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ABSTRACT

Irrigation in the Eastern US receives little attention compared to the West, but farmers in humid states of the US, traditionally reliant on rainfall, have more than tripled irrigation 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 where and when CPIS installations occur and their benefits in terms of annual crop yield, irrigated acreage, crop selection, and reduction in drought-related insurance payouts. To do so, we create a novel data set derived from a deep learning model capable of automatically identifying the location of CPIS during drought years along with annual county level crop, weather, and insurance data. The results indicate CPIS installations in Illinois are significantly more common over alluvial aquifers after droughts. Additionally, counties with a higher presence of CPIS do not have higher average crop yields, a shift to more water intensive crops, 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.

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1. Introduction

Irrigation has long served as an adaptation to increase crop yields and provide resilience during severe drought in arid regions (Troy, et al., 2015; Zhang, et al., 2015; Tack, et al., 2017; Edwards & Smith, 2018; Zaveri & Lobell, 2019). The17 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 & 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, there is a persistent trend in 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 emerged and its effect on cropping patterns, crop yields, and federal crop insurance payouts.

Economist have not paid significant attention to the irrigation potential of rain-fed agriculture. This is an oversight given that freshwater availability will shape irrigation adaptation over the long run. Freshwater availability limitations in arid and historically irrigated regions (e.g., the Western US) means climate change adaptation may require less irrigation, but more humid regions, like the eastern US, can still expand irrigation (Elliot et al., 2014). In a global study, Rosa et al. (2020) estimated that irrigation could be expanded as an adaptation strategy with little negative effects on water resources on 35% of current rain-fed crops. This, of course, will take costly investments to accomplish (Elliott et al., 2014) and similarly scaled projects to those in the mid-twentieth century in the US may be unreasonable to expect (Schlenker et al., 2005). But shorter distances from the more abundant streams in humid areas and technological advances have lowered the costs to tap underground water resources efficiently, reducing the need for large projects to garner economies of scale. Instead, individuals can now make the investment decision on their own.

Irrigation expansion in the US has often been by center pivot irrigation systems (CPIS) since their invention in 1948 by Frank Zybach (Anderson, 2018). Today, some 57% of irrigated acreage in the US is done so by a sprinkler with higher percentages in the humid regions (Hrozencik & Aillery, 2021). In arid states, 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 particularly important for corn and soybeans, major crops in the Midwest, as summertime drought is correlated with low corn and soybean yields (Mishra & Cherkauer, 2010).

Negri et al. (2005) found that the tails of weather distributions matter more than the means in predicting irrigation uptake, albeit based on cross-sectional variation. Temporally, farmers also tend to invest in irrigation shortly after experiencing a drier year (Smith & Edwards, 2021). In Illinois, severe, state-wide droughts occurred in 1988, 2005, and 2012 with the most recent severe drought prior to 1988 occurring in 1964 (State Climatologist Office for Illinois, 2015). 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 (ISWS, 2015).

We explore the trends in CPIS adoption and their benefits as a form of drought risk mitigation in Illinois given the upward trends in precipitation means and variation as well as irrigation. The question is interesting because CPIS are expensive and alternatives do 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 (USDA, 2021). We consider whether CPIS uptake confers the benefits found in the West – crop switching, increased yields, resilience, and expanded cropland – 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 at the county level in 1959 and 1969, but not since and state records vary greatly. To circumvent this data shortage, we leverage a deep learning model to identify the locations of CPIS from satellite imagery. The model extends that of Cooley, Maxwell, & Smith (2021), which was utilized to identify CPIS over the Ogallala aquifer, a much more arid region. Our focus on Illinois among the Midwest states is largely because the Illinois State Water Survey conducted a survey in 2012 and 2014 in which CPIS were manually identified from aerial photography and well records for the entire state, providing a ground truth to train the model with. Still, deploying the model in a humid region where the iconic "circles" of CPIS are less detectable limits performance. Accordingly, we run the model on drought years when the circles are most apparent and fill in the interim years via a linear trend. Results are robust to alternative assumptions for the non-drought years.

We aggregate 30 x 30-meter resolution CPIS data to the field and county level and combine it with annual land coverage 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). In addition, we draw on county-level statistics from the USDA Agriculture Censuses. We also collect weather data from both NOAA and PRISM to address climate variation and various other hydrologic and topographic data.

We find that adoption of CPIS in Illinois is strongly correlated with the presence of alluvial aquifers (and not other groundwater or streams) and often spurred by experiencing relatively drier years. In addition, larger farms are more likely to adopt CPIS. Notably, soil suitability and topography offer little predictive value but counties with slightly less valuable farmland prior to irrigation have adopted CPIS more extensively.

In terms of the effect of CPIS installation, we find there is not a shift from other types of crops to corn or soybeans as a result of CPIS installation, but there is a shift from soybeans to corn or a shift in the frequency of corn in the crop rotation which is particularly interesting given that corn has greater water use efficiency than soybeans (Dietzel, et al., 2015). 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, 2014). Furthermore, there is no significant correlation between CPIS installation and average crop yield or irrigated acreage in Illinois. 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 literature regarding 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 (e.g., Koundouri, Nauges, & Tzouvelekas, 2006; Baerenklau & Knapp, 2007; Torkamani & Shajari, 2008; Pfeiffer & Lin, 2014; Christine, et al., 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).

We also expand on the small literature on supplemental irrigation. The value of supplemental water reserves for irrigated areas goes back to work by Tsur (1990) and Tsur & Graham-Tomasi (1991) that identified and quantified the quasi-option value of groundwater reserves. More recent work has shown the supplemental water rights in the Western US as an adaptation to reduced rain and higher temperatures (Bigelow & Zhang, 2018) that adds real value to the farms (Brent, 2017). Our efforts are distinct in that we consider new irrigation adoption solely in a primarily rain-fed region.

Our work also builds on the substantial body of research concerning the effects of advancements in technology on agricultural production (e.g., 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, Maxwell, & Smith, 2021). 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 (e.g., Smith & Goodwin, 1996; Annan & Schlenker, 2015; Connor & Katchova, 2020; Wang, Rejesus, & Aglasan, 2021).

Finally, the deep learning model used to automatically identify CPIS for this study exemplifies the use of machine learning methods to extract and classify information from unstructured data in economics (e.g. Athey, 2019; Storm, Baylis, & Heckelei, 2020), and to the growing literature regarding automated CPIS identification by examining a humid region rather than the more arid regions where similar models have been deployed (e.g. Zhang et al., 2018; Deines, et al., 2019; Saraiva et al., 2020; Valencia O. M., et al, 2020; Tang et al., 2021; Cooley, Maxwell, & Smith, 2021).

The rest of this paper is organized into five additional numbered sections. Section 2 presents background information and a theoretical model showing how increased droughts can induce more irrigation investment despite access to 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. Background and Theoretical Framework

a. Illinois Agriculture and Climate

At nearly $1,000 per acre as of the 2017 agriculture census, Illinois' farmland is among the most valuable in the US. More valuable farmland is found in the Northeast, where nonproductivity factors likely drive the land values higher, and along the West Coast in California and Washington. Illinois produced over one billion dollars' worth of crops in 2017, just behind Iowa and, more distantly, California. Unlike California, where specialty crops are prevalent, Illinois (and Iowa) grow mostly corn and soy with Illinois producing the most soy and the second most corn in 2017. Given these crops are often grown in rotation on the same fields, the relative ranking of Illinois and Iowa may often swap. They are the only two states in the top-five states for both corn and soy yields per acre.

