Center Pivot Irrigation Systems as a Form of Drought Risk Mitigation in Humid Regions

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By:

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Abstract: Irrigation in the Eastern US receive little attention compared to the West, but farmers in humid states of the US, traditionally reliant on rainfall, have more than tripled since 1978. We examine this trend in Illinois where there has been a nearly threefold increase in center pivot irrigation systems (CPIS) installations since 1988. Specifically, we analyze the benefits of CPIS installation in terms of annual crop yield, irrigated acreage, crop selection, and reduction in drought-related insurance payouts, known as indemnity. The question is particularly interesting as the majority of Illinois farmers have crop insurance and are already producing high-value, water-intensive crops. Utilizing a novel deep learning method to automatically identify the location of CPIS during drought years along with annual county level crop, weather, and insurance data, we examine how crop production has changed on the extensive and intensive margins in areas that have installed CPIS. The results suggest that counties with a higher presence of CPIS do not have higher average crop yields, a shift in crop selection, or an expansion of cropland. However, in drought years CPIS presence does have a significant positive effect on corn yield and a significant negative effect on indemnity payments for both soybeans and corn. The results provide insights into an emerging trend of irrigation in humid regions, raising potential policy considerations for crop insurance and signaling a potential need to address water rights as demand increases.

JEL Codes: Q15, Q18, Q25, Q54

Keywords: Machine learning, climate change, agriculture, technology

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Notes: Relative to 1978, 17 western states are at 1.013021, since 1997, 1.004046. The eastern states are 3.259 (2.899 dropping TN, 14x) and 1.46878. (1.37)

1. Introduction

Irrigation has long served as an adaptation to increase yields and provide resilience during severe drought in arid regions (Troy et al 2015, Zhang et al 2015, Tack et al 2017, Edwards and Smith 2018, Zaveri and Lobell 2019). For instance, the 17 arid states of the US, commonly delineated as those to the west of the 100th meridian were quick to adapt water policy to spur irrigation in the 19th century (Leonard and Libecap 2019), attracted huge public investment to build large dams in the 20th century, and tapped groundwater resources with abandonment after the 1940s (Edwards & Smith 2018). In total, these efforts brought some 40 million acres under irrigation by 1978. Since then, however, these states have stagnated in irrigated acreage. Meanwhile, a persistent trend is irrigation uptake in the humid states as can be seen in Figure 1. These humid states, on average, have more than tripled their irrigated acreage since 1978 and today over one-third of irrigated acreage in the US is east of the 100th meridian. This paper explores the benefits of irrigation investment in more humid regions in the context of climate change trends and existing crop insurance. Specifically, we look at Illinois where irrigated acreage has increased nearly five-fold since 1978, to consider how irrigation investment has affected cropping patterns, crop yields, and federal crop insurance payouts.

Consistent with the trends in the US, water availability limitations in historically irrigated regions make adapting to climate change there more difficult, but more humid regions, like the eastern US, can support expanded irrigation (Elliot et al. 2014). Irrigation expansion in the US has often been by center pivot irrigation systems (CPIS) since their invention in 1948 by Frank Zybach (Anderson, 2018). In the arid regions, these self-propelled irrigation systems transformed the agriculture industry; farmers were able to adopt more water-intensive plants, sustain higher crop yields, and utilize more land as cropland (Evans, 2001). With the line of aridity shifting east (Seager, et al., 2018), these upsides may explain continued irrigation increases in the Great Plains region. But in the Midwest, where natural rainfall was already sufficient to feed the more profitable, more water-intensive crops like corn and soybeans, average rainfall has *increased*.

Despite the increasing average rainfall across the Midwest, the variability of precipitation extremes is also increasing (Ford, Chen, & Schoof, 2021). Additionally, the length and frequency of dry periods during the summer is predicted to increase across the Midwest throughout the twenty-first century (Grady, Chen, & Ford, 2021), and the intensity of droughts in humid regions

may also be greater when they do occur (Trenberth, et al., 2014). This is a particularly important for corn and soybeans as summertime drought is correlated with low corn and soybean yields (Mishra & Cherkauer, 2010). Farmers also tend to invest in irrigation in response to drier years for use when there is insufficient soil moisture (Smith & Edwards, 2021). In Illinois specifically, severe droughts occurred in 1988, 2005, and 2012 with the most recent severe drought prior to 1988 occurring in 1964 (State Climatologist Office for Illinois). The 2012 drought caused a large decline in crop yields bringing statewide corn production down to 105 bushels per acre from 157 bushels per acre in 2011 (Illinois Department of Natural Resources, 2013). Irrigated acreage in Illinois, overwhelmingly consisting of CPIS, has increased by 54% from 1997 to 2015 (Stubbs, 2016) with 833 new CPIS installed statewide in the two years following the 2012 drought (Illinois State Water Survey).

Figure 1: Percent Change in Irrigated Acres in the U.S., 1997-2013 (USDA NASS, 2021)

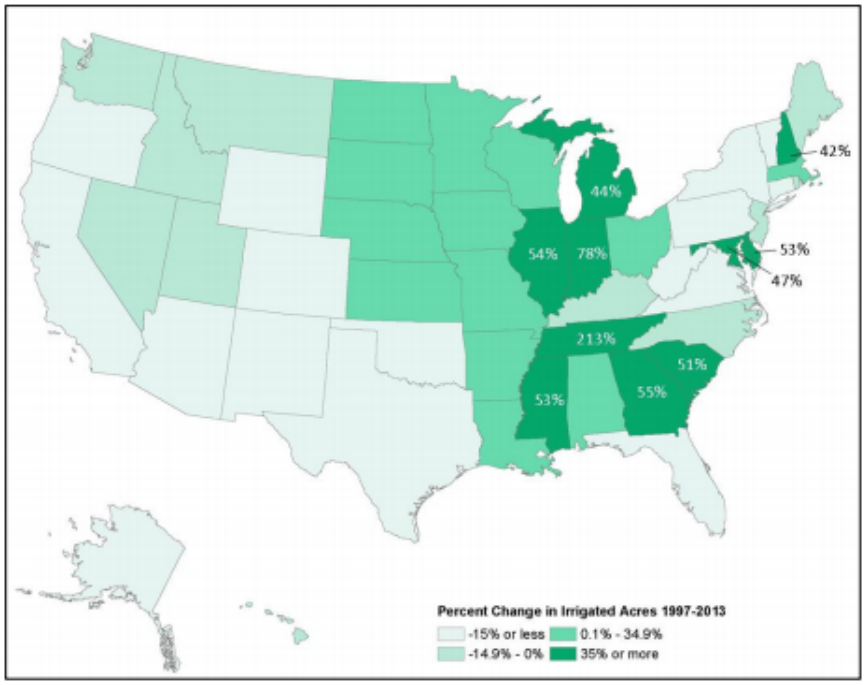


Figure 1: Percent Change in Irrigated Acres in the U.S., 1997-2013 (USDA NASS, 2021). States with darker green experienced a greater percent change in irrigated acres over the observed period.

We explore the benefits of CPIS as a drought risk mitigation in Illinois given the upward trends precipitation means and variation as well as irrigation. The question is interesting because CPIS are expensive while alternatives exist. The capital costs to setup a new CPIS on 160 acres (irrigating about 128 acres) is upwards of $153,000 (Sherer 2018). Meanwhile, farmers have

crop insurance to insulate themselves from droughts and other disasters, and Illinois farmers have been increasing their coverage, going from 87% and 85% for corn and soybeans respectively in 2016 to 96% and 93% in 2020 (United States Department of Agriculture). We consider whether CPIS uptake confers the benefits found in the West – crop switching, increased yields, resilience – and how crop insurance payouts are affected.

