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

Daniel Cooley and Steven M. Smith

4.1 Introduction

Farmers confronting climate change can undertake a variety of adaptation strategies to cope. Broadly speaking they can hedge financially (i.e., crop insurance or income diversification) or adapt production processes, such as crop and seed variant choices, fertilizer and pesticide use, soil management, planting and harvesting adjustments, and irrigation (Smit and Kinner 2002). While all options may prove instrumental to a farmer's success and subsequently our aggregate food security, we focus on the role of new irrigation in this chapter. This adaptation is particularly important to understand because it has the potential to interact with other adaptation strategies (such as crop insurance or switching crops) and has deleterious externalities to others relying on the water resources. The latter concern is exacerbated by the fact that newly installed irrigation tends to be in more humid regions where fewer laws govern the use of water, and other non-irrigators such as power plants and municipal water supplies are likely to be affected (Fuchs et al.

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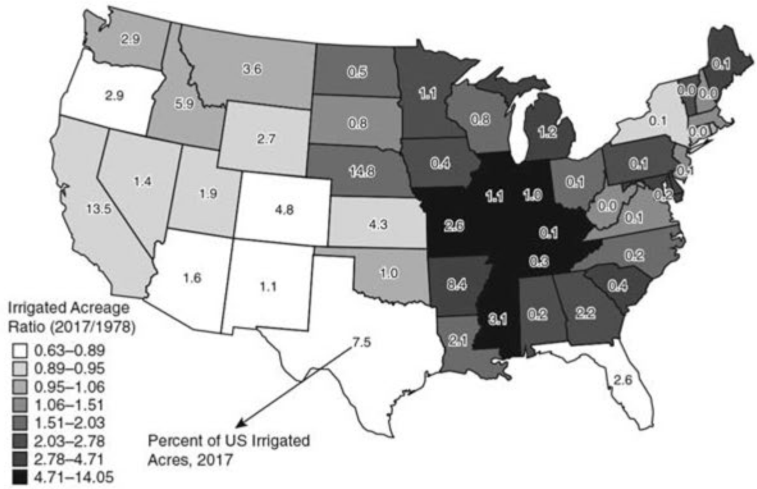

Fig. 4.1 Irrigated acres in the US, 1978–2017

Note: States with darker shading 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.

Source: Underlying data come from the USDA Census (Haines, Fishback, and Rhode 2018; USDA 2019).

2012). As farmers take up more irrigation in response to climate change, it is important to begin to understand some of the causes and effects of this adaption strategy in historically rainfed regions.

Irrigation has long served as an adaptation to increase crop yields and provide resilience during severe drought in arid regions (Troy, Kigpen, and Pal 2015; Zhang, Lin, and Sassenrath 2015; Tack, Barkley, and Hendricks 2017; Edwards and Smith 2018; Zaveri and Lobell 2019). 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). This region attracted huge public investment to build large dams in the 20th century, and tapped groundwater resources with abandonment after the 1940s (Edwards and 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 humid states, as can be seen in figure 4.1. 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 chapter explores the benefits of irrigation investment in more humid regions in the context of climate change trends and existing crop insurance coverage. Specifically, we look at Illinois, where irrigated acreage has increased nearly fivefold since 1978, to consider how irrigation investment has emerged and its effect on cropping patterns, crop yields, and federal crop insurance payouts.

Economists have not paid significant attention to the irrigation potential of rainfed 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 in those regions may not take the form of additional 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 percent of current rainfed crops. This, of course, will take costly investments to accomplish (Elliott et al. 2014), and similarly scaled projects to those in the mid-20th century in the US may be unreasonable to expect (Schlenker, Hanemman, and Fisher 2005). However, 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 percent of irrigated acreage in the US is fed by a sprinkler with higher percentages in humid regions (Hrozencik and Aillery 2021). In arid states, these self-propelled irrigation systems transformed the agricultural 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, and Schoof 2021). Additionally, the length and frequency of dry periods during the summer is predicted to increase across the Midwest throughout the 21st century (Grady, Chen, and 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 and Cherkauer 2010).

Negri, Gollehon, and Aillery (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 and Edwards 2021). In Illinois, severe, statewide 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 percent from 1997 to 2015 (Stubbs 2016), and 833 new CPIS were 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 set up 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 percent and 85 percent for corn and soybeans respectively in 2016 to 96 percent and 93 percent 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 only in 1959 and 1969, 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, and 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 with which to train the model. 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 × 30 m resolution CPIS data to the county level and combine it with annual 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 effects of CPIS installation, we find some evidence that where CPIS are installed 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 and Lin 2014). Furthermore, there is no significant correlation between CPIS installation and average crop yield 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 due to moral hazard (Annan and Schlenker 2015).

Broadly, our results contribute to 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, and Tzouvelekas 2006; Baerenklau and Knapp 2007; Torkamani and Shajari 2008; Pfeiffer and 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 and Roberts 2009; Burke and Emerick 2016) under the argument that it is poor proxy for non-irrigated areas as similar adaptations are not expected (Schlenker, Hanemman, and Fisher 2005). Yet, the East is increasing irrigation, although average effects on production are not well identified (Smith and Edwards 2021).