Meanwhile, Illinois is closer to the middle of the distribution in terms of growing season precipitation (April-September). The annual average for Illinois counties, stretching back to 1900, is 579 mm of precipitation. For comparison, counties in California saw just 116 mm during that period. Wetter states, primarily in the southeast, averaged over 650 mm with Florida, the wettest, averaging 888 mm. At 20 degrees Celsius, Illinois is also near the middle of the states in terms of average monthly temperature during the growing season as well. The upshot is that Illinois, relative to the other continental states, is not an extreme case, but rather a temperate-humid setting.

Figure 2 shows that while temperatures in Illinois have not exhibited a meaningful trend, precipitation has increased, but also become more variable. The plots are local polynomial fits for the county level, annual growing season weather variables across time. Precipitation has exhibited an upward trend since 1960, going from around 565 mm to nearly 650 mm, a 15 percent increase. Temperature is lower now than in 1940, but it higher compared to most recent baselines like 2000. The shifts are also relatively slight, ranging from 19.7 degrees to about 19.9. We should note, however, the annual averages omit important within season variation that matters for corn production (see Berry et al., 2014, for instance).

Panel b of figure 2 shows that the precipitation, although greater on average, has also become more variable. The plots are again local polynomial for county-year measures, but for a rolling, 10-year standard deviation. As the average precipitation began to increase, around 1940, so did the standard deviation, increasing from about 105 mm up to 145 mm. Therefore, the wetter years are interspersed with drier years, on average. Again, no clear trend emerges for temperature given that is highly sensitive to how far back one looks.

A severe drought occurred in 2012 in Illinois as with much of the Corn Belt. Berry et al. (2014) estimated corn losses upwards of 20 percent. However, the authors do not account for irrigation in their estimates. On average, at the time, this may have been a reasonable assumption, but 15 counties in Illinois that year did irrigate over 5 percent of their harvested crops, with one county topping out at 41 percent. Illinois farmers have drastically increased their irrigated acreage. In 1950, Illinois had just 140 irrigated farms with 1,510 acres irrigated. In 2017, 2,541 farms reported irrigating a total of 607,442 acres, or roughly as much as New Mexico, an arid state associated with irrigation. The Illinois figures still only amount to 5 percent of the farms and just 2.3 percent of the acres, meaning many there are yet to adopt irrigation.

An alternative to irrigation, from the farmers' perspective, is crop insurance. Indemnity is the compensation paid by an insurance company to cover crop damages because of a qualifying event such as drought, fire, or flooding, making it broader than covering drought alone. 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, & Edwards, 2021). Uptake in Illinois is extensive and provides substantial protection from droughts. In 2005, Illinois farmers collected nearly $25 million in indemnity payments. More eye opening, in 2012, the most severe drought, they received $2.9 billion.

b. Analytical Framework

Given that Illinois has increased irrigation capacity despite being humid and getting wetter on average, we provide a theoretical model to provide some insight into the decision process for installing a CPIS as a form of drought risk mitigation. Furthermore, we include crop insurance as an alternative mitigation tool given its prevalence and moral-hazard-inducing potential. We assume that the farmer's choice is between having insurance without irrigation or having both irrigation 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).

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

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

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

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 $\big(\bar{y} - y(w_t, p_t)\big)$ at the cost of the premium for the level of insurance protection that the farmer has opted into $(c(b))$. 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. 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.

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

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

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

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

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:

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

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.

To this point, we have largely ignored the cost function or other factors not explicitly modeled that would influence CPIS adoption and effects. On the cost side, access to water is the most critical. This is especially true in Illinois where water rights are based on the riparian doctrine, limiting the potential irrigators to those with fields adjacent or above water resources. Suitability of the land to operate a CPIS is important, which generally could include topography, but Illinois is known to be relatively flat. The field or farm sizes may also matter, exhibiting some economies of scale due to technological aspects or the farm operation and desire or ability to self-insure through CPIS. Finally, aspects not modeled could include technological diffusion through learning due to neighbors' choices. In sum, we aim to test the following hypotheses with empirical data:

i. Areas with lower cost access to fresh water resources develop more irrigation
ii. Flatter and larger farms adopt more irrigation capacity
iii. Areas with higher yields and more corn develop more irrigation capacity
iv. Areas increase irrigation capacity as the incidence of dry years increase rather than average precipitation trends
v. More irrigation capacity does not lead to crop switching or an expansion of cropland
vi. In average precipitation years, CPIS does not affect yields, but increases yields in drought years
vii. CPIS reduce indemnity (crop insurance) payments

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 (Finkelstein & Nardi, 2016). More relevant 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, 2015). 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 than other options 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.

To overcome this challenge, we utilize deep learning, a type of machine learning that uses neural networks to replicate the learning process of humans. Deep learning is particularly useful for processing unstructured data such as the satellite imagery used for this paper as it requires very little human input. The goal is to get the predictions of the deep learning model to mirror the state of the real world known as the ground truth by minimizing the difference between the two. The model does this by guessing the correct label of inputs, checking how it performed against the ground truth, then recalibrating itself before repeating the process. For a more expansive and technical treatment of the subject, see Goodfellow et al. (2016).

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 natural precipitation reducing the distinct boundary between the irrigated area and surrounding land cover most years (e.g. Zhang et al., 2018; Deines, et al., 2019; Saraiva et al., 2020; Valencia O. M., et al, 2020; Tang et al., 2021; Cooley, Maxwell, & Smith, 2021). 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 to predict their locations as is the case with previous attempts at detecting CPIS with satellite imagery (Zhang et al., 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 where the area beyond a CPIS is distinct enough to be detected.

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 through transfer learning. Transfer learning is a training technique that applies the weights and values from a model intended for one purpose to another model in order to expedite the learning process and minimize the loss of the model. 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 randomly 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 3 provides a comparison of the ground truth (yellow) and model output (red) in Illinois. To evaluate the performance of the model, four metrics are utilized at the pixel level: accuracy, specificity, precision, and recall. Accuracy is simply the number of correctly identified pixels over the total number of pixels. Precision is the number of correctly identified CPIS pixels over the total number of CPIS pixels predicted by the model regardless of correctness compared to the ground truth. Recall is the number of correctly identified CPIS pixels over the total number of CPIS pixels as given by the ground truth. Lastly, specificity is the number of correctly identified background (non-CPIS) pixels identified by the model over the number of background pixels given by the ground truth.

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 et al., 2018; Saraiva et al., 2020; Cooley et al., 2021). 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.

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, we assume that CPIS are durable through time. 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.

In Illinois, CPIS is the dominant form of irrigation. We compared the share of Illinois counties with irrigation during the 2012 growing season from the USDA Census that year to the hand collected CPIS data from the Illinois State Water Survey from that year and found the relationship between the two incredibly tight. Shown in Figure A1 of the appendix, the binary regression yielded a coefficient of 1.05 and a constant of -0.003 and an R-Square value of 0.94. Furthermore, the 2015 USGS water use data for Illinois shows that 100% of the ~600,000 acres of irrigated cropland in Illinois were irrigated by sprinkler which aligns well with the Illinois State Water Survey's estimate of center pivot irrigation systems irrigating approximately 625,000 acres of cropland in Illinois in 2014 (USGS, 2018; ISWS, 2015). Therefore, we view CPIS as the primary technology for irrigation and a good measure of the capital constraint for acreage irrigated in any particular year.

CPIS in Illinois can only be accurately predicted by the deep learning model during drought years, 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 may not 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 4.

