012)	(0.014)	(0.012)	(0.013)	(0.014)	(0.013)	(0.010)	(0.014)
Observations	826	826	826	826	826	826	548	548	548
Adjusted R^2	0.855	0.893	0.850	0.862	0.903	0.859	0.858	0.896	0.870
Panel C: 100km Sample									
Aquifer×Post-shock	0.072***	0.055***	0.042***	0.055***	0.041***	0.032**	0.082***	0.057***	0.042***
	(0.012)	(0.013)	(0.014)	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.014)
Observations	562	562	562	562	562	562	284	284	284
Adjusted R^2	0.878	0.906	0.858	0.887	0.914	0.868	0.888	0.915	0.885
State-period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-interacted Controls	No	No	No	Yes	Yes	Yes	No	No	No
Pure treatment/Control	No	No	No	No	No	No	Yes	Yes	Yes

Notes: Unit of analysis is county-period average (pre-period is 1920-1940 and post-period is 1980-2000). Republican Vote is the Republican party's share of the two-party vote in presidential, senatorial, or gubernatorial elections, depending on specification. Aquifer is a cross-sectional measure of the share of county land overlying Ogallala aquifer (lower order term absorbed by county fixed effects). Post-shock is a time dummy variable taking a value of one for the post-shock period and zero otherwise. Control variables interacted with time. Analysis estimated by OLS. Standard errors adjusted for clustering by county and state-period reported in parentheses: *p<0.1; **p<0.05; ***p<0.01.

6.2 Main Results with 2000-2020 endline

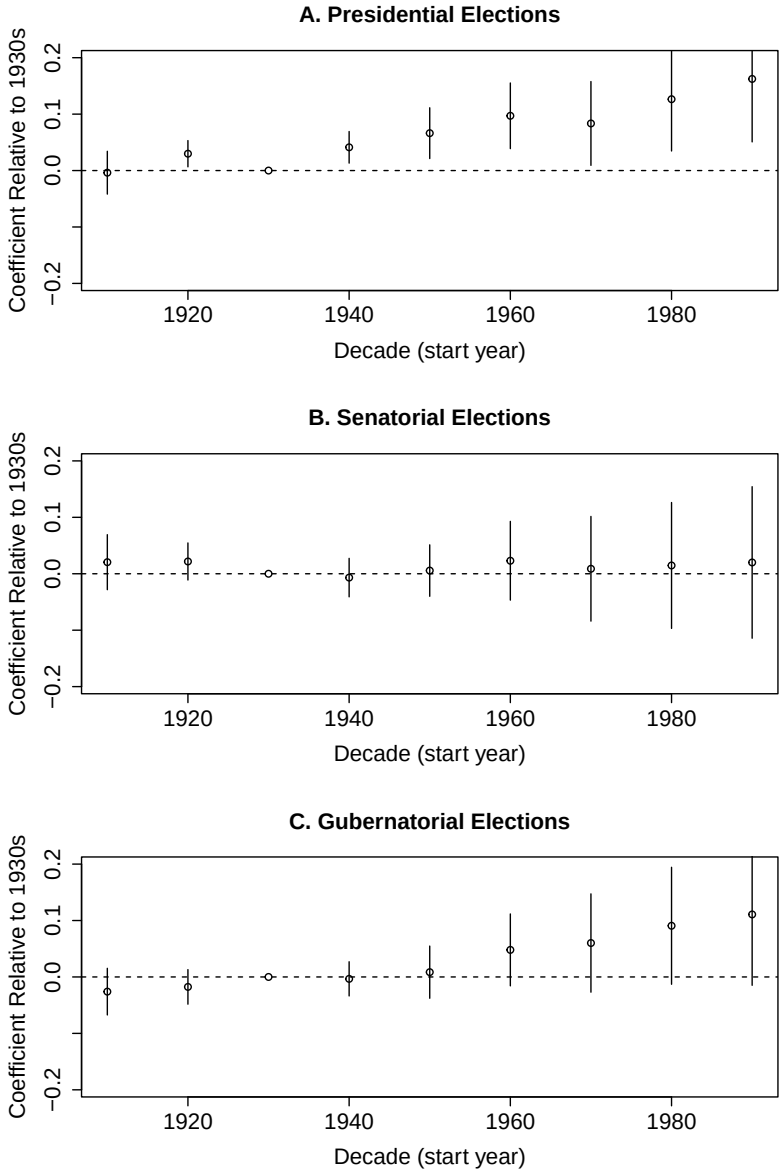
TABLE A8. Impact of Technological Shock on Conservative Voting (2000-2020 Endline)