We also expand on the small literature regarding supplemental irrigation. The value of supplemental water reserves for irrigated areas goes back to work by Tsur (1990) and Tsur and 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 and 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 rainfed 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, and Zilberman 1979; Zilberman 1984; Lau and 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., Pfeiffer and Lin 2014). Technological choice is important as CPIS have been associated with more resilience than other forms of irrigation (Cooley, Maxwell, and 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 and Goodwin 1996; Annan and Schlenker 2015; Connor and Katchova 2020; Wang, Rejesus, and 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, and 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 et al. 2020; Tang et al. 2021; Cooley, Maxwell, and Smith 2021).

4.2 Background and Theoretical Framework

4.2.1 Illinois Agriculture and Climate

At nearly \$8,000 per acre as of 2021, Illinois's cropland is among the most valuable in the US. More valuable cropland is found in the Northeast, where non-productivity factors likely drive the land values higher, and in California (USDA 2021). Illinois produced over \$1 billion 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 often swaps.

Meanwhile, Illinois is close 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,

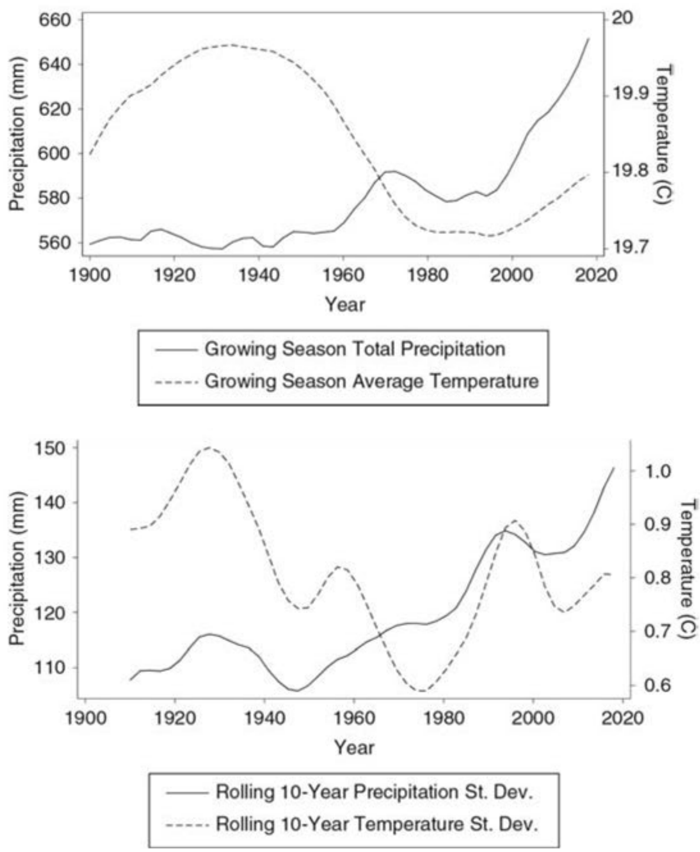

Fig. 4.2 County-level weather in Illinois from 1900 to 2017

Note: Panel A shows the annual growing season total precipitation (solid) and growing season average temperature (dashed) 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.
Source: Data for both come from PRISM.

the wettest, averaging 888 mm. At 20°C, 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 4.2 shows that while temperatures in Illinois have not exhibited a clear trend, precipitation has increased while also becoming 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 is higher compared to more recent baselines like 2000. The shifts are also relatively slight, ranging from 19.7°C to about 19.9°C. We should note, however, the annual averages omit important within season variation that matters for corn production (see Berry, Roberts, and Schlenker 2014, for instance).

Panel b of figure 4.2 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 temporal standard deviation, increasing from about 105 mm up to 145 mm. Therefore, the wetter years are interspersed with drier years. Again, no clear trend emerges for temperature given that it is highly sensitive to how far back one looks.

A severe drought occurred in 2012 in Illinois as with much of the Corn Belt. Corn yields in Illinois counties were about 50 percent lower in 2012 than either 2007 or 2017. Berry, Roberts, and Schlenker (2014) predicted corn losses of 20 percent across the Corn Belt. 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. Illinois irrigation still only amounts to 5 percent of the farms and just 2.3 percent of the acres, meaning many there are yet to adopt irrigation but could potentially do so in the future.

An alternative adaptation to irrigation is crop insurance. Notably, coverage is broader than for only droughts and can include flooding, fire, pests, or even commodity prices. Crop insurance generally comes in two forms: yield protection and revenue protection. Yield protection guarantees a payout—known as "indemnity"—equal to a percentage of a farmer's average crop yield. The average crop yield is measured as the mean of that farmer's previous 10 years of harvest, so if a crop loss event occurs, the insurance will pay a percentage of the difference between the average crop yield and the realized crop yield in the current year's prices. Revenue protection works similarly, but the insurance company pays out a percentage of the farmer's average revenue instead of their average crop yield. The biggest difference is that if farmers opt into revenue protection, they are able to submit insurance claims for drops in crop value (Plastina, Johnson, and Edwards 2021). In addition to the option of yield or revenue protection, farmers are also able to select a coverage level, between 50 percent and 85 percent, which determines the percentage of lost yield or revenue a farmer receives as indemnity.