The rest of the data collected comes from standard sources. USDA Censuses provide agriculture and irrigation statistics at the county level. 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. We also draw on annual county level temperature and precipitation data constructed by Smith & Edwards (2021) from PRISM data. Soil quality and other geographic information was derived from the Gridded National Soil Survey Geographic (gNATSGO) Database for Illinois. Summary statistics for the data may be found in the appendix in tables A1 and A2.

4. Methods

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

We conduct tests for irrigation and CPIS installation at the county level given the longer time period available from the agricultural census. We estimate several versions of the following equation:

$$Irr_{iy} = \alpha_0 + \overrightarrow{\boldsymbol{W}}_i + \overrightarrow{\boldsymbol{X}}_i + \overrightarrow{\boldsymbol{C}}_{it} + \boldsymbol{\delta}_t + \varepsilon_{iy} \tag{10}$$

Irrigation in county *i* in year *y* is measured either by the share of the county irrigated that year according to the census or the share with a CPIS captured in drought years by our machine learning (1988, 2005, 2012). $\overrightarrow{\boldsymbol{W}}_i$ is a vector of freshwater availability and their coefficients. These measures include the share of the county over an aquifer, share within a 15-mile buffer of a large stream, and the share over an alluvial aquifer where an alluvial aquifer is one that is closely connected, hydrologically, to a stream. $\overrightarrow{\boldsymbol{X}}_i$ is a vector of time-invariant county measures like topography, average weather and variation, 1940 (pre-irrigation) farm characteristics, or, in some specification, just county fixed effects. $\overrightarrow{\boldsymbol{C}}_{it}$ is a vector of time varying weather variables. The main ones are locally normalized weather disturbances from Smith & Edwards (2021) measuring how many standard deviations away from the county mean that years' weather is. More attention is given to "severe" years indicated as being more than 1.5 standard deviations drier or hotter than average. Finally, $\boldsymbol{\delta}_t$ is a vector of year fixed effects.

For cropland and crop choice we can be spatially precise because CDL data, like our CPIS data, is available at the 30-meter resolution. However, rather than aggregating the non-CPIS land coverage to the include the entirety of the state, we divide it into Public Land Survey System (PLSS) sections. These are typically 640 acres (one square mile). For this analysis, we also are temporally precise by limiting the sample to 2012 and 2014, two years in which we know from the Illinois State Water Survey when the CPIS were installed. 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 exclude areas that had a CPIS installed by 2012 to avoid polluting the model with "pretreated" data. We estimate the following equation:

$$S_{Lt} = \gamma_0 + \gamma_1 time_t + \gamma_2 treated_l + \gamma_3 time_t treated_L + \varepsilon_{Lt} \quad (11)$$

S_{Lt} is the share of the land with a particular land coverage. We consider corn, soybeans, both corn and soybeans, other crops, and non-cropland in separate regressions. The $time$ variable picks up the difference in land coverage share between 2012 and 2014. The $treatment$ variable captures any distinctions between land where a CPIS was installed during the observation period and all other land in the state. Finally, the DID estimate (γ_3) which is the primary variable of interest, captures the effect of CPIS installation on land coverage.

Third, 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:

$$\log(y_{it}) = \rho_0 + \rho_1 CPIS_{it} + \rho_2 CPIS_{it} * D_t + \rho_3 D_t + \rho_4 P_{it} + \rho_5 T_{it} + \boldsymbol{X}_i + \delta_t + \varepsilon_{it} \quad (12)$$

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. As in equation 10, $\boldsymbol{X}_i$ 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 2014.

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

$$\log\,(I_{itc}) = \beta_0 + \beta_1 CPIS_{it} + \ \beta_2 P_{it} + \beta_3 T_{it} + \boldsymbol{X}_i + \delta_t + \varepsilon_{it} \tag{13}$$

Indemnity (I_{it}) is logged and defined as the insurance payout in dollars for each drought-related claim in each county (i) during year (t) for a specific crop (c). We estimate it only for corn and soybean payments. The rest of the model follows the same specifications as equation 12 except that the drought indicator and interaction are dropped as drought indemnity payments only occur in three drought years. CPIS share is still the coefficient of interest, and we control for precipitation and temperature since the state-wide drought is not uniformly felt in terms of actual weather. Finally, we include county and year fixed effects.

5. Results

In terms of where, access to an alluvial aquifer is the dominant factor predicting irrigation in Illinois. A series of regressions provided in the appendix (table A3) supports the claim and we will discuss it further, but figure 5 first provides main point. It plots the year fixed effects and the year fixed effects interacted with the share of the county overlaying an alluvial aquifer from a simple county-fixed effect model. Irrigation has steadily grown, on average, since 1964, but almost solely where an alluvial aquifer is present.

Additional context is garnered from the additional regressions reported in the appendix. Across all specifications, alluvial aquifer access is a statistically and economically significant predictor of irrigation. In specification 4 (with the most covariates), 100 acres of land over an alluvial aquifer is associated with an additional 4 irrigated acres. Given that just 0.5 acres per 100 are irrigated in Illinois, this is significant increase. Comparing this to alternative water resources is illuminating: being near a large stream or a non-alluvial aquifer does not increase irrigation in Illinois. In the West, these are significant predictors of irrigation (Edwards & Smith, 2018).

Measured at the county level, soil suitability and slope are not statistically significant predictors, although point estimates are in the direction one would expect. Pre-irrigation farm characteristics (1940) show a slight, but consistent, reduction in irrigation where farm values were higher. Corn yields, specifically, are not predictive. Counties with larger average farms are associated with more irrigation. Finally, the weather variables suggest that counties with smaller variations in temperature and that have more precipitation on average are likely to irrigate more. To explore the time-varying component more, we introduce county fixed effects.

Table 1 shows that counties are more sensitive to precipitation shocks than temperature shocks in irrigation decisions. Column (1) presents estimates from regressing the fraction of the county irrigated in a census year on the prior five years', county-specific normalized precipitation and temperature bins. These are constructed as 1-5 with higher numbers indicating "drought" conditions. There is considerable variation both across and within year for these measures (see figure A2 for boxplots). Additional controls are current year precipitation and temperature, and year fixed effects. Experiencing relatively drier years in the past 5 years increases the share irrigated in a given year. No effect is found for temperature. Column (2) replaces the average bin over the past five years with an indicator variable equal to 1 if any of the past five years fell in the most severe bin (greater than 1.5 standard deviations drier or warmer). Again, a severe dry year in the past five leads to more irrigation. Finally, column (3) interacts the indicators with the share of the county over an alluvial aquifer. Here, the statistical significance is weakened, but the effect appears to be driven by counties with access to the alluvial aquifer.

These irrigation decisions, in any given year, are constrained by the installed capacity. This capacity, meanwhile, need not be deployed in a particular year. Accordingly, we consider similar specifications in columns (4) – (6) but with CPIS share as the dependent variable and no controls for current year weather given that CPIS installation is not a within-season decision. To accurately capture CPIS from the machine learning model, we use only the state-wide drought years, limiting the sample to just three years, straining our ability to pick up statistical significance. Still, the pattern is similar. Particularly in column (6), we find that experiencing at least one severe dry year in the past five years where an alluvial aquifer is present increases CPIS by 0.075 acres per county acre. Overall, it appears county level CPIS adoption in Illinois is limited to areas with alluvial aquifers and done in response to recently experienced dry years by local standards.

Table 2 shows the effect of CPIS investment on crop choices in Illinois. It displays coefficients as the estimated percent change in corn, soybeans, other crops, and non-cropland land coverage. Standard errors are in parentheses. The first row shows the difference between the share of land coverage in 2012 and 2014. The second row describes the difference between the treated group, areas that had a CPIS installed between 2012 and 2014, and the control group which is the rest of the state minus CPIS installed prior to 2012. The results show that there is not a statistically significant number of newly installed CPIS on land that was not already being used to grow crops as the share of non-crop land coverage did not change as a result of CPIS installation. This indicates that CPIS installation is not directly linked to an expansion of cropland. Additionally, there is not a shift from other crops to corn or soybeans as a result of CPIS installation.