A critical part of this research is knowing where and when CPIS are installed. The agricultural census reported on this specific irrigation technology in 1959 and 1969, but not since and state records vary greatly. To circumvent this data shortage, we leverage a deep learning process to identify the locations of CPIS from satellite imagery. The model extends that of Cooley, Smith, & Maxwell (2021), which was utilized to identify CPIS over the Ogallala aquifer, a much more arid region. Illinois conducted a survey in 2014 of CPIS, providing a ground truth to help train the model. Still, deploying the model in a humid region where the "circles" of CPIS are less detectable limits the performance. Accordingly, we run the model on drought years when the circles are more apparent and fill in the interim years via a linear trend. Results are robust to alternative assumptions. The data generation process represents a small contribution to the field of machine learning insofar as most of the previous work on automatic identification of CPIS has focused on more arid regions where the distinctive circular pattern is clearer (Zhang, Yue, Di, & Wu, 2018) (Deines, et al., 2019) (Saraiva, Protas, Salgado, & Souza, 2020) (Valencia O. M., et al., 2020) (Cooley, Maxwell, & Smith, 2021).

We aggregate the 30 x 30 meter resolution CPIS data to the field and county level, and combine it with annual data from the Cropland Data Layer (CDL), crop production from USDA's National Agricultural Statistics Service (NASS), and Illinois crop insurance data from the USDA's Risk Management Agency (RMA). We also collect weather data from NOAA to address climate variation.

We find that there is no significant correlation between CPIS installation and crop choice, crop yield in non-drought years, or irrigated acreage in Illinois. This is a significant result as irrigation improvements in other regions with a more arid or semiarid environment have resulted in increased average crop yield, a switch to thirstier crops, and even an increase in cropland (Pfeiffer & Lin, 2010). However, corn yield during drought years shows a positive correlation with CPIS presence at the county level, and the sum of money paid by the insurance to the

insured, known as indemnity, is negatively correlated with CPIS presence at the county level during drought years for both corn and soybeans. Taken in combination, these results imply that the primary benefit of installing a CPIS in Illinois is drought risk mitigation despite the high rate of crop insurance coverage in Illinois. This result is particularly interesting in the light of previous research that suggests greater crop insurance coverage disincentivizes farmers from adapting to drought (Annan & Schlenker, 2015).

Broadly, our results contribute the agricultural adaptation to climate change. Most notably, we explore a novel setting that has been largely neglected in previous work more directly related to irrigation improvements (Koundouri, Nauges, & Tzouvelekas, 2006) (Baerenklau & Knapp, 2007) (Torkamani & Shajari, 2008) (Pfeiffer & Lin, 2010) (Christine, Fuss, Szolgayova, Strauss, & Schmid, 2012). In the economics literature, irrigated agriculture has often been discarded when analyzing the effect of climate change (e.g. Schlenker & Roberts, 2009; Burke & Emerick, 2016) under the argument that it is poor proxy for non-irrigated areas as similar adaptations are not expected (Schlenker et al. 2005). Yet, the east is increasing irrigation although average effects on production are not well identified (Smith & Edwards, 2021). Our work also builds on the substantial body of research concerning the effects of advancements in technology on agricultural production (Griliches, 1957) (Ruttan, 1960) (Just, Schmitz, & Zilberman, 1979) (Zilberman, 1984) (Lau & Yotopoulos, 1989). Furthermore, this research focuses on the shift from unirrigated land to land irrigated by CPIS rather than marginal improvements to existing irrigation technologies (e.g. Pfieffer & Lin 2014). Technological choice is important as CPIS has been associated with more resilience than other forms of irrigation (Cooley, Smith, & Maxwell 2021). Finally, the results also speak to the potential for moral hazard with crop insurance, where insured farmers strategically underinvest in yield enhancing activities during extreme weather events (Smith & Goodwin, 1996; Annan and Schlenker 2015; Connor and Katchova, 2020; Wang, Rejesus & Aglasan 2021).

The rest of this paper is organized into five additional numbered sections Section 2 presents a model showing how increased droughts can induce more irrigation investment despite crop insurance. Section 3 discusses the deep learning model and other data sources. Econometric methods are described in section 4 before we present the results in section 5. We discuss the implications of the study and possibilities for future research in the concluding section 6.

2. Model

We provide a theoretical model to provide some insight in to the decision process for installing a CPIS as a form of drought risk mitigation when crop insurance is available. We assume that the farmer's choice is between having no irrigation and insurance only or having both a CPIS and insurance simultaneously. To focus on the decision for drought risk mitigation, we assume average production is unchanged and set aside the potential losses of too much precipitation. The farmers' profits ($\pi(w_t, p_t)$) can be thought of as a function of irrigated water (w_t) and precipitation (p_t) in a given year, and their expected profits are the sum of annual profits from the present to time T multiplied by the weighted probability of a normal precipitation year $(1-\alpha)$ or below average precipitation year (α).

$$E[\pi(w_t, p_t)] = \sum_{t=1}^{T} \pi(w_t, p_t) - c(k) \tag{1}$$

$$\pi(w_t, p_t) = (1-\alpha)\bar{y} + \alpha[y(w_t, p_t) + i(w_t, p_t) - c(w_t)] - \frac{c(k)}{T} \tag{2}$$

$$s.t. \quad w_t \leq k\,, \;\; 0 \leq \alpha \leq 1$$

For simplicity, the value of the crop is normalized to 1 and taken as a constant. Precipitation (p_t) is a random variable that follows a stationary process with an average of $\bar{p}$. Irrigated water w_t is constrained by $w_t \geq 0$ and $w_t \leq k_t$ where k_t is installed irrigation capacity. The profit function is composed of crop yield $y(\cdot)$, net insurance payment $i(\cdot)$, the cost of irrigated water $c(w_t)$, and the annualized cost of irrigation capacity $\frac{c(k)}{T}$. The yield function is a concave production function for an arbitrary crop where the inputs w_t and p_t are perfectly substitutable. The benchmark crop yield ($\bar{y}$) is the upper limit of the crop yield function achieved when precipitation reaches the average value ($\bar{p}$) where neither insurance nor irrigated water are necessary. Lastly, α is the probability that a given year will have lower than average rainfall and is therefore a value between 0 and 1. The insurance payout in a given period is:

$$i\big(y(w_t, p_t)\big) = \; b\big(\bar{y} - y(w_t, p_t)\big) - c(b) \tag{3}$$

$$s.t. \quad 0 \leq b \leq 1$$

The insurance pays a guaranteed percentage (b) of the lost crop yield at the cost of the premium ($c(b)$). The greater the quantity of irrigated water w_t, the smaller the gap between the benchmark crop yield and the realized crop yield in the current year. Indemnity is the

compensation paid by an insurance company to cover crop damages as a result of a qualifying event such as drought, fire, or flooding. The specifics of the coverage can take different forms. Yield protection is based on historic crop yield and guarantees a percentage of each farmer's average crop yield over the last 10 years while revenue protection guarantees a certain percentage of annual revenue by paying out the difference between an insured farmer's realized revenue and the guaranteed revenue (Plastina, Johnson and Edwards 2021). By normalizing the price of crops to one, our model ignores the difference between the specific coverage types. The percentage of guaranteed crop yield or revenue is selected by the farmer, and premiums reflect the difference in this choice by increasing with greater levels of insurance protection.