Uptake of crop insurance in Illinois is extensive and provides substantial protection from droughts. As of 2020, 96 percent of corn acreage is insured and 93 percent of soy acreage, up from previous years (USDA 2021). In 2005, Illinois farmers collected nearly \$25 million in indemnity payments due to the drought. More eye opening, in 2012, the most severe drought, they received \$2.9 billion.

4.2.2 Analytical Framework

Given that Illinois has increased irrigation capacity despite being humid and getting wetter on average, we provide a formal theoretical model to provide some insight into the decision process for installing a CPIS as a form of drought risk mitigation. We include crop insurance as an alternative mitigation tool given its prevalence and moral-hazard-inducing potential. We also discuss additional factors as extensions to the model that would implicitly affect the functional forms to further generate hypotheses about the cause and effects of CPIS installations in the Corn Belt.

Assume that the farmers' choice is between having insurance without irrigation or having both irrigation and insurance simultaneously. To focus on the decision for drought risk mitigation, also assume that 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 irrigation 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).

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

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

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

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 $\bar{p}$. Irrigation 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 irrigation water $c(w_t)$, and the annualized cost of irrigation capacity $[g(k)] / T$. 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 irrigation 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:

$$i(y(w_t, p_t)) = b(\bar{y} - y(w_t, p_t)) - f(b), \quad s.t.\ 0 \le b \le 1. \tag{3}$$

The insurance pays a guaranteed percentage (b) of the lost crop yield ($\bar{y} - y(w_t, p_t)$) at the cost of the premium for the level of insurance protection that the farmer has opted into ($f(b)$). The greater the quantity of irrigation 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.

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

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

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

where $\Delta y = y(w_t, p_t) - y(0, p_t)$.

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:

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

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

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

$$\text{(8.b)} \qquad \frac{\partial \mathcal{L}}{\partial k} = -\frac{\partial}{\partial k}\frac{g(k)}{T} + \lambda \leq 0,$$

$$\text{(8.c)} \qquad \frac{\partial \mathcal{L}}{\partial \lambda} = k - w_t \geq 0.$$

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

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

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 irrigation water has increased to farmers in Illinois, incentivizing them to install a CPIS.

To this point, we have largely ignored the factors that may create distinctions in the functional forms across space and time. As mentioned above, the average capital costs, $g(k)$, for a new CPIS are around \$150,000 on 160 acres (Sherer 2018). Although this does not explicitly vary across space, variation of the land, both physical and legal, will create differential costs to customize the system appropriately. On the physical side, flatter areas with cheaper access to water will drive down installation costs. Given the relative flatness of Illinois, water access is likely to be much more critical, especially since water rights are based on the riparian doctrine, limiting potential irrigators to those with fields adjacent or above water resources. 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, public policy in the form of subsidies would influence the farmer's costs. While many programs exist to subsidize water conservation alterations on existing irrigation systems (e.g., USDA's EQIP program), we have not turned up any large-scale programs to help bring rainfed plots under irrigation.

Beyond water access, the pumping costs, $c(w_t)$, will vary by depth to water and saturated thickness as will the price of local energy sources. While we do not have data on the water, we proxy it by the type of water resource (surface, groundwater, or alluvial aquifer). No information on energy prices is available. Finally, although we treated the cost of insurance in the model as constant within a crop, there is variation of $f(b)$, most importantly based on whether irrigation is present or not. Generally, irrigated crops are given a relative discount, meaning the cost of insurance will be reduced if CPIS is installed. Furthermore, should CPIS maintain higher average yields, the payout on insurance claims will also be higher given they rely on field specific average production, offering an additional benefit when considering the interaction with insurance.

In terms of the yield function, $y(w_t, p_t)$, the greater sensitivity to water means larger gaps in profits between irrigated and non-irrigated fields. Although offset by insurance claims, given those are paid out as a percentage, a larger gap will still produce a larger absolute income loss. Relative to soy, corn exhibits both higher and more variable yields, and, although more resistant to extreme heat, greater sensitivity to moisture availability (Zipper, Qiu, and Kucharik 2016). Accordingly, we expect more CPIS installations where more corn is grown and the average yields are higher.