However, CPIS installation does affect the choice farmers make between soybeans and corn. There is approximately an 8.65% decrease in soybeans in conjunction with a 10.66% increase in corn as a result of CPIS installation. This may be due to the newly irrigated land being able to support a different crop rotation pattern such as corn-corn-soybeans instead of corn-soybeans or continuous soybeans indicating that CPIS provide some flexibility in crop rotation patterns. It may also be that farmers installing CPIS are more risk-averse than other farmers and take the additional measure of increasing the mix of corn to soybeans as corn is less heat sensitive than soybeans. Lastly, it may be that farmers with newly installed CPIS want to make the most of their irrigated water and increase the mix of corn to soybeans as corn is the more water efficient crop (Dietzel, et al., 2015).

This result is distinct from patterns observed in arid regions, where irrigation or improved irrigation efficiency leads to an uptake of thirstier 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 soybeans 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).

Table 3 shows the results from estimating equation 11. The yield values are logged, and CPIS presence is measured as a share of cropland. Therefore, coefficients can be roughly interpreted as the correlation between a percent change in crop yield and a percentage point change in CPIS presence. None of the plausible range for CPIS presence is correlated with average crop yield. However, CPIS presence during a drought year has a significant effect on crop yield for corn, but no significant effect on soybeans. During a drought year, an additional 1% of cropland with CPIS is correlated with an approximately 0.46% increase in corn yield per acre across the county. Scaling this to a PLSS section level, a single center pivot occupies between 20% and 39% of the section, so our results imply that the installation of a new CPIS would improve corn yield in a drought year by about 9% to 18%, depending on the size of the center pivot. Given that average corn yield in a drought year is roughly 99 bushels per acre, this is significant at both a statistical and economic scale. We also find that soybean yield is more sensitive to both heat and precipitation than corn yield.

Finally, in table 4 we provide the estimates for equation 13, connecting CPIS to indemnity payments. Indemnity amounts are logged, and the share of CPIS is measured as CPIS acreage in a county divided by the cropland acreage of that county. CPIS presence has statistically significant negative effect on drought indemnity for both corn and soybeans. The coefficients imply that another 1% of cropland with a CPIS share decreases insurance payouts for corn by approximately 6.34% and soybeans by about 2.81%. This could be because farmers that are disproportionately impacted by drought conditions are more likely to be early adopters of CPIS thus being the ones with the most to benefit from their installation by virtue of relying less on crop insurance payouts. Additionally, the average county only has 8 insurance claims filed during a drought year, so a single foregone claim amounts to a large percentage change in indemnity payments.

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. 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, spur a shift to more water-intensive crops, 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 goes 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.

These results are most pertinent in the context of investing in irrigation as an adaptation to climate change. Our theoretical model suggests that the probability of a drought event in any given year plays a significant role in a farmer's decision to invest in irrigation even when their crops are insured. We show that, despite the increasing mean precipitation, the variability of precipitation in Illinois is increasing. Our county-level analysis provides evidence that recent local precipitation shocks are correlated with increased shares of irrigation. Moreover, irrigation may not a viable option for farmers in areas not overlying an aquifer or near a stream. This is important to note as much of the eastern US remains unirrigated, but further adaptation is likely to continue, especially in similarly endowed regions.

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 if it is put to "reasonable use" (Cain et al., 2017). Overextraction of water will produce negative externalities for both other local water 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 (ISWS, 2015).

This study is limited in its ability to inform policy decisions about pumping limits, spacing rules, or other ways to prevent greater-than-optimal water 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 (e.g., Valencia O. M., et al., 2020).

Additional analysis is warranted. Although we identified county-scale factors for CPIS installation, we have said little about what determinants of CPIS adoption within counties. The next logical thing to look at is why CPIS are installed in some areas and not others at a higher spatial resolution. Some factors may be similar to county level variation. CPIS require some kind of water 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, 2014; Environmental Working Group, 2020), or other factors that may make one area more susceptible to drought than another.

We also only consider the drought-side of the increasing variability of precipitation in Illinois and the eastern US more broadly, but the variability will also increase flooding events that may influence farmer decisions about investing in irrigation. While CPIS installation does seem to provide some assurance during more frequently occurring droughts, it may bring about other concerns about groundwater depletion, water rights, cropland retirement, crop subsidies, and field erosion that are worth additional study. Additionally, further research could be done to determine how generalizable the results of this study are to other humid regions. Illinois was used primarily due to the CPIS ground truth available, but the field of machine learning is rapidly growing and advancing, so it may be possible to quickly identify CPIS in other humid regions in the near future. Still, the preponderance of corn in the state makes it an important case study since corn is the most irrigated crop by acreage (25%) in the US (Hrozencik & Aillery, 2021). However, 85 percent of corn acreage is not irrigated, leaving plenty of rain-fed acres that may consider the adoption of irrigation. These results from Illinois 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.