	Republican Share of Two-party Vote											
	Baseline			Reweighted			Time-interacted Covariates			Pure Treatment/Control		
	President	Senator	Governor	President	Senator	Governor	President	Senator	Governor	President	Senator	Governor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Full Sample												
Aquifer×Post-shock	0.121***	0.111***	0.103***	0.115***	0.096***	0.097***	0.083***	0.078***	0.075***	0.122***	0.104***	0.103***
	(0.022)	(0.021)	(0.017)	(0.021)	(0.016)	(0.012)	(0.023)	(0.022)	(0.017)	(0.020)	(0.014)	(0.010)
Aquifer	0.007	0.003	0.012	0.005	0.006	0.012	0.013	0.009	0.010	0.005	0.007	0.015
	(0.015)	(0.013)	(0.012)	(0.018)	(0.011)	(0.010)	(0.013)	(0.014)	(0.012)	(0.018)	(0.010)	(0.009)
Observations	1,350	1,350	1,350	1,350	1,350	1,350	1,336	1,336	1,336	1,072	1,072	1,072
Adjusted R^2	0.796	0.879	0.844	0.894	0.946	0.915	0.810	0.885	0.851	0.793	0.876	0.844
Panel B: 200km Sample												
Aquifer×Post-shock	0.088**	0.073***	0.072***	0.085**	0.069***	0.070***	0.059*	0.052**	0.054**	0.095***	0.073***	0.077***
	(0.032)	(0.023)	(0.024)	(0.030)	(0.018)	(0.022)	(0.029)	(0.024)	(0.022)	(0.031)	(0.017)	(0.021)
	0.006	0.007	0.014	0.006	0.008	0.015	0.014	0.013	0.012	0.003	0.010	0.018
	(0.019)	(0.015)	(0.015)	(0.020)	(0.013)	(0.014)	(0.016)	(0.016)	(0.015)	(0.023)	(0.013)	(0.014)
Observations	826	826	826	826	826	826	826	826	826	548	548	548
Adjusted R^2	0.813	0.897	0.857	0.877	0.939	0.903	0.840	0.908	0.874	0.812	0.896	0.861
Panel C: 100km Sample												
Aquifer×Post-shock	0.048	0.038	0.041	0.052	0.039*	0.044*	0.032	0.026	0.031	0.056	0.038*	0.047*
	(0.033)	(0.023)	(0.024)	(0.033)	(0.021)	(0.023)	(0.033)	(0.025)	(0.024)	(0.035)	(0.019)	(0.022)
Aquifer	0.017	0.019	0.024	0.017	0.019	0.026	0.019	0.017	0.017	0.015	0.022	0.029
	(0.019)	(0.014)	(0.016)	(0.020)	(0.013)	(0.016)	(0.016)	(0.015)	(0.015)	(0.024)	(0.014)	(0.016)
Observations	562	562	562	562	562	562	562	562	562	284	284	284
Adjusted R^2	0.856	0.921	0.883	0.888	0.941	0.908	0.886	0.933	0.904	0.867	0.927	0.893
State-period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-interacted Controls	No	No	No	No	No	No	Yes	Yes	Yes	No	No	No
Pure treatment/Control	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes

Notes: Unit of analysis is county-period average (pre-period is 1920-1940 and post-period is 2000-2020). Outcome is the Republican party's share of the two-party vote in presidential, senatorial, or gubernatorial elections, depending on specification. Aquifer is a cross-sectional measure of the share of county land overlying Ogallala aquifer. Post-shock is a time dummy variable taking a value of one for the post-shock period and zero otherwise. Columns (1)-(3) reports baseline specification. In columns (4)-(6) regression weights are applied to recover pooled average of within-state difference-in-difference estimates weighted by number of observations in each state. Controls (see text) included as lower-order terms and interacted with post-shock variable in columns (7)-(9). Columns (10)-(12) include only counties fully inside/outside aquifer. Analysis estimated by OLS. Standard errors adjusted for clustering by county and state-period reported in parentheses: *p<0.1; **p<0.05; ***p<0.01.