Our model generates few predictions about the effects of CPIS systems, but the model does contain a few assumptions worth testing. At root is that we modeled the CPIS adoption as a mode of self-insurance against drought. If true, we do not expect to see crop switching or an expansion of cropland. However, in more arid regions crop switching to more water-sensitive, but higher-paying, crops has been observed following irrigation investments (e.g., Pfeiffer and Lin 2014). In Illinois, farmers that avoided corn due to its greater sensitivity to precipitation variation may see an opportunity to maintain corn in the rotation more often. Second, we assumed no changes to yields during normal precipitation years. However, yields may trend higher if farmers are able to smooth out dry periods during the year or supplement drier conditions even if the growing season is not a full-blown drought. Furthermore, installing irrigation may reduce the need to use drought-resistant seed variants which often sacrifice yields under non-drought conditions to have higher drought yields (Yu, Miao, and Khanna 2021). Finally, the model assumes farmers will deploy the CPIS in drought years. Accordingly, we expect yield losses to be mitigated in drought years in areas with more CPIS. A corollary to this is that drought-related insurance payouts should also be lower in these areas.

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 increases 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 reduces indemnity (crop insurance) payments.

4.3 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 and Nardi 2016). More relevant for this chapter, the ISWS also manually identified CPIS from aerial imagery of the entire state in 2012 and 2014, which revealed a 14.2 percent increase in CPIS between the two periods (Illinois State Water Survey 2015). One of the reasons our chapter 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 cover 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 chapter 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, Bengio, and Courville (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 et al. 2020; Tang et al. 2021; Cooley, Maxwell, and 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, Maxwell, and Smith (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 30 m 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 from the irrigated area 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 30 × 30 m resolution top-of-atmosphere (TOA) reflectance satellite imagery collected from Google Earth Engine's Landsat database. The data were randomly divided into three parts for use in training, validation, and testing, with the training set receiving 80 percent of the total data and the remainder being allocated equally between validation and testing sets.

Figure 4.3 provides a comparison of the ground truth (dark gray) and model output (black) 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 percent, 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 percent, which is in line with other CPIS detection models (e.g., Zhang et al. 2018; Saraiva et al. 2020; Cooley, Maxwell, and Smith 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 percent suggesting that the model predicts

Fig. 4.3 Deep learning output for locating CPIS in Illinois, 2012
Note: Black portions are the predicted locations of CPIS from the deep learning model while dark gray portions are the ground truth from the manually labelled CPIS.

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 data set in which there are many more negative examples than positive examples of CPIS presence, 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 data set, it was thrown out of the final data set. 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 was 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 4A.1 of the appendix, the binary regression yields a coefficient of 1.05, 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 percent 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 to 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 and 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. A comparison between CPIS presence in 1988 and 2014 is provided in figure 4.4.

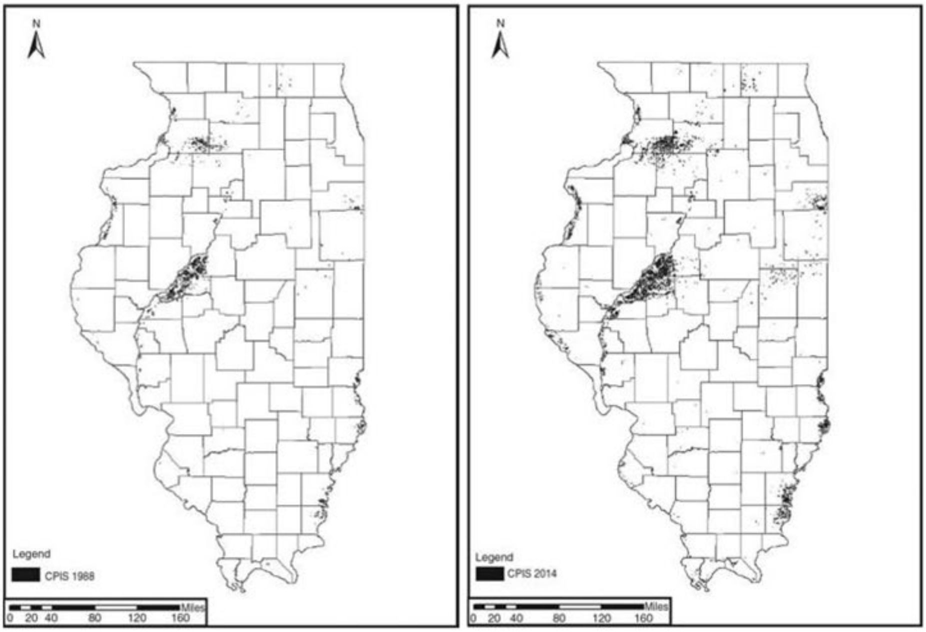

Fig. 4.4 Illinois CPIS in 1988 and 2014

Note: 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.

The rest of the data collected come from standard sources. USDA censuses provide agriculture and irrigation statistics at the county level roughly every five years, 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 to 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 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 and 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 table 4A.1.

4.4 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 normal and drought years. Fourth, we consider how indemnity payouts in drought years are associated with CPIS.