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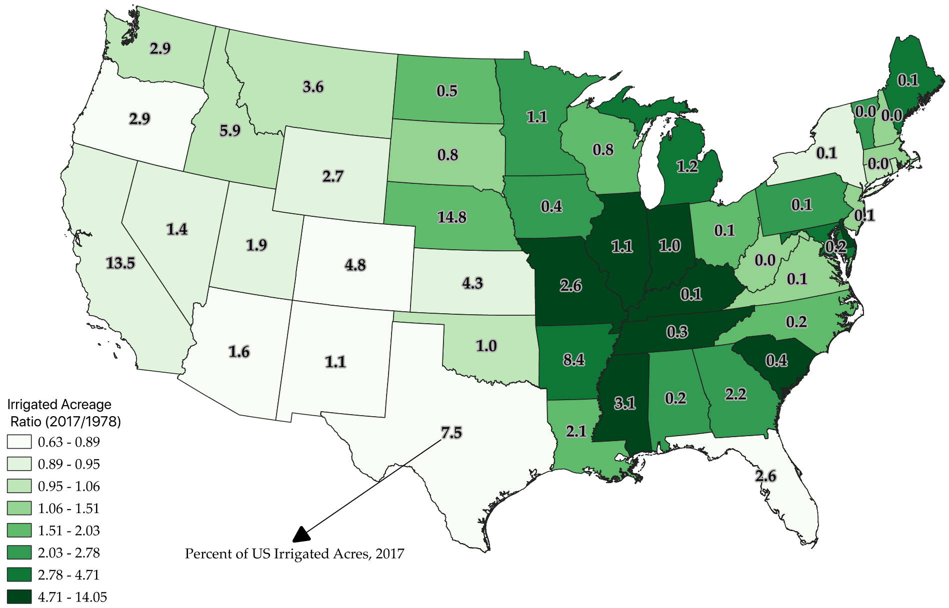
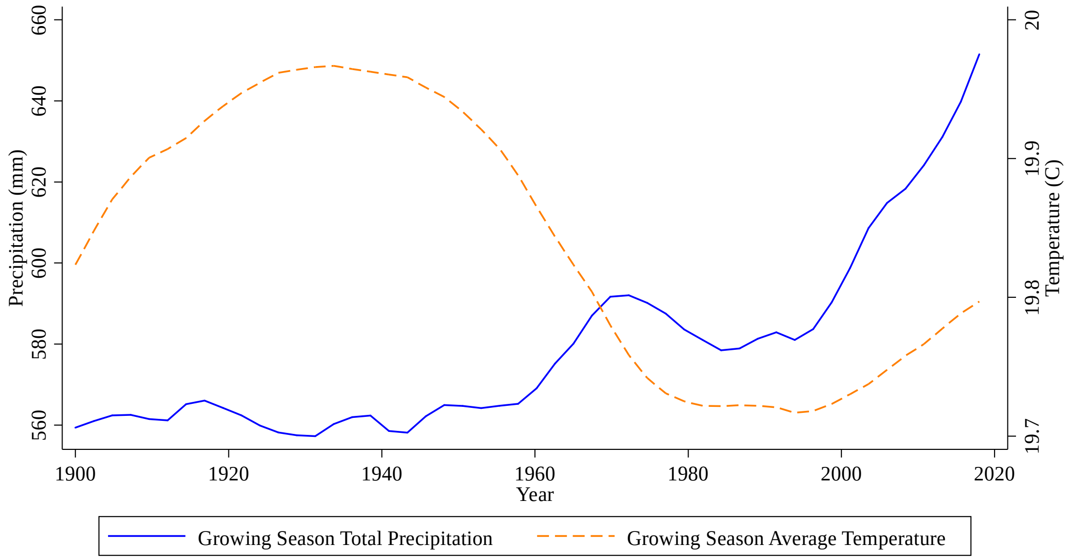
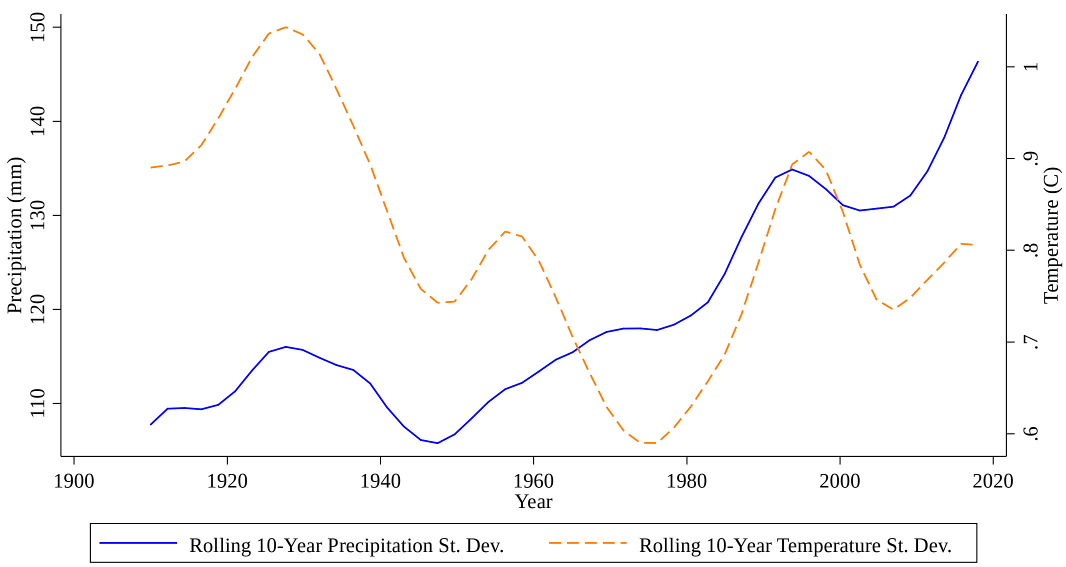


Figure 1: Irrigated Acres in the U.S., 1978-2017. *States with darker green experienced a greater percent change in irrigated acres over the observed period. States with larger numbers contain a greater percentage of the nation's irrigated acreage as of 2017. Underlaying data come from the USDA Census (Haines et al., 2018; USDA, 2019).*



Panel (a): Seasonal Weather Averages



Panel (b): Seasonal Weather Rolling Standard Deviations

Figure 2: County-level weather in Illinois from 1900 to 2017. *Panel A shows the annual growing season total precipitation (solid, blue) and growing season average temperature (dashed, orange) using a local polynomial to plot the state level averages. Panel b shows the standard deviation for the weather variables based on a 10-year rolling calculation. Data for both come from PRISM.*

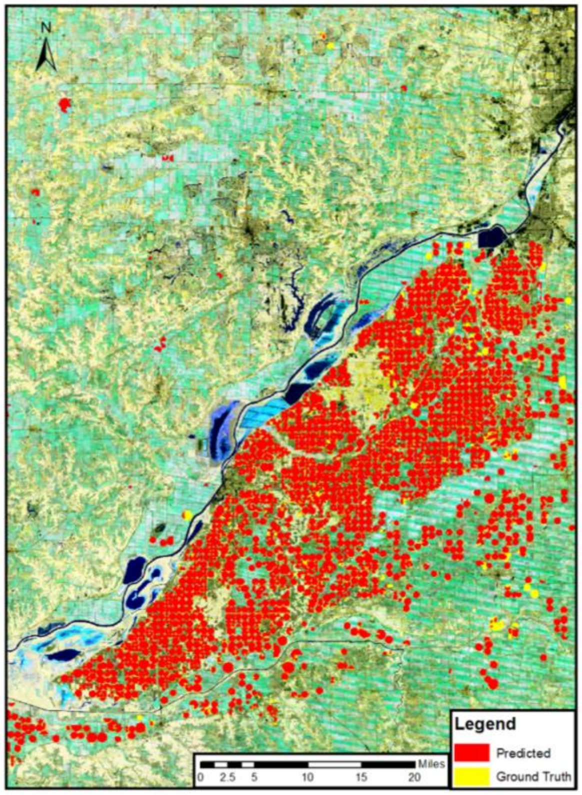


Figure 3: Deep learning output for locating CPIS in Illinois, 2012. *Red portions are the predicted locations of CPIS from the deep learning model while yellow portions are the ground truth from the manually labelled CPIS.*

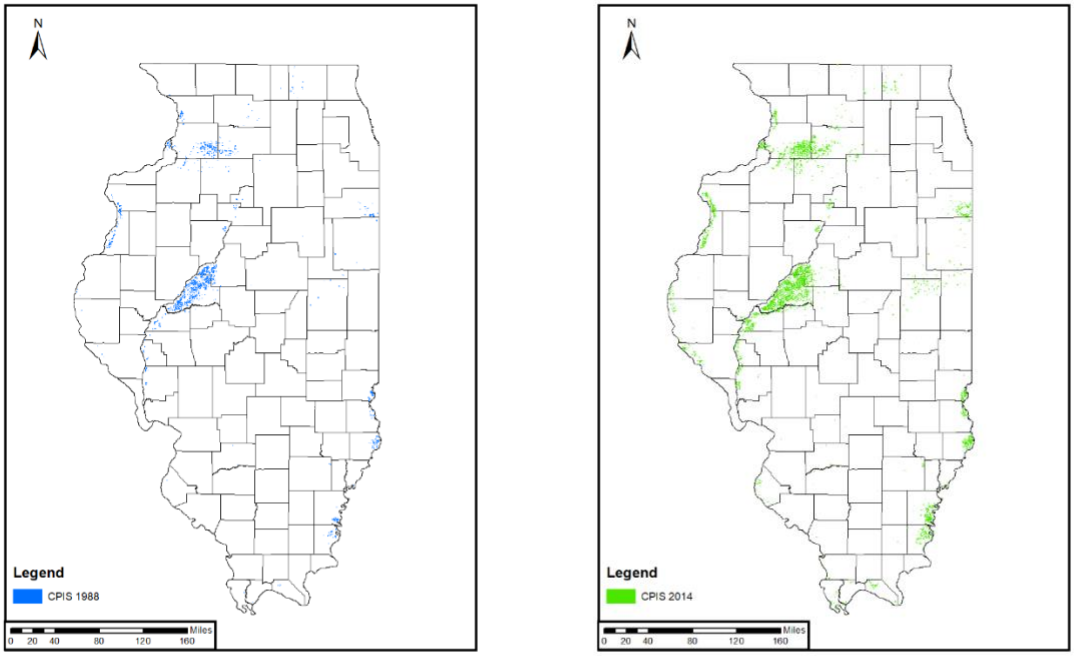


Figure 4: Illinois CPIS in 1988 and 2014. *Panel A shows the location of CPIS in 1988 as predicted by the deep learning model. Panel B shows the location of CPIS in 2014 according to a manually labelled data set produced by the Illinois State Water Survey. There was nearly a threefold increase in CPIS between the two periods, but new CPIS were not uniformly distributed across the state, instead being concentrated in a few areas.*