If CPIS are an effective form of drought mitigation above and beyond that of insurance alone, the expected value of profits in a farm without a CPIS $(0, p_t)$ would be below that of a farm with a CPIS (w_t, p_t), where there is some positive amount of irrigation.

$$\pi(0, p_t) = \sum_{t=1}^{T}(1-\alpha)\bar{y} + \alpha[y(0, p_t) + \big(\bar{y} - y(0, p_t)\big)b - c(b)] \tag{4}$$

$$\pi(w_t, p_t) = \sum_{t=1}^{T}(1-\alpha)\bar{y} + \alpha[y(w_t, p_t) + \big(\bar{y} - y(w_t, p_t)\big)b - c(b) - c(w_t)\,] - \frac{c(k)}{T} \tag{5}$$

$$\pi(w_t, p_t) - \pi(0, p_t) = \sum_{t=1}^{T}\alpha[(1-b)\Delta y - c(w_t)] - \frac{c(k)}{T} \tag{6}$$

$$\text{where} \quad \Delta y = y(w_t, p_t) - y(0, p_t)$$

For CPIS installation to be an effective form of drought mitigation for a farmer, equation 6 must be positive. In other words, the value of the difference in crop yield as a result of irrigation multiplied by the uninsured percentage of the crop must be greater than the cost of water and annualized cost of irrigation capacity for a farmer to consider installing a CPIS. However, this does not give us the full story. Additionally, we see that as the probability of a below average precipitation year increases, the expected value of irrigation also increases which gives us some insight as to why farmers may be installing CPIS more rapidly in recent years as dry spells have gotten more frequent. We can further examine this effect on the margin by creating a Lagrangian from equation 2 for a given year:

$$\mathcal{L} = (1-\alpha)\bar{y} + \alpha[y(w_t, p_t) + i(w_t, p_t) - c(w_t)] - \frac{c(k)}{T} + \lambda(k - w_t) \tag{7}$$

Using the definition of $i(y(w_t, p_t))$ from equation 3 and taking the derivative, our first order conditions are:

$$\frac{\partial \mathcal{L}}{\partial w} = \alpha \left[\frac{\partial}{\partial w} y(w_t, p_t) - b \frac{\partial}{\partial w} y(w_t, p_t) - \frac{\partial}{\partial w} c(w_t) \right] - \lambda \leq 0 \tag{8.a}$$

$$\frac{\partial \mathcal{L}}{\partial k} = -\frac{\partial}{\partial k} \frac{c(k)}{T} + \lambda \leq 0 \tag{8.b}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = k - w_t \geq 0, \tag{8.c}$$

From these first order conditions, we are mostly interested in equation 8.a where at the optimal point we may rearrange to find:

$$\alpha \left[(1 - b) \frac{\partial}{\partial w} y(w_t, p_t) - \frac{\partial}{\partial w} c(w_t) \right] \leq \lambda \tag{9}$$

The Lagrange multiplier (λ) is a measure of the shadow price of irrigation capacity. Given our Kuhn-Tucker conditions, farmers either irrigate until the marginal net benefit of water is equal to the Lagrange multiplier or do not irrigate at all. The marginal net benefit of water is positively influenced by the marginal value of the uninsured crop yield and negatively influenced by the marginal cost of water. From this equation, we also see that as the probability of a dry year (α) increases, the marginal net benefit of a unit of water also increases. It follows that as dry spells have been getting more common and intense, the value of irrigated water has increased to farmers in Illinois, incentivizing them to install a CPIS. We now turn to the data to test whether these assumptions in the model hold empirically.

3. Data

Historically, identifying the location of CPIS has been challenging in areas that do not hold publicly accessible records for such things. CPIS identification largely remains a tedious process of visually inspecting aerial or satellite imagery and manually marking their boundaries. This identification method was used to detect CPIS in the Northern Atlantic Coastal Plain (NACP) from satellite imagery in 2013 and indicated that about 271,900 acres were irrigated primarily by CPIS (Extension, U.S. Geological Survey and University of Delaware Agricultural, n.d.). More relevantly for this paper, the ISWS also manually identified CPIS from aerial imagery of the entire state in 2012 and 2014 which revealed a 14.2% increase in CPIS between

the two periods (Illinois State Water Survey, n.d.). One of the reasons this paper focuses on Illinois is the high-quality of the data provided by the ISWS as it is more complete and shows variation through time rather than being a static snapshot. However, the ISWS data only covers three years of development within which there is only one drought year in 2012 leaving something to be desired.

While there has been a recent breakthrough in CPIS identification through deep learning methods in arid and semiarid regions where the distinctive crop circles left by CPIS are quite clear, humid regions like Illinois pose a greater difficulty due to the CPIS there not being used as frequently which results in an indistinct boundary between the irrigated area and surrounding land cover (Zhang, Yue, Di, & Wu, 2018), (Saraiva, Protas, Salgado, & Souza, 2020). However, we deployed a deep learning method that is able to predict the historical locations of CPIS in Illinois by using the pre-trained model described in Cooley et al. (2021) based on the work of Saraiva et al. (2020). This method is particularly useful as it does not rely on the CPIS being a specific size or shape in order to predict their locations as is the case with previous attempts at detecting CPIS with satellite imagery (Zhang, Yue, Di, & Wu, 2018). However, this comes at the cost of a fuzzy border around the CPIS as the model can struggle with determining the exact boundary of the CPIS when utilizing 30m resolution imagery. Additionally, this method still leaves large time gaps between observations as it is only reliable during severe drought years.

The model was pre-trained on CPIS over Nebraska which allowed us to warm-start the process of detecting CPIS in Illinois where the boundaries of CPIS are less distinct. The model was then retrained using manually labelled GIS data from Illinois in 2012 and 30m x 30m resolution top-of-atmosphere (TOA) reflectance satellite imagery collected from Google Earth Engine's Landsat database. The data was divided into three parts for use in training, validation, and testing with the training set receiving 80% of the total data and the remainder being allocated equally between validation and testing sets.

Figure 2 provides a comparison of the ground truth and model output in Illinois. The model's accuracy and specificity ratings are well over 99% which is due to the very large number of non-CPIS pixels in the state of Illinois that the model correctly identified. The recall rate of the model is 85.4% which is in line with other CPIS detection models (Zhang, Yue, Di, & Wu, 2018), (Saraiva, Protas, Salgado, & Souza, 2020). A good portion of the loss in recall rate at

the pixel level can be accounted for by the model's inability to accurately define the boundaries of the CPIS resulting in misidentified pixels near the edges of the crop circle left by the CPIS.