To test the first four hypotheses concerning irrigation uptake (*i* through *iv*), we draw on both our CPIS measures and, given the longer time period available, the agriculture census information on irrigated acres. The latter, however, does not necessarily capture capacity as installed CPIS may not be deployed in a given year. To test the hypotheses, we estimate several versions of the following equation:

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

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). $\vec{W}_i$ 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. $\vec{X}_i$ 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. $\vec{C}_{it}$ is a vector of time varying weather variables. The main ones are locally normalized weather disturbances from Smith and Edwards (2021) measuring how many standard deviations away from the county mean that year's weather is. More attention is given to "severe" years indicated as being more than 1.5 standard deviations drier or hotter than average. Finally, $\vec{\delta}_t$ is a vector of year fixed effects.

For tests of the effects of irrigation in this setting, hypotheses *v* to *vii*, we estimate the following equations:

$$y_{it} = \rho_0 + \rho_1 CPIS_{it} + \rho_2 CPIS_{it} * D_t + \rho_3 D_t + \rho_4 P_{it} + \rho_5 T_{it} + \vec{X}_i + \vec{\delta}_t + \varepsilon_{it}. \tag{11}$$

$CPIS_{it}$ is the CPIS presence in county i in year t, where the non-drought years are filled in as previously described. In these specifications, we capture CPIS in a given county by 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. D_t is a drought indicator equal to one in years determined to qualify for drought insurance payments. In addition, we control for precipitation (P_{it}) and temperature (T_{it}) as linear functions. $\vec{X}_i$ 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, $\bar{\boldsymbol{\delta}}_t$ represents year fixed effects.

In order to assess changes in crop patterns, we use the share of the cropland in corn, soy, both, other, or any crop as the outcome of interest. To reduce variation due to changes in the denominator, we use the maximum observed planted cropland in the county to provide a measure of cropland capacity. For this specification, we drop the drought indicator as we are measuring planted acres, not harvested acres, and this ex ante decision by the farmer is not expected to depend on later growing season weather realizations.

Next, we consider crop yield measured as bushels harvested per planted acre. Given the dominance of corn and soy, we focus on the yields of those crops in a county by year. We also log the yields so we can interpret the coefficients as percent changes in yield. 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. The sample is from 1988 through 2012.

Finally, to explore the connection between insurance and CPIS we use indemnity payouts as the outcome. Indemnity 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. We estimate it only for corn and soybean payments. In this case we also remove the drought year indicator as payments for drought losses in non-drought years are uniformly zero. In other words, the sample includes only observations in 1988, 2005, and 2012.

4.5 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 4A.2) supports this claim and we will discuss it further, but figure 4.5 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

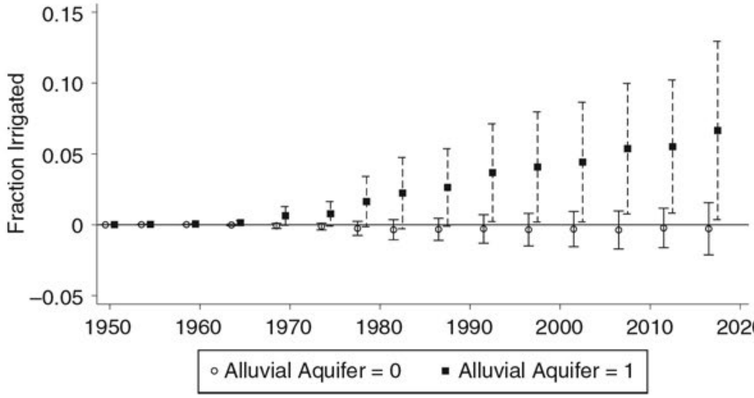

Fig. 4.5 Predicted share of county irrigated by year and aquifer access

Note: 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. Circles are for counties with no alluvial aquifer and squares are the year-fixed effect interacted with the continuous share of the county overlapping an alluvial aquifer, scaled to 100 percent.

with an additional 4 irrigated acres. Given that just 0.5 acres per 100 are irrigated in Illinois, this is a 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 and Smith 2018). Although we do not have data on depth-to-water for these alluvial aquifers, they tend to be relatively close to the surface, meaning it is associated with lower costs, both for the drilling of the wells and subsequent pumping. This likely contributes to its role in predicting where CPIS has been installed.

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. This is counter to expectations, but it may be capturing that some early adopters (e.g., Mason County in the 1960s) had less productive soils absent irrigation, incentivizing the initial wave development for average yield effects, not just for resilience benefits. Also counter to expectations, corn production in the 1940s is not predictive of later CPIS installation. Meanwhile, 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 4.1 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

Table 4.1 **CPIS and irrigation uptake timing**

	Fraction Irrigated			CPIS Share		
	(1)	(2)	(3)	(4)	(5)	(6)
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 × Alluvial Aquifer Share			0.0354			0.0918***
			(0.0222)			(0.0245)
Severe Temp. × 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)		

Note: 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 use 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. ***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 4A.2 for boxplots). Additional controls are current year precipitation and temperature, and year fixed effects. Experiencing relatively drier years in the past five 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 statewide 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 4.2 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 cropland land coverage. The strength of the evidence is sensitive to how we fill in the CPIS measures in between drought years and is, generally, imprecisely estimated. Still a few patterns emerge. First, it appears corn acreage has increased with CPIS installations, between 0.13 and 0.17 depending on the CPIS measure. Second, it appears the gain in corn is from a reduction in soybeans. Each version has a negative point estimate on soybean share and positive point estimate on corn share, but statistical significant only when using the CPIS minimum, which we deem the least likely case. Furthermore, other than when CPIS maximum is used, the share of both (combined corn and soy) is relatively close to zero. However, we do note that overall crop shares have positive point estimates, meaning some corn expansion may have occurred.