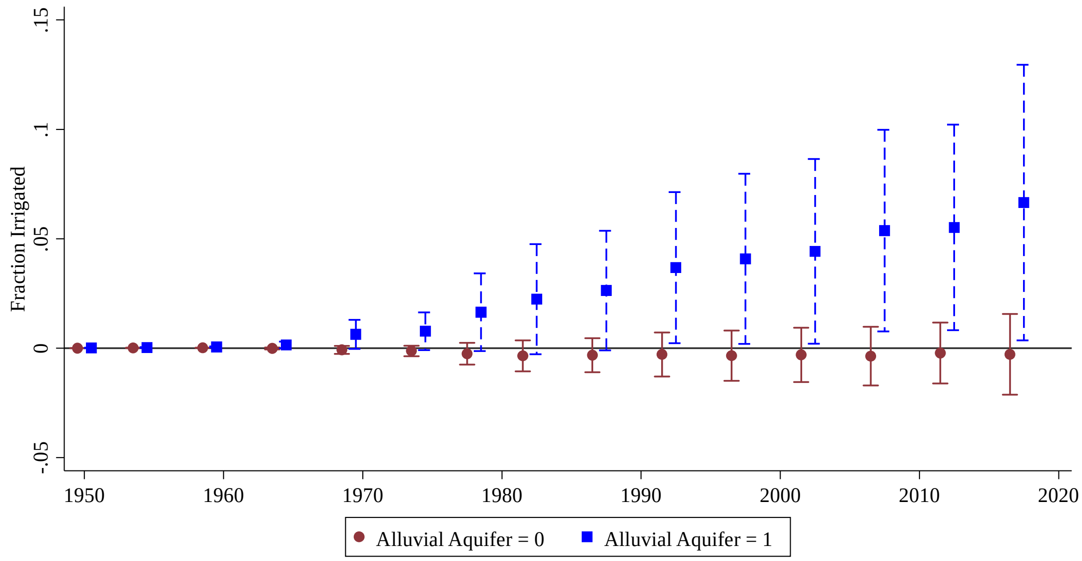


Figure 5: Predicted share of county irrigated by year and aquifer access. *Coefficient estimates and their 95th percentile confidence intervals for year-fixed effects are plotted from a two-way fixed effect regression estimating the fraction irrigated, by total county acres. Red circles are for counties with no alluvial aquifer and blue squares are the year-fixed effect interacted with the continuous share of the county overlapping an alluvial aquifer, scaled to 100 percent.*

Table 1: CPIS and Irrigation Uptake Timing

	(1)	(2)	(3)	(4)	(5)	(6)
	Fraction Irrigated			CPIS Share		
Average PPT Bin Prior 5 Years	0.00200*			0.00318		
	(0.00110)			(0.00304)		
Average Temp. Bin Prior 5 Years	-0.000898			-0.00935		
	(0.00194)			(0.00640)		
Severe PPT in Prior 5 years		0.00348*	-0.00810		0.00552	-0.0168***
		(0.00208)	(0.00562)		(0.00397)	(0.00575)
Severe Temp. in Prior 5 Years		-0.00182	0.00447		-0.00453	0.000715
		(0.00223)	(0.00332)		(0.00342)	(0.00259)
Severe PPT x Alluvial Aquifer Share			0.0354			0.0918***
			(0.0222)			(0.0245)
Severe Temp. x Alluvial Aquifer Share			-0.0206			-0.0115
			(0.0136)			(0.00766)
Constant	0.0695	0.0684	0.0558	0.0232	0.00414***	0.00372***
	(0.0524)	(0.0494)	(0.0412)	(0.0228)	(0.00131)	(0.00124)
Observations	1632	1632	1632	303	303	303
Adjusted R-squared	0.123	0.127	0.171	0.824	0.827	0.863
Years	Census, 1950-2017			Recent Droughts (1988, 2005, 2012)		

Notes: This table presents the results of estimating equation 10. Measures are at the county-level. Columns (1) – (3) use reported irrigation (as a share of county acres) in USDA Census Years from 1950 to 2017. Columns (4) – (6) uses CPIS capacity (as a share of county acres) from our machine learning output during more recent drought years. Average bins (PPT and Temp) are five discrete bins based on county specific variation from long-run averages, constructed such that higher numbers are drier (lower precipitation) and hotter (higher temperatures). Severe PPT and Severe Temp are indicator variables for experiencing at least one bin-five year in the prior five years. All models include county and year fixed effects. Also, unreported, are controls for current production year precipitation and temperature for columns (1) – (3) that measure actual irrigation decisions instead of capacity. Robust standard errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1

Table 2: Effects of Newly Installed CPIS on Crop Selection and Cropland Expansion

	(1) Share Both	(2) Share Corn	(3) Share Soybeans	(4) Share Other Crops	(5) Share Non-Crop
Time	0.07	-2.02***	2.09***	0.28***	-0.49***
	(0.06)	(0.13)	(0.14)	(0.06)	(0.06)
Treated	36.25***	29.93***	0.68	2.56**	-39.21***
	(2.38)	(2.85)	(2.25)	(0.88)	(2.37)
Diff-in-Diff	2.10	10.18***	-8.21***	-0.52	-0.68
	(1.23)	(2.84)	(1.95)	(1.037)	(0.804)
Observations	128754	128754	128754	128754	128754

Notes: This table presents the results of estimating equation 11. Measures are at the PLSS section level. Areas irrigated by CPIS by 2012 are excluded. Land coverage data was taken from the Cropland Data Layer. CPIS share estimates were derived from a deep learning model. The coefficients represent the average percent change in land coverage share. The first row shows the difference in land coverage share between 2012 and 2014. The second row shows the difference in land coverage share between the areas treated via CPIS installation during the observation period and all other areas. The third row shows the difference in the time and treatment effects to give us our DID estimate. Column (1) is the share of both corn and soybeans land coverage. Columns (2) and (3) are the share of land coverage for their respective crops. Column (4) is the share of land coverage for all other crops with a share of 1% or more. Column (5) is all other land-coverage types. Std. errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1