6.3 Controlling for county-specific time trends

FIGURE A9. Pre- and Post-shock Trends Controlling for County-specific Linear Trends



Notes: Plot depicts coefficient on aquifer coverage variable interacted with decadal dummy variables, with the 1930s left out as the reference category. Vertical bars are 95% confidence intervals. Vertical axis range is plus or minus one standard deviation of the outcome. All specifications control for state-year and county fixed effects and are based on 100km buffer sample of counties. All specifications also control for county-specific linear time trends. Analysis estimated by OLS. Standard errors adjusted for clustering within counties and state-years.

7 Campaign Finance Patterns

7.1 Data

We utilize data from the Database on Ideology, Money in Politics, and Elections (DIME): Public version 2.0 (`https://data.stanford.edu/dime`), which consists of a database containing over 130 million political contributions made by individuals and organizations to local, state, and federal elections spanning the period from 1979 to 2014. Our main measures focus on contributions in the period 1980-2000 (which corresponds to the endline period in our difference-in-differences analysis).

To link contributions to counties, we use the contributor database and subset the data to contributors' whose most recent state address corresponds to one of the 10 Great Plains states (1,946,355 records). We then use the zipcode attached to each row to assign a contributor to a zipcode, and then use shapefiles of zip codes and county boundaries (circa 1990) to assign each contributor to a county. Approximately 87 percent of contributors could be linked to a zip code using this procedure (in future work, other address information could be utilized to address some of the missingness).

To measure the "partisan bias" of campaign contributions in a county for the period 1980-2000, we use the contributor CFscore – which represents a common-space scaling of contributors' ideological ideal point inferred from patterns of giving (see Bonica, Adam. 2014. "Mapping the Ideological Marketplace." *American Journal of Political Science*, 58 (2): 367- 387.). In one measure, we simply average contributor CF scores. In another measure, we construct a dollar-weighted average of contributor CF scores.

7.2 Descriptive Analysis

Our interest is in whether campaign contributions originating inside the boundaries of the Ogallala aquifer, where capital-intensive agriculture and agribusiness thrive, have a more conservative bias than campaign contributions originating outside of the aquifer. We investigate this proposition by regressing mean CF score and dollar-weighted mean CF score on the share of county land overlapping the Ogallala aquifer, controlling for state fixed effects and pruning the sample in some specifications to 200km and 100km buffer zones along the boundary of the Ogallala aquifer in each state. This means that comparisons are between counties in the same state in proximity to the Ogallala aquifer boundary. In Figure A21 we provide maps of the data. In Table A8 we report regression results.

7.3 Interpretation and Future Work

The findings indicate that on average campaign contributions/contributors in counties with greater overlap with the Ogallala aquifer have a higher CF Score (where a higher CF score corresponds to a higher level of conservatism). This could reflect the conservative bias of agribusiness interests and affluent farmers and landowners that are concentreated in areas of capital-intensive agriculture.

TABLE A9. Partisan Bias in Campaign Contributions

	Dependent variable:					
	Mean CF score			Dollar-weighted CF		
	(1)	(2)	(3)	(4)	(5)	(6)
Aquifer	0.300***	0.239***	0.187***	0.199***	0.161**	0.096
	(0.031)	(0.032)	(0.034)	(0.059)	(0.069)	(0.080)
Observations	713	424	289	712	423	289
Adjusted R^2	0.445	0.444	0.420	0.105	0.105	0.101

Notes: Unit of analysis is county. Outcome is mean CF score of contributors or dollar-weighted mean CF score. Aquifer is share of county land overlapping the Ogallala aquifer. Analysis estimated by OLS: *p<0.1; **p<0.05; ***p<0.01.

However, this is likely to represent just a small fraction of the total role of agribusiness money in politics, which may flow not just from but into districts where agribusiness is a major activity as past studies have found in the case of other geographically concentrated industries (see e.g. "DiSalvo, Richard W., and Zhao Li. 2022. “Economic Geography and Corporate Political Activity: Evidence from Fracking and State Campaign Finance.” Working Paper).

Future studies might use a different unit of analysis – for instance state legislative constituencies – and systematically track agribusiness firm donations, both in-district and out-of-district, to constituencies where agribusiness is concentrated to explore the role of agribusiness money in politics, which may be used to shape the political agenda, persuade voters, and elect friendly legislators in areas susceptible to legislation and regulation.

Such designs might potentially investigate time variation arising from technology-related shocks to the geograhical location of capital-intensive agriculture and agribusiness intensity occuring since 1979, when campaign finance data becomes systematically available due to disclosure laws. Alternatively, future work could take a pursely cross-sectional approach that exploits highly spatially disaggregated campaign contribution (which can potentially be geolocated down to the address and firm level).