The expansion of corn may be due to the newly irrigated land being able to support a different crop rotation pattern such as continuous corn or corn-corn-soybeans instead of corn-soybeans or continuous soybeans indicating

Table 4.2 **Effects of CPIS presence on crop selection and cropland expansion**

	corn share (1)	soybeans share (2)	both share (3)	other share (4)	crop share (5)
CPIS max (%)	0.17	−0.01	0.18	0.03	0.00
	(0.29)	(0.33)	(0.14)	(0.13)	(0.00)
Observations	3162	3162	3162	3162	3162
Adjusted R-squared	0.64	0.43	0.58	0.81	0.75
County FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
CPIS trend (%)	0.16	−0.12	0.06	0.04	0.14
	(0.15)	(0.12)	(0.15)	(0.14)	(0.15)
Observations	2529	2529	2529	2529	2529
Adjusted R-squared	0.75	0.36	0.49	0.6	0.22
County FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
CPIS min (%)	0.13*	−0.18**	0.04	0.12	0.15
	(0.07)	(0.08)	(0.09)	(0.12)	(0.11)
Observations	2529	2529	2529	2529	2529
Adjusted R-squared	0.55	0.36	0.49	0.61	0.22
County FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y

Note: This table presents the results of estimating equation 11 when crop share is the dependent variable. Measures are at the county level. Land coverage data was taken from USDA NASS. CPIS share estimates were derived from a deep learning model and represent the share of the maximum cropland observed in a county irrigated via CPIS. The first panel assumes that all CPIS observed in the next drought were built immediately following the previous one. The second panel assumes a linear trend between drought years. The final panel assumes that all of the CPIS observed in a drought year were installed in that year. Columns 1–3 are the share of corn, soybeans, and both corn and soybeans. Column 4 is the share of all other field crops. Column 5 is the share of all cropland relative to the maximum observed cropland in a county. Std. errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 irrigation water and increase the mix of corn to soybeans as corn is the more water-efficient crop and more sensitive to water amounts (Dietzel et al. 2015).

Table 4.3 shows the results from estimating equation 11 for corn and soybean yields. 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 statistically significantly correlated with average crop yield, although

Table 4.3 **Effects of CPIS presence on crop yield (logged)**

	corn yield (1)	corn yield (2)	corn yield (3)	soybeans yield (4)	soybeans yield (5)	soybeans yield (6)
CPIS max × drought (%)	0.46**			−0.15		
	(0.24)			(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
			(0.21)			(0.16)
Observations	2529	2529	2529	2529	2529	2529
Adjusted R-squared	0.73	0.73	0.73	0.65	0.65	0.65
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Note: This table presents the results of estimating equation 11 when crop yield is the dependent variable. Measures are at the county level. CPIS estimates are derived from a deep learning model. Crop yields are taken from USDA NASS data. 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 three rows report the effect of the range of plausible CPIS shares on crop yield during a drought year, and the last three 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 soybean yield. County and year fixed effects were included in all specifications. Std. errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the point estimates tend to be positive. This leaves open the possibility that average yields do increase, but the effect is hard to detect at the county-level aggregation. 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 percent of cropland with CPIS is correlated with an approximately 0.46 percent increase in corn yield per acre across the county. Scaling this to a PLSS section level, a single center pivot occupies between 20 percent and 39 percent 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 percent to 18 percent, 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 4.4 we provide the estimates for equation 11 for indemnity

Table 4.4 **Effects on indemnity payouts in drought years**

	(log) Indemnity Corn (1)	(log) Indemnity Soybeans (2)
Share CPIS	−6.34** (2.65)	−2.81*** (0.62)
Observations	2550	2550
Adjusted R-squared	0.60	0.43
County FE	Y	Y
Year FE	Y	Y

Note: This table presents the results from estimating equation 11 when indemnity payouts are the dependent variable. 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 percentage point increase of 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 percentage point of cropland with a CPIS decreases insurance payouts for corn by approximately 6.34 percent and soybeans by about 2.81 percent. This could be because farmers who 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 eight insurance claims filed during a drought year, so a single foregone claim amounts to a large percentage change in indemnity payments.

4.6 Discussion and Conclusion

This chapter has provided insights into the use of irrigation, specifically center pivots, as an agricultural adaptation to climate change in more humid regions. Although just one possible adaptation, the eastern US states have tripled their irrigation since the 1980s, making it an important adaptation to understand. Installing CPIS in Illinois has affected crop rotations, corn yields, and indemnity payments during drought years. 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 and expand crop acreage, which suggests that the environmental factors of the setting play a large role in the effect irrigation technology has on both production and a farmer's decision to invest in CPIS. This chapter 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 be 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). In a report about the 2012 drought, the ISWS pointed out that Illinois has very limited management authority with no regulation of groundwater sources, no regulation of riparian water use, and few identified alternative municipal water supplies (Fuchs 2021). The latter is important because 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. For instance, Lake Decatur provides water for nearly 90,000 people and dropped to critical levels in 2012 (Fuchs et al. 2012). 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). Although these specifics are for Illinois, many of the eastern states also lack oversight of this growing use of water.

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 are 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 et al. 2020).

Additional analysis is warranted. Although we identified county-scale factors for CPIS installation, we have said little about what determines CPIS adoption within counties. 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 and Perry 2018), county-level differences in agriculture subsidies (Pfeiffer and Lin 2014; Environmental Working Group 2020), or other factors that may make one area more susceptible to drought than another.

Other adaptations may also warrant consideration; both why farmers choose irrigation rather than another option and how irrigation alters the use of other adaptations. For instance, how does irrigation alter crop insurance choices. Although we found irrigation lowers indemnity payouts and other work has found insurance coverage leads to increasing in water application (Deryugina and Konar 2017), less is known about how transitioning to irrigation affects coverage choices.

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 or alternative adaptations. 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 percent) in the US (Hrozencik and Aillery 2021). However, 85 percent of corn acreage is not irrigated, leaving plenty of rainfed 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.

Appendix

Raw Data Sources:

- Manually identified CPIS, ISWS (2015)
- Land coverage, USDA NASS (2021)
- 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, Fishback, and Rhode (2018), USDA (2019)
- Water resource availability, USGS (2002, 2003, 2014)
- Soil quality and elevation, USDA NRCS (2011)

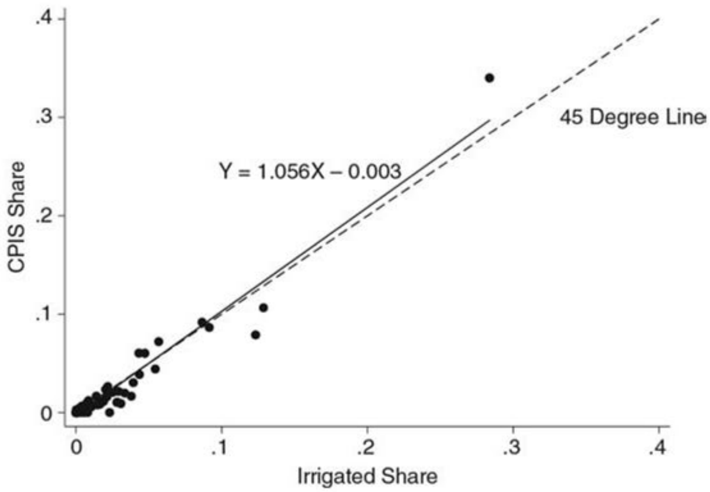

Fig. 4A.1 Comparison of irrigated acreage (USDA Census) to CPIS (ISWS Ground Truth) in 2012 across Illinois counties

Note: Shares are based on total county acres. Linear fit from a binary OLS estimate is compared with the 45-degree line.

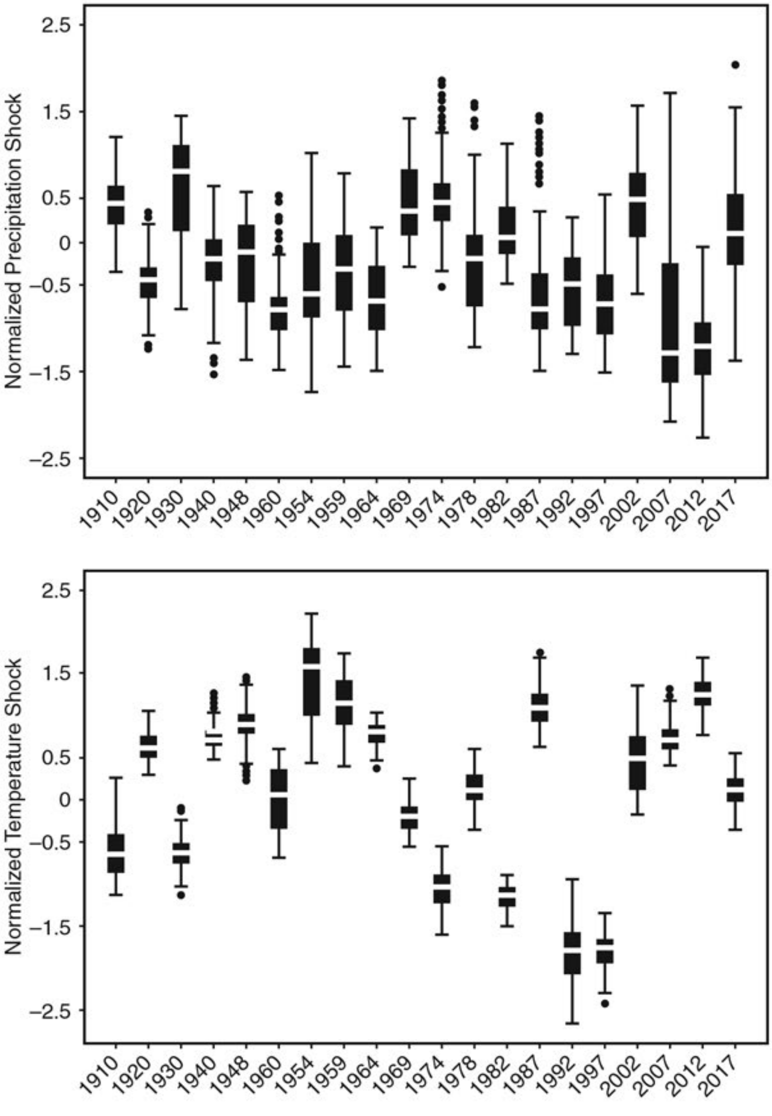

Fig. 4A.2 Illinois county localized weather variation by census year.

Note: Panel A plots the boxplot for the normalized growing season precipitation shock based on historical PRISM data. Each county's average from 1900 to 2017 and standard deviations are utilized to measure the scale of the local shock from "average." Panel B does the same for average growing season temperature.

Table 4A.1 **Summary statistics for the county-level analysis**

Variable	Count	Mean	Std. Dev.	Min	Max	Description and underlying source
Fraction Irrigated	1632	0.00586	0.0225	0	0.380	Share of the county's acres irrigated in a given year (Haines et al. 2018 and USDA 2019)
Fraction with CPIS	303	0.00876	0.0309	0	0.340	Share of the county's acres with a CPIS detected in a drought year (1988, 2005, 2012)
Crop Land (A)	2541	229616.3	130741.7	0	687500	Acreage of major field crops: wheat, winter wheat, soybeans, sorghum, oats, and corn (CDL)
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 Share (%)	3187	46.51	15.99	0	100	Share of maximum observed cropland in a county with planted corn (USDA NASS)
Soybeans Share (%)	3187	40.53	10.6	0	100	Share of maximum observed cropland in a county with planted soybeans (USDA NASS)
Both Share (%)	3187	86.04	15.78	0	100	Share of maximum observed cropland in a county with both planted corn and soybeans (USDA NASS)
Other Share (%)	3187	12.73	12.62	0	100	Share of maximum observed cropland in a county with other planted field crops (USDA NASS)
Crop Share (%)	3187	85.47	16.02	0	100	Share of maximum observed cropland in a county with planted field crops (USDA NASS)
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 Indemnity ($)	2550	1069697	6734805	0	135000000	Insurance payment to the insured in dollars for drought claims on corn in a given year (USDA RMA)
Soybeans Indemnity ($)	2550	86159.45	658645.9	0	14000000	Insurance payment to the insured in dollars for drought claims on soybeans in a given year (USDA RMA)
Average Precip (1900–2017)	102	579.1	14.07	544.0	613.9	Total growing season (April - September) precipitation (mm) averaged from 1900 to 2017 (PRISM)
Standard Deviation Precip	102	124.5	8.616	108.5	147.9	Temporal standard deviation of the counties annual precipitation from 1900 to 2017 (PRISM)

Average PPT Bin Prior 5 Years	1632	2.920	0.431	1.600	4	Average standardized bins in the prior 5 years. Bins based on county specific normalized precipitation distribution with higher bins drier: 1 = [x > 1.5], 2 = [0.5 < x < 1.5], 3 = [–0.5 < x < 0.5], 4 = [–1.5 < x < –0.5], 5 = [x < –1.5] (Smith & Edwards 2021)
Severe PPT	303	0.122	0.328	0	1	At least one of the prior 5 years had a precipitation bin equal to 5
Average Temperature (1900-2017)	102	19.84	1.211	17.27	22.09	Average growing season (April-September) temperature (C) averaged from 1900 to 2017 (PRISM)
Standard Deviation of Temperature	102	0.834	0.0254	0.755	0.905	Temporal standard deviation of the counties annual temperature from 1900 to 2017 (PRISM)
Average Temp. Bin Prior 5 Years	1632	2.961	0.419	1.600	4.200	Average standardized bins in the prior 5 years. Bins based on county specific normalized temperature distribution with higher bins hotter: 1 = [x < –1.5], 2 = [–1.5 < x < –0.5], 3 = [–0.5 < x < 0.5], 4 = [0.5 < x < 1.5], 5 = [x > 1.5] (Smith & Edwards 2021)
Severe Temperature	303	0.257	0.438	0	1	At least one of the prior 5 years had a temperature bin equal to 5
Alluvial Aquifer Share	102	0.301	0.239	0	1	Share of the county overlaying an alluvial aquifer
Large Stream Share	102	0.512	0.405	0	1	Share of the county within 15 miles of a strahler order stream 3 or greater (USGS 2014)
Aquifer