Table 3: Effects on Crop Yield

	(1) corn yield	(2) corn yield	(3) corn yield	(4) soybeans yield	(5) soybeans yield	(6) soybeans yield
CPIS max × drought (%)	0.46**			-0.15		
	(0.19)			(0.13)		
CPIS trend × drought (%)		0.42**			-0.16	
		(0.19)			(0.14)	
CPIS min × drought (%)			0.49**			-0.10
			(0.21)			(0.15)
CPIS max (%)	0.40			0.14		
	(0.30)			(0.20)		
CPIS trend (%)		0.20			0.07	
		(0.24)			(0.17)	
CPIS min (%)			-0.09			-0.11
			(0.22)			(0.16)
Rain (in)	0.20***	0.20***	0.20***	0.40***	0.40***	0.40***
	(0.07)	(0.07)	(0.07)	(0.05)	(0.05)	(0.05)
Temp (F)	-3.17***	-3.18***	-3.20***	-3.70***	-3.71***	-3.72***
	(0.32)	(0.32)	(0.31)	(0.27)	(0.27)	(0.27)
Observations	2529	2529	2529	2529	2529	2434
County FE	N	N	N	N	N	N
Year FE	Y	Y	Y	Y	Y	Y

Notes: This table presents the results of estimating equation 12. Measures are at the county level. CPIS estimates are derived from a deep learning model. Crop yields are taken from USDA NASS data. Unreported weather covariates are from NOAA's Climate at a Glance web tool. Yield values are logged, and coefficients may be interpreted as local approximations of the percent change in crop yield when there is a 1 percent change in the share of cropland irrigated via CPIS. The first 3 rows report the effect of the range of plausible CPIS shares on crop yield during a drought year, and the last 3 rows report the average effect of CPIS on crop yield. Columns (1) through (3) are logged corn yield and columns (4) through (6) are logged soybeans yield. County and year fixed effects were included in all specifications. Std. errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1

Table 4: Effects on Indemnity Payouts in Drought Years

	(1) (log) Indemnity Corn	(2) (log) Indemnity Soybeans
Share CPIS	-6.34**	-2.81***
	(2.65)	(0.62)
Observations	2550	2550
County FE	Y	Y
Year FE	Y	Y

Notes: This table presents the results from estimating equation 13. Indemnity quantity and cause are from the USDA's Risk Management Agency. CPIS estimates are derived from a deep learning model. Unreported weather covariates are from NOAA's Climate at a Glance web tool. Indemnity values are logged, and coefficients may be interpreted as local approximations of the percent change in indemnity amount when there is a 1 percent change in CPIS share. Column (1) reports logged indemnity values for corn and column (2) reports logged indemnity values for soybeans. County and year fixed effects were included in both specifications. Std. errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1

APPENDIX

Raw Data Sources:

- Manually identified CPIS, ISWS (2015)
- Land coverage, USDA NASS (2021)
- PLSS section borders, BLM (2020)
- County borders, Illinois Geospatial Data Clearinghouse (2003)
- Temperature and precipitation, NOAA (2021); PRISM (2014)
- Indemnity payments, USDA-RMA (Ret. 2021)
- Top-of-atmosphere reflectance satellite imagery, USGS/Google (Ret. 2021)
- County level annual crop yield, USDA NASS (Ret. 2021)
- County level census data, Haines et al. (2018), USDA (2019)
- Water resource availability, USGS (2002, 2003, 2014),
- Soil quality and elevation, USDA NRCS (2011)

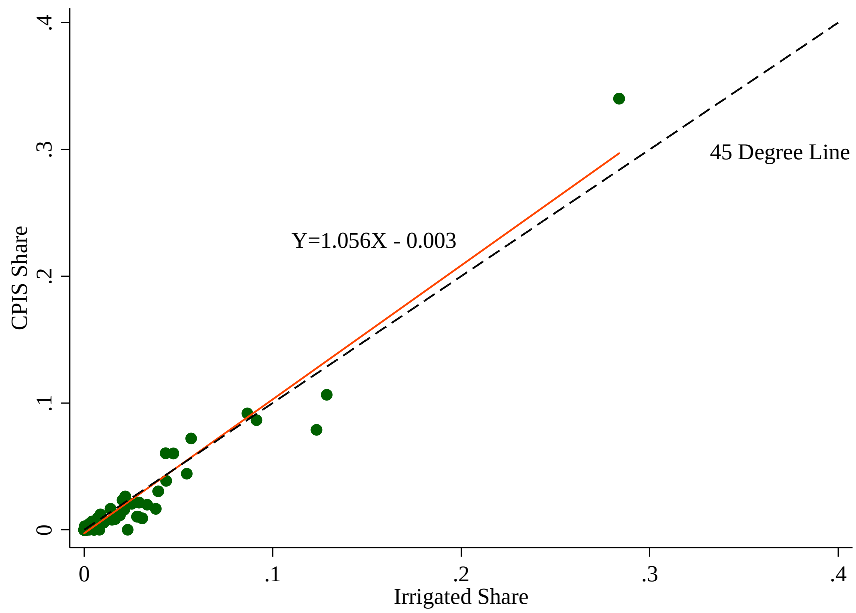


Figure A1: Comparison of irrigated acreage (USDA Census) to CPIS (ISWS Ground Truth) in 2012 across Illinois Counties. *Shares are based on total county acres. Linear fit from a binary OLS estimate is compared with the 45-degree line.*

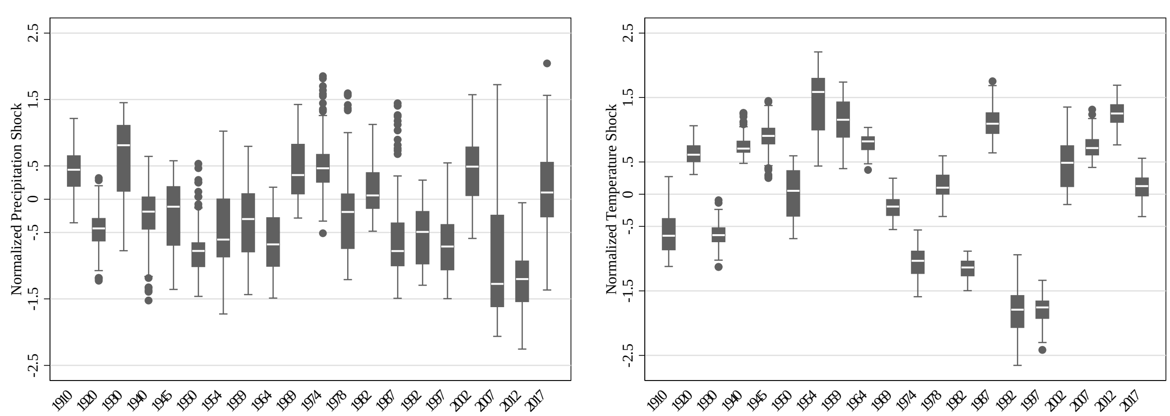


Figure A2: Illinois county localized weather variation by census year. *Panel A plots the boxplot for the normalized growing season precipitation shock based on historical PRISM data. Each counties average from 1900 to 2017 and standard deviation are utilized to measure the scale of the local shock from "average". Panel B does the same for average growing season temperature.*