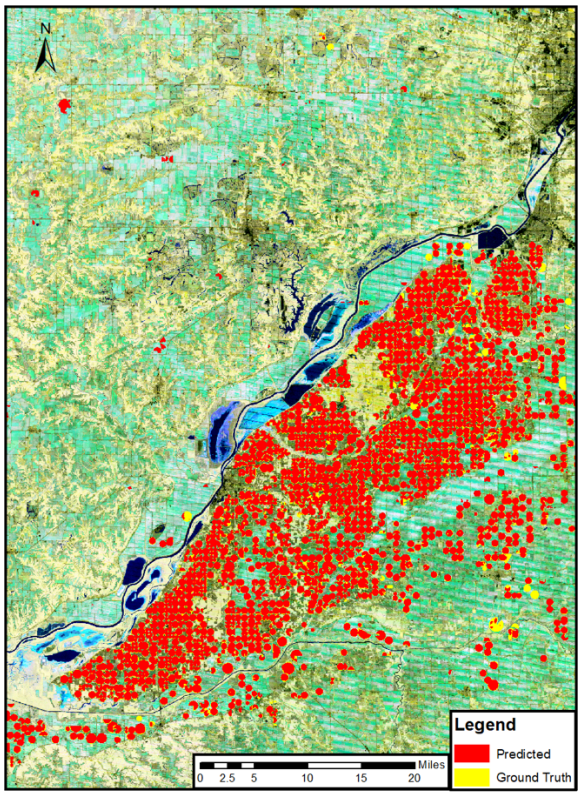


Figure 2: Deep learning output for locating CPIS in Illinois.

Perhaps the most relevant portion of the score is the precision of the model which has a rating of 54.5% suggesting that the model predicts a large number of false positives. This may be due to the indistinct nature of the CPIS boundaries in such a humid climate, the massively unbalanced dataset where there are many more negative examples than positive examples, or some combination of the two. As such, the model is limited in its usefulness for detecting newly installed CPIS.

However, CPIS are extremely durable through time (Irrigation Education, 2016). While they occasionally change shape or move to a newly dug well, they tend to persist on the same plot of land for many decades. With this in mind, the model was put to use detecting CPIS in previous drought years and the results were compared the CPIS identified via aerial imagery in 2012. If a predicted CPIS fell within an area where there is not one manually labelled in the 2012 dataset, it was thrown out of the final dataset. This process takes advantage of the model's high

recall rate while limiting the impact of its low precision. The key assumption with this method is that if a CPIS were installed prior to 2012, it would still show up in the 2012 imagery even if it is a slightly different shape or size

Because CPIS can only be accurately predicted by the deep learning model during drought years in the humid region, so it is not possible to directly identify how CPIS installation is correlated with indemnity payouts and crop yield. In order to work around this complication, gaps between observations were filled in using linear interpolation from one observation to the next. With the dramatic increase in CPIS seen from 2012-2014 after the drought in 2012 though, a linear trend does not seem to accurately portray how CPIS have developed in the state through time. So, two other methods were employed to bookend the possibilities: one in which all of the CPIS observed in a drought year were installed immediately following the previous drought year and one in which all of the CPIS observed in a drought year were freshly installed in that year. The latter seems to be the least likely case as it carries with it the implication that CPIS were installed immediately before a drought occurred while the former case suggests that the CPIS were installed immediately after a drought scare, aligning with more general trends in irrigation and recent droughts (Smith & Edwards, 2021). Filling the CPIS observation gaps allows for the inclusion of non-drought year data to get a better idea of the baseline for crop yield, precipitation, and temperature through time. The model's remaining inaccuracy is assumed to not be biased in any particular direction as it was trained on drought years and only utilized to predict CPIS locations during other drought years in areas known to have CPIS installed at some point before 2012. The overall output, for both 1988 and 2014, is provided in figure 3.

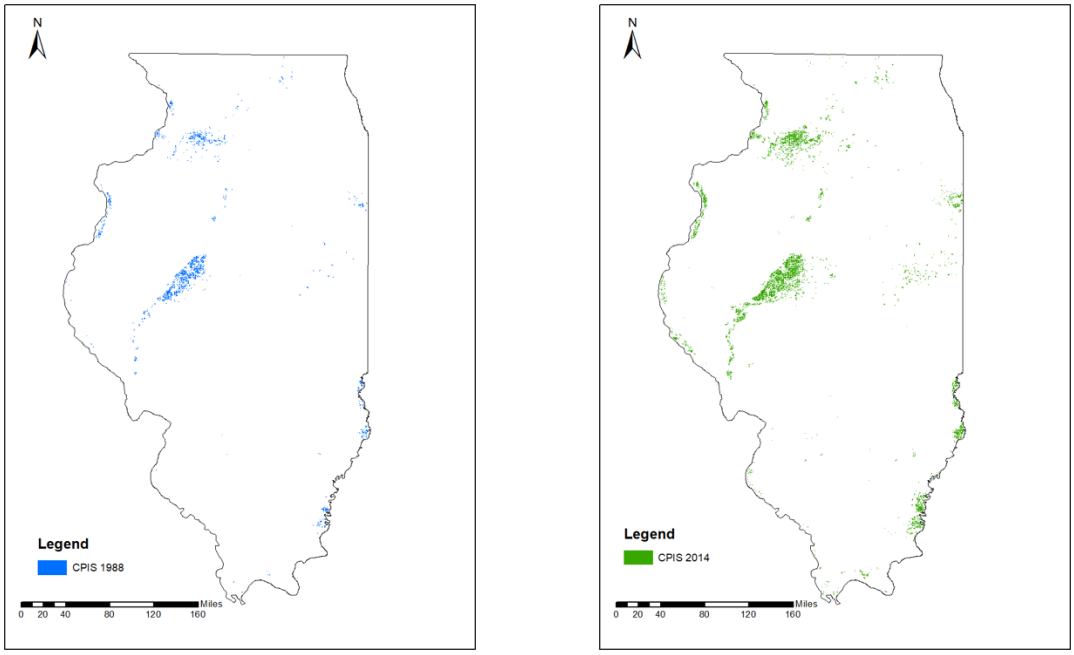


Figure 3: Illinois CPIS in 1988 and 2014

The rest of the data collected comes from standard sources. The Cropland Data Layer (CDL) 30m resolution land coverage GIS data and estimated annual crop data at the county level were gathered from the USDA's National Agricultural Statistics Service (NASS). Illinois crop insurance data regarding the indemnity amount, crop loss, and cause of loss for insurance claims from 1988-2020 were collected from the cause of loss and summary of business files from the USDA's Risk Management Agency (RMA) For additional covariates, we gather precipitation and temperature data by county from 1988 to 2012 were found using the NOAA National Centers for Environmental Information, Climate at a Glance online application. Soil quality and other geographic information was derived from the Gridded National Soil Survey Geographic (gNATSGO) Database for Illinois.

4. Methods

We conduct three empirical analyses. First, we consider how CPIS affects cropping patterns. Second, we test for yield effects both in regular and drought years. Third, we consider how indemnity payments payouts in drought years are associated with CPIS.

For cropland and crop choice we can be spatially precise because CDL data, like our CPIS data, is available at the 30-meter resolution. We also are temporally precise by limiting the sample to 2012 and 2014, two years in which we know from the Illinois survey when the CPIS went in. The model is a simple two-period system where 2012 is the pretreatment period and 2014 is the post-treatment period. Areas that had a CPIS installed between the two periods are the treatment group, and all other acreage in Illinois is the control group. We estimate the following equation:

$$S_{lt} = \gamma_0 + \gamma_1 time_t + \gamma_2 treatment_l + \gamma_3 time_t treatment_L + \varepsilon_{Lt} \quad (10)$$

S_{it} is the share of the land with a particular land cover. We consider corn, soybeans, and non-cropland in separate regressions. Given the two-periods, the time trend is equivalent to time fixed effects and picks up trends in cropping that are uniform across the state, such as expected market prices. The $treatment$ group control captures any distinctions common to land being brought under CPIS between 2012 and 2014. Finally the DID estimate (γ_3) which is the primary variable of interest, captures any changes after the installation of CPIS in Illinois.

Second, conditional on planting corn or soybeans, we consider crop yields. Because the yield data is for the county level, we aggregate the CPIS measure from the deep learning model to the county level, dividing the CPIS area by the area of field crops in the county. Using field crops as the denominator allows for an additional acre irrigated by CPIS to count differently for counties with different crop acreage and composition and excludes crops that couldn't be irrigated via CPIS from being taken into consideration. With this, we run the following regression at the county-year level:

$$\log(y_{it}) = \rho_0 + \rho_1 CPIS_{it} + \rho_2 CPIS_{it} * D_t + \rho_3 D_t + \rho_4 P_{it} + \rho_5 T_{it} + \boldsymbol{X}_i + \delta_t + \varepsilon_{it} \quad (11)$$

Crop yield (y_{it}), measured as bushels harvested per planted acre, is logged so we can interpret the coefficients as percent changes in yield. $CPIS_{it}$ is the CPIS presence in county *i* in year *t*, where the non-drought years are filled in as previously described. D_t is a drought indicator equal to one in years determined to qualify for drought insurance payments. We are interested in both the average effect of CPIS (ρ_1) and its interaction in drought years (ρ_2) as a measure of resilience. In addition, we control for precipitation and temperature as linear

functions. $\boldsymbol{X}_i$ is either a vector of time-invariant controls and their coefficients (elevation, variation in elevation, and soil class) or, in our preferred model, county-level fixed effects. With so few available covariates due to data scarcity, the chance for significant omitted variable bias is high. Grouping at the county level using fixed effects helps to account for those time invariant omitted variables that may be different across counties and correlated with crop yield and CPIS presence. Additionally, while using county fixed effects does reduce the variation that the model has to work with, an inspection of the data reveals that the variables of interest retain at least a third of their variation when comparing within-county standard deviation to between-county standard deviation. Last, δ_t represents year fixed effects. The sample is from 1988 through 2020.

Finally, to explore the connection between insurance and CPIS, we estimate a final equation as follows:

$$I_{it} = \beta_0 + \beta_1 y_{it} + \beta_2 CPIS_{it} + \sigma_i + \delta_t + \varepsilon_{it} \quad (12)$$

Indemnity (I_{it}) is defined as the insurance payout in dollars for each drought-related claim in each county (i) during drought year (t). The drought indicators are not in this equation as insurance payouts for drought only occur during drought years. Because of this, the indemnity model only covers drought years which means that there are only three years' worth of observations to work. We still include county and year fixed effects. The indemnity model is estimated for were run for corn and soybeans corn and soybean payments only.

5. Results

Table 1 shows CPIS investment has little effect on crop choices in Illinois. It displays the estimated percent change in corn, soybeans, and non-cropland acreage when CPIS are added. There is not a significant difference between the change in crops grown in the rest of the state and the change in crops grown specifically in the areas of newly installed CPIS before or after they were installed. Additionally, there is not a statistically significant number of newly installed CPIS on land that was not already being used to grow crops. This indicates that CPIS are not being installed disproportionately in areas that tend to grow more corn or soybeans.

Table 1: Effects of Newly Installed CPIS on Crop Selection and Cropland Expansion

	(1) Corn Acreage	(2) Soybeans Acreage	(3) Non-Cropland Acreage
Year	-0.0105	0.0108	0.00509
	(0.261)	(0.235)	(0.0561)
Treatment	-107.8	87.68	16.05
	(526.6)	(473.0)	(113.1)
Diff-in-diff	0.0537	-0.0436	-0.00810
	(0.262)	(0.235)	(0.0562)
Constant	21.47	-21.46	-9.952
	(526.3)	(472.8)	(189.8)
Observations	1666	1666	1666

Notes: Std. error in parentheses.

This result is distinct from patterns observed in arid regions, where irrigation or improved irrigation efficiency leads to an uptake of more water thirsty crops. This is likely because the overwhelming majority of the cropland in Illinois is planted with corn and soybeans already, which are high-value, water-intensive crops. Beyond the time period of the regression model presented, the share of corn in Illinois has been decreasing statewide while the less water-intensive soybean share has been increasing from 2012 to 2018, but regardless of irrigation type, likely because average returns on soybeans have been higher than corn across the state since 2014 and that trend is projected to continue through the 2021 growing season (Schnitkey, 2021).

In table 2 we show coefficient estimates of equation 11 without county fixed effects. The regression suggests that higher CPIS presence has a significantly positive correlation with the percent change in crop yield for both corn and soybeans for the entire range of plausible CPIS presence in non-drought years. For instance, based on the CPIS trend, an acre with CPIS produces 7.49 percent more corn on average. For soybeans, yields are 9.29 percent higher. This indicates that CPIS either increase yields or are more likely to be installed in areas already with higher yields, making the mitigation investment potentially more valuable. In fact, during drought years the CPIS are also associated with maintaining higher yields for corn by nearly 20 percent. However, there is no effect on the resilience of soybean production. Because county

level fixed effects were left out of this regression, the regression coefficients may be significantly impacted by some omitted variable biasing crop yield and CPIS presence which also makes the assumption of unconfoundedness mentioned earlier far less plausible.

Table 2: Effects on Illinois Crop Yield, No County Fixed Effects

	(1) corn yield	(2) corn yield	(3) corn yield	(4) soybeans yield	(5) soybeans yield	(6) soybeans yield
CPIS max	0.000728			0.00087		
	(0.00028)			(.00024)		
CPIS trend		0.000749			0.000929	
		(0.000325)			(0.000278)	
CPIS min			0.000637			0.000879
			(0.000393)			(0.000336)
rain (in)	-0.000539	-0.000584	-0.000695	0.00232	0.00229	0.00217
	(0.00096)	(0.00096)	(0.00096)	(0.00082)	(0.00082)	(0.00082)
temp (F)	-0.0146	-0.0155	-0.0170	-0.0237	-0.0245	-0.0259
	(0.0047)	(0.0047)	(0.0046)	(0.0040)	(0.0040)	(0.0039)
elev (ft)	0.000350	0.000285	0.000175	0.000487	0.000425	0.000316
	(0.00034)	(0.00033)	(0.00033)	(0.00029)	(0.00028)	(0.00028)
elev std (ft)	0.00244	0.00244	0.00244	0.00303	0.00303	0.00303
	(0.00061)	(0.00061)	(0.00061)	(0.00052)	(0.00052)	(0.00052)
soil quality	-0.0397	-0.0393	-0.0384	-0.0618	-0.0615	-0.0606
	(0.0095)	(0.0095)	(0.0095)	(0.0081)	(0.0081)	(0.0081)
CIPS max × drought	0.00206			-0.000875		
	(0.000788)			(0.000668)		
CPIS trend × drought		0.00205			-0.000929	
		(0.000805)			(0.000683)	
CPIS min × drought			0.00217			-0.000880
			(0.000836)			(0.000710)
Constant	6.067	6.059	6.059	4.799	4.795	4.795
	(0.890)	(0.891)	(0.892)	(0.729)	(0.730)	(0.732)
Observations	1144	1144	1144	1149	1149	1149
R-squared	0.7277	0.7274	0.7267	0.6495	0.6489	0.6475
County FE	N	N	N	N	N	N
Year FE	Y	Y	Y	Y	Y	Y

Notes: Std. errors in parentheses. Yield values are logged. CPIS values are in percentages of county field crop acreage. Soil quality is based on the USDA's land capability classification where higher numbers indicate lower suitability for commercial crop use *(USDA)*.

Table 3 shows the results from running the regression from equation 11 with the inclusion of fixed effects. One major change from the previous model is that the range of plausible CPIS presence is no longer significantly correlated with a percent change in crop yield in non-drought years in this model. This is consistent with CPIS investment more likely to occur in more productive regions of Illinois. Additionally, the sign of rain and temperature are what was expected.

Table 3: Effects on Crop Yield with County Fixed Effects

	(1) corn yield	(2) corn yield	(3) corn yield	(4) soybeans yield	(5) soybeans yield	(6) soybeans yield
CPIS max	0.000387			0.000135		
	(0.00086)			(0.000631)		
CPIS trend		0.000306			0.0000108	
		(0.000736)			(0.000543)	
CPIS min			-0.000262			-0.000343
			(0.000710)			(0.000523)
rain (in)	0.00199	0.00199	0.00199	0.00426	0.00427	0.00427
	(0.000756)	(0.000756)	(0.000756)	(0.00475)	(0.00475)	(0.00475)
temp (F)	-0.00211	-0.00214	-0.00220	-0.0157	-0.0158	-0.0158
	(0.00645)	(0.00645)	(0.00645)	(0.00475)	(0.00475)	(0.00475)
CPIS max × drought	0.00335			0.0000541		
	(0.000720)			(0.000530)		
CPIS trend × drought		0.00333			0.0000812	
		(0.000745)			(0.000549)	
CPIS min × drought			0.00357			0.000264
			(0.000787)			(0.000580)
Constant	6.063	6.064	6.069	4.058	4.059	4.062
	(0.420)	(0.420)	(0.420)	(0.307)	(0.307)	(0.307)
Observations	2423	2423	2423	2434	2434	2434
R-squared	0.6915	0.6915	0.6915	.5806	0.5806	0.5806
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Notes: Std. errors in parentheses. Yield values are logged. CPIS values are in percentages of county field crop acreage.

As before, however, CPIS presence during a drought year still has a significant effect on crop yield for corn, but no significant additive effect on soybeans. The magnitude of the resilience in drought years is magnified relative to estimates without fixed effects. A CPIS acre maintains yields 33.3 percent higher for corn during a drought year.

Finally, in table 4 we provide the estimates for equation 12, connecting CPIS to indemnity payments. CPIS presence has statistically significant negative effect on drought indemnity for both corn and soybeans. Interestingly, crop yield carries the expected negative sign for both corn and soybeans but is only statistically significant in the case of corn. Recall from table 3 that the effect of CPIS presence on soybeans yield was also insignificant. This may be because soybeans and corn are commonly swapped for one another on cropland in different years, and soybeans are planted later in the year and are more sensitive to heat than corn, so if the signs of drought are obvious when the time comes to consider planting soybeans, farmers may simply forego doing so regardless of whether or not they have a CPIS. Crop insurance commonly covers prevented planting, so the farmers would still be compensated without showing a lower crop yield as the soybeans were never planted.

Table 4: Effects on Indemnity Payouts in Drought Years

	(1) indemnity corn	(2) indemnity soybeans
soybeans yield (bu/A)		-192686.3 (186609.4)
corn yield (bu/A)	-115608.1 (34093.85)	
CPIS	-229423.5 (116599.1)	-291969.7 (119808.2)
Constant	9174470.6 (2811708)	5661878.5 (5242175)
Observations	281	289
R-squared	0.6706	0.6412
County FE	Y	Y
Year FE	Y	Y

Notes: Std. errors in parentheses. CPIS values are in percentages of county field crop acreage.

6. Discussion and Conclusion

This paper has provided evidence regarding how the adoption of CPIS in Illinois has affected crop yield and indemnity payments at the county level and crop selection and expansion of cropland at the farm level. This paper has also provided weak evidence that counties in Illinois with higher CPIS presence have a parallel trend in crop yield to those with no CPIS presence implying that the greater adoption of CPIS seen in some counties is not impacting crop yield significantly. The results of this study are significant as they diverge from previous work regarding how improvements in irrigation technology tend to increase average crop yields, influence crop selection, and expand irrigated acreage which suggests that the environmental factors of the setting play a large role in the effect irrigation technology has on both production and the farmer's decision to invest in CPIS. This paper shows that CPIS provide a measure of drought risk mitigation that seems to go above and beyond that provided by crop insurance alone which would provide a reason for Illinois farmers to install them despite the lack of other benefits like those seen in western regions.

Additional analysis is warranted. So far we have said little about what actually determines when and where CPIS investment occurs in more humid regions beyond where yields were initially higher. The next logical thing to look at is why CPIS are installed in some areas and not others. The simplest answer is simply that CPIS cannot be installed in all areas. CPIS require some kind of groundwater source which is most commonly alluvial aquifers created by nearby waterways in Illinois. While there are shallow and deep bedrock aquifers in the state, they are less common, and it remains that not all cropland has access to a sufficient groundwater supply to merit installing a CPIS. For areas that have access to groundwater, differences in CPIS installation across locations could be driven by peer effects (Sampson & Perry, 2018), county level differences in agriculture subsidies (Pfeiffer & Lin, 2010) (Environmental Working Group), or other factors that may make one area more susceptible to drought than another. Future iterations of this paper hope to include such questions, potentially providing an instrumental variable to further address endogeneity beyond the county fixed effects.

The increase in CPIS presence and resulting pumping could lead to necessary policy decisions being made to prevent excess pumping in the future, especially during times of low water supply when the CPIS will be used the most. At present, groundwater rights in Illinois are

dictated through the Reasonable Use Rule established by the Water Use Act of 1983 which provides the right to extract groundwater to the owner of the overlying land as long as it is put to "reasonable use" (Texas A&M University School of Law, 2017). Overextraction of groundwater will produce negative externalities for both other local groundwater users through cones of depression and possibly other riparian water rights holders in the case of alluvial groundwater extraction. This problem is further complicated by the lack of available pumping data for the area, the delay in CPIS identification, and the fact that most CPIS in Illinois are located near rivers where they overlie alluvial aquifers (Illinois State Water Survey (ISWS), Prairie Research Institute, 2021).

This study is limited in its ability to inform policy decisions about pumping limits, spacing rules, or other ways to prevent greater-than-optimal groundwater extraction during drought years as a result of the proliferation of CPIS in Illinois due to the lack of available data. Probably the most relevant of the complications mentioned above is the lack of pumping data as this makes it extremely difficult to determine an accurate cost function at the farm level. The state has only required that individual irrigators report groundwater pumping since 2015, and the only other pumping data available is in annual aggregate for the state from 1987 onward which is not fine enough detail to identify anything about where or when the pumping is occurring at the CPIS level (Illinois Department of Natural Resources, 2015). However, future studies could attempt to gather or estimate this data through farmer surveys or clever utilization of detailed hydrological and evapotranspiration data which has seen some recent success (Valencia O. , et al., 2020).

Future analysis could attempt to quantify the benefits of installing CPIS as a means of drought risk mitigation if more data regarding groundwater pumping becomes available. It also seems possible to generate a testable hypothesis from the theoretical model presented in the discussion section of the paper in order to provide a more robust argument that the model accurately represents the decision-making process. Alternatively, further research could be done to determine how generalizable the results of this study are to other humid regions. Still, these results from Illinois are important first steps that show farmers are willing to invest in irrigation as a form of drought mitigation even if average yield enhancements are not present.

References

Anderson, J. (2018, 09 10). *How Center Pivot Irrigation Brought the Dustbowl Back to Life*. (Smithsonian Magazine) Retrieved from https://www.smithsonianmag.com/innovation/how-center-pivot-irrigation-brought-dust-bowl-back-to-life-180970243/

Annan, F., & Schlenker, W. (2015). Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat. *American Economic Review, 105*(5), 262-266.

Baerenklau, K. A., & Knapp, K. C. (2007). Dynamics of Agricultural Technology Adoption: Age Structure, Reversibility, and Uncertainty. *American Journal of Agricultural Economics, 89*(1), 190-201.

Christine, H., Fuss, S., Szolgayova, J., Strauss, F., & Schmid, E. (2012). Investment in Irrigation Systems Under Precipitation Uncertainty. *Water Resource Management, 26*, 3113-3137.

Cooley, D., Maxwell, R. M., & Smith, S. M. (2021). Center Pivot Irrigation Systems and Where to Find Them: A Deep Learning Approach. *Frontiers in Water*, 178.

Deines, J. M., Kendall, A. D., Crowley, M. A., Rapp, J., Cardille, J. A., & Hyndman, D. W. (2019). Mapping Three Decades of Annual Irrigation Across the High Plains Aquifer Using Landsat and Google Earth Engine. *Remote Sensing of Environment*, 111400.

Environmental Working Group. (n.d.). *Illinois Farm Subsidy Information*. Retrieved Sep 1, 2021, from EWG: https://farm.ewg.org/region.php?fips=17000&statename=Illinois

Evans, R. G. (2001, 07). *Center Pivot Irrigation.* Retrieved from https://www.ars.usda.gov/ARSUserFiles/21563/center%20pivot%20design%202.pdf

Extension, U.S. Geological Survey and University of Delaware Agricultural. (n.d.). *Center Pivot Irrigation*. (First Map) Retrieved 05 07, 2021, from https://firstmap.gis.delaware.gov/arcgis/rest/services/Hydrology/DE_Pivot_Irrigation/MapServer/0

Ford, T. W., Chen, L., & Schoof, J. T. (2021, March). Variability and Transitions in Precipitation Extremes in the Midwest United States. *Journal of Hydrometeorology, 22*, 532-545. doi:10.1175/JHM-D-20-0216.1

Grady, K. A., Chen, L., & Ford, T. W. (2021, Dec). Projected Changes in Spring and Summer Precipitation in the Midwestern United States. *Frontiers in Water*. doi:10.3389/frwa.2021.780333

Griliches, Z. (1957). Hybrid Corn: An Exploration in the Economics of Technological Change. *Econometrica*, 501-522.

Illinois Department of Natural Resources. (2013, 03). *The Drought of 2012.* Retrieved from https://www2.illinois.gov/dnr/WaterResources/Documents/TheDroughtOf2012.pdf

Illinois Department of Natural Resources. (2015). *Action Plan for a Statewide Water Supply Planning and Management Program.* Chicago, Illinois: Office of Water Resources.

Illinois State Water Survey (ISWS), Prairie Research Institute. (2021). *Illinois Maps*. (ISWS) Retrieved 07 08, 2021, from https://www.isws.illinois.edu/maps

Illinois State Water Survey. (n.d.). *Illinois Center Pivot Irrigation*. (Illinois Geospatial Data Clearinghouse) Retrieved 05 07, 2021, from http://clearinghouse.isgs.illinois.edu/data/hydrology/illinois-center-pivot-irrigation

Irrigation Education. (2016, 08 12). *Do Your Pivot Pipelines Last As Long As They Should?* (irrigation.education) Retrieved 06 16, 2021, from http://blog.irrigation.education/blog/do-your-pivots-last-as-long-as-they-should

Just, R. E., Schmitz, A., & Zilberman, D. (1979). Technological Change in Agriculture. *Science*, 1277-1280.

Koundouri, P., Nauges, C., & Tzouvelekas, V. (2006). Technology Adoption Under Production Uncertainty: Theory and Application to Irrigation Technology. *American Journal of Agricultural Economics, 88*(3), 657-670.

Lau, L. J., & Yotopoulos, P. A. (1989). The Meta-Production Function Approach to Technological Change in World Agriculture. *Journal of Development Economics*, 241-269.

Mishra, V., & Cherkauer, K. A. (2010, July). Retrospective Droughts in the Crop Growing Season: Implications to Corn and Soybean Yield in the Midwestern United States. *Agricultural and Forest Meteorology, 150*(7-8), 1030-1045. doi:doi.org/10.1016/j.agrformet.2010.04.002

NOAA National Centers for Environmental Information. (2021, Aug). *Climate at a Glance: County Time Series*. Retrieved from NCDC.NOAA: https://www.ncdc.noaa.gov/cag/

Pfeiffer, L., & Lin, C.-Y. C. (2010). Does Effiicient Irrigation Technology Lead to Reduced Groundwater Extraction?: Empirical Evidence. *Agricultural and Applied Economics Association.* Denver, Colorado.

Ruttan, V. W. (1960). Research on the Economics of Technological Change in American Agriculture. *Journal of Farm Economics*, 735-754.

Sampson, G. S., & Perry, E. D. (2018). The Role of Peer Effects in Natural Resources Appropriation - The Case of Groundwater. *American Journal of Agricultural Economics, 101*(1), 154-171.

Saraiva, M., Protas, E., Salgado, M., & Souza, C. (2020). Automatic Mapping of Center Pivot Irrigation Systems from Satellite Images Using Deep Learning. *Remote Sensing, 12*(3), 558.

Schnitkey, G. (2021, 01 26). *Farmdoc.* Retrieved from https://farmdoc.illinois.edu/handbook/historic-corn-soybeans-wheat-and-double-crop-soybeans

Seager, R., Lis, N., Feldman, J., Ting, M., Williams, P. A., Nakamura, J., . . . Henderson, N. (2018). 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), 1-22.

Smith, S., & Edwards, E. (2021, Nov). Water Storage and Agricultural Resilience to Drought: Historical Evidence from the United States. *Environmental Research Letters, 16*(12). doi:10.1088/1748-9326/ac358a

Soil Survey Staff. (2020, 12 01). *The Gridded National Soil Survey Geographic (gNATSGO) Database for Illinois.* (USDA Natural Resource Conservation Service) Retrieved 06 09, 2021, from https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/?cid=nrcseprd1464625

State Climatologist Office for Illinois. (n.d.). *Drought Trends in Illinois*. (ISWS) Retrieved 06 14, 2021, from www.isws.illinois.edu/statecli/climate-change/ildrought.htm

State of Nebrasksa Open Data. (2019, 04 18). *2005 Center Pivots in the Central Platte River Basin*. Retrieved from https://www.nebraskamap.gov/datasets/8e7b99d90da84c82889e00ba8f90ef41_0?geometry=-108.327%2C40.017%2C-90.936%2C42.898

Stubbs, M. (2016). Irrigation in U.S. Agriculture: On-Farm Technologies and Best Management Practices. *Congressional Research Service*.

Texas A&M University School of Law. (2017). *Groundwater Laws and Regulations: A Preliminary Survey of Thirteen U.S. States.* Retrieved 05 08, 2021, from https://law.tamu.edu/docs/default-source/faculty-documents/groundwater-laws-reg-13states.pdf?sfvrsn=0

Torkamani, J., & Shajari, S. (2008). Adoption of New Irrigation Technology Under Production Risk. *Water Resources Management, 22*, 229-237.

Trenberth, K. E., Dai, A., Van Der Schrier, G., Jones, P. D., Barichivich, J., Briffa, R., & Sheffield, J. (2014). Global Warming and Changes in Drought. *Nature Climate Change, 4*(1), 17-22. doi:10.1038/nclimate2067

United States Department of Agriculture. (n.d.). *Illinois Crop Insurance*. (Risk Management Agency) Retrieved 05 01, 2021, from https://www.rma.usda.gov/en/RMALocal/Illinois/State-Profile

USDA. (n.d.). *Land Capability Classification.* Retrieved Sep 1, 2021, from NRCCD: http://www.ncrcd.org/files/4414/0968/3285/NRCS_Land_Capability_Classes.pdf

USDA NASS. (2021, 03 16). *Data and Statistics*. (USDA) Retrieved 06 09, 2021, from https://www.nass.usda.gov/Data_and_Statistics/index.php

USDA National Agricultural Statistics Service. (2008-2020). *Cropland Data Layer.* Retrieved from www.nass.usda.gov/Research_and_Science/Cropland/Release/index.php

USGS/Google. (n.d.). *USGS Landsat 5 TM Collection 1 Tier 1 TOA Reflectance*. (Earth Engine Data Catalog) Retrieved 06 16, 2021, from https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LT05_C01_T1_TOA

Valencia, O. M., Johansen, K., Solorio, B. J., Li, T., Houborg, R., Malbeteau, Y., . . . McCabe, M. F. (2020). Mapping Groundwater Abstractions from Irrigated Agriculture: Big Data, Inverse Modeling, and a Satellite-Model Fusion Approach. *Hydrology and Earth System Sciences*, 5251-5277.

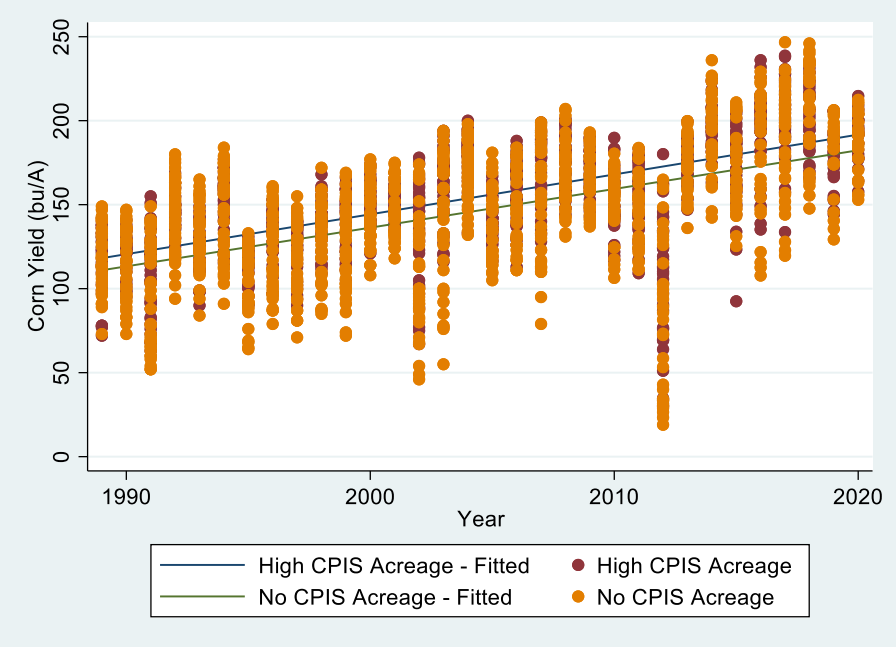
Valencia, O., Johansen, K., Solorio, B., Li, T., Houborg, R., Malbeteau, Y., . . . McCabe, M. (2020). Mapping Groundwater Abstractions from Irrigated Agriculture: Big Data, Inverse Modeling, and a Satellite-Model Fusion Approach. *Hydrology and Earth System Sciences, 24*, 5251-5277.

Zhang, C., Yue, P., Di, L., & Wu, Z. (2018). Automatic Identification of Center Pivot Irrigation Systems from Landsat Images Using Convolutional Neural Networks. *MDPI Agriculture, Special Issue:*(Remote Sensing in Agricultural System).

Zilberman, D. (1984). Technological Change, Government Policies, and Exhaustible Resources in Agriculture. *American Journal of Agricultural Economics*, 634-640.

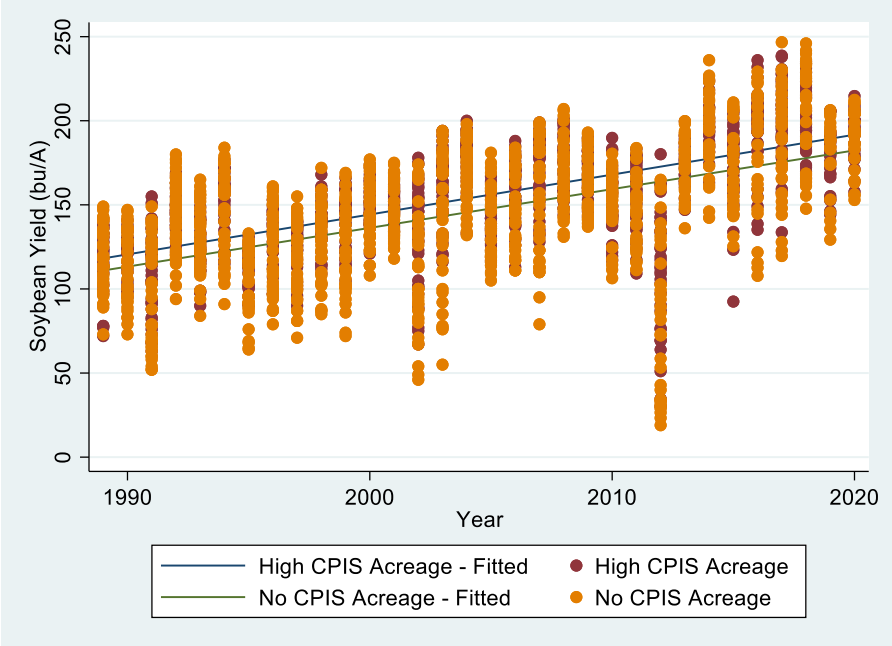
Appendix

Figure A 1: Illinois Corn Yield in BU/Acres, 1989-2020 (USDA NASS, 2021)



Notes: Crop yield measured in bushels per acre and divided by county. Red dots represent counties with high CPIS presence and orange dots represent counties with no CPIS presence. The fitted lines are lines of best fit for high CPIS acreage counties (blue) and no CPIS presence counties (green) and show roughly parallel trends.

Figure A 2: Illinois Soybeans Yield in BU/Acres, 1989-2020 (USDA NASS, 2021)



Notes: Crop yield measured in bushels per acre and divided by county. Red dots represent counties with high CPIS presence and orange dots represent counties with no CPIS presence. The fitted lines are lines of best fit for high CPIS acreage counties (blue) and no CPIS presence counties (green) and show roughly parallel trends.