Table A1 Summary Statistics for PLSS Section Level Analysis

Variable	Count	Mean	Std. Dev.	Min	Max	Description
Corn Share (%)	117502	32.45	24.23	0	100	The share of a PLSS section identified as planting corn, calculated in ArcGIS (CDL)
Soybeans Share (%)	117502	23.41	19.16	0	100	The share of a PLSS section identified as planting soybeans, calculated in ArcGIS (CDL)
Other Crop Share (%)	117502	1.7	4.97	0	100	The share of a PLSS section identified as planting a field crop other than soybeans or corn, calculated in ArcGIS (CDL)
Non-Crop Share (%)	117502	41.5	33.12	0	100	The share of a PLSS section identified as having land cover unrelated to cropland, calculated in ArcGIS (CDL)
Treated Corn Share (%)	1666	66.27	37.2	0	100	The share of the treated area identified as planting corn, calculated in ArcGIS (CDL)
Treated Soybeans Share (%)	1666	23.04	33.35	0	100	The share of the treated area identified as planting soybeans, calculated in ArcGIS (CDL)
Treated Other Crop Share (%)	1666	4.25	16.55	0	100	The share of the treated area identified as planting a field crop other than soybeans or corn, calculated in ArcGIS (CDL)
Treated Non-Crop Share (%)	1666	5.77	13.28	0	100	The share of the treated area identified as having land cover unrelated to cropland, calculated in ArcGIS (CDL)
Control Corn Share (%)	115844	31.96	23.64	0	100	The share of a PLSS section in the control group identified as planting corn, calculated in ArcGIS (CDL)
Control Soybeans Share (%)	115844	23.42	18.87	0	100	The share of a PLSS section in the control group identified as planting soybeans, calculated in ArcGIS (CDL)
Control Other Crop Share (%)	115844	1.66	4.58	0	83.33	The share of a PLSS section in the control group identified as planting a field crop other than soybeans or corn, calculated in ArcGIS (CDL)
Control Non-Crop Share (%)	115844	42.01	33.04	0	100	The share of a PLSS section in the control group identified as having land cover unrelated to cropland, calculated in ArcGIS (CDL)

Table A2 Summary Statistics for the County Level Analysis

Variable	Count	Mean	Std. Dev.	Min	Max	Description
Crop Acreage (A)	2541	229616.3	130741.7	0	687500	Acreage of major field crops: wheat, winter wheat, soybeans, sorghum, oats, and corn (CDL)
Trend CPIS Acreage (A)	2550	2769.38	10454.35	0	122593	Acreage irrigated via CPIS as predicted by the deep learning model, gap years filled using linear interpolation
Min CPIS Acreage (A)	2550	2052.88	8488.31	0	122593	Acreage irrigated via CPIS as predicted by the deep learning model, gap years filled by the values in the previous drought
Max CPIS Acreage (A)	2550	3493.73	12506.34	0	122593	Acreage irrigated via CPIS as predicted by the deep learning model, gap years filled by the values in the next drought
Trend CPIS Share (%)	2550	1.28	4.62	0	58.12	Share of cropland irrigated by CPIS, calculated from predicted acreage, gap years filled using linear interpolation
Min CPIS Share (%)	2550	0.95	3.8	0	55.05	Share of cropland irrigated by CPIS, calculated from predicted acreage, gap years filled by the values in the previous drought
Max CPIS Share (%)	2550	1.61	5.47	0	60.27	Share of cropland irrigated by CPIS, calculated from predicted acreage, gap years filled by the values in the next drought
Corn Yield (bu/A)	2523	135.11	32.97	19	207	Annual corn yield in bushels per acre (USDA NASS)
Soybeans Yield (bu/A)	2529	41.42	8.41	14.86	63.55	Annual soybeans yield in bushels per acre (USDA NASS)
Corn Yield (log)	2523	4.85	0.3	2.73	5.34	Logged annual corn yield (USDA NASS)
Soybeans Yield (log)	2529	3.73	0.22	2.76	4.17	Logged annual soybeans yield (USDA NASS)
Elevation (m)	2550	183.17	35.31	112	251	Elevation above sea level in meters, (USDA NRCS)
Soil Quality	2550	2.39	0.8	0.97	5.83	Soil quality as defined by the USDA NRCS
Corn Indemnity ($)	2550	1069697	6734805	0	135000000	Insurance company payment to the insured in dollars for drought claims on corn in a given year (USDA RMA)
Soybeans Indemnity ($)	2550	86159.45	658645.9	0	14000000	Insurance company payment to the insured in dollars for drought claims on soybeans in a given year (USDA RMA)

Table A3: Irrigation Uptake

	(1)	(2)	(3)	(4)	(5)	(6)
	Fraction Irrigated					
Alluvial Aquifer Share	0.0284**	0.0373**	0.0385***	0.0403***	0.0404***	0.0182***
	(0.0143)	(0.0146)	(0.0125)	(0.0123)	(0.0123)	(0.00670)
Large Stream Share	0.0147***	0.00759*	-0.00280	-0.00235	-0.00242	-0.00104
	(0.00505)	(0.00429)	(0.00448)	(0.00450)	(0.00450)	(0.00298)
Aquifer Share	-0.00401	0.000391	0.00550	0.00545	0.00557	0.00426
	(0.00401)	(0.00346)	(0.00351)	(0.00341)	(0.00341)	(0.00303)
Average Soil Suitability		0.00912	0.00853	0.00661	0.00658	-0.000403
		(0.00719)	(0.00557)	(0.00575)	(0.00572)	(0.00225)
Average Slope		-0.00129	-0.000941	-0.00115	-0.00115	-0.0000440
		(0.00100)	(0.000690)	(0.000718)	(0.000717)	(0.000357)
Slope Range		0.000161	0.000189	0.000217	0.000216	0.000206
		(0.000166)	(0.000158)	(0.000148)	(0.000148)	(0.000132)
Longitude		-0.00496	-0.00188	-0.00404	-0.00409	0.00141
		(0.00321)	(0.00250)	(0.00427)	(0.00428)	(0.00144)
Latitude		0.00419	0.00693**	0.00698**	0.00700**	0.00220
		(0.00294)	(0.00330)	(0.00315)	(0.00316)	(0.00160)
Farm Value per Acre (1940)			-0.0000770***	-0.0000760**	-0.0000752**	-0.0000512***
			(0.0000268)	(0.0000301)	(0.0000298)	(0.0000181)
Corn Yield per Acre (1940)			0.0000909	0.0000204	0.0000160	0.000322
			(0.000276)	(0.000282)	(0.000282)	(0.000221)
Ave. Farm Acreage (1940)			0.000158*	0.000166**	0.000167**	0.0000279
			(0.0000856)	(0.0000815)	(0.0000816)	(0.0000437)
Total Population (1940)			3.63e-09	5.47e-09**	5.46e-09**	2.76e-09*
			(2.21e-09)	(2.63e-09)	(2.62e-09)	(1.56e-09)
Temporal PPT St. Dev.				0.0000212	0.0000173	
				(0.000355)	(0.000355)	
Temporal Temp. St. Dev.				-0.147**	-0.150**	
				(0.0610)	(0.0608)	
Average PPT Bin Prior 5 Years					0.00316**	
					(0.00136)	
Average Temp. Bin Prior 5 Years					-0.00213	
					(0.00246)	
Constant	-0.0150**	-0.596	-0.426	-0.494	-0.499	0.0516
	(0.00624)	(0.375)	(0.315)	(0.435)	(0.433)	(0.147)
Observations	1632	1632	1632	1632	1632	1616
Adjusted R-squared	0.195	0.273	0.313	0.323	0.324	0.248

Notes: *This table presents the results of estimating equation 10. Measures are at the county-level. The outcome is reported irrigation (as a share of county acres) in USDA Census Years from 1950 to 2017. Alluvial aquifer share is the share of the county overlaying an aquifer defined by the USGS (2002). Large stream share is the portion of the county overlaying a 15-mile buffer around a Strahler Order Stream of 3 or greater (USGS 2014). Aquifer share is the share overlaying a non-alluvial aquifer (USGS 2003). All columns included unreported year fixed effects. Columns sequentially add geographical controls (column 2), pre-irrigation farm and demographic attributes (column 3), long term weather variability (column 4), recent localized weather variation (column 5). Column 6 returns to the column 3 specification but removes Mason County, the most densely irrigated county, as a robustness check. Robust Standard errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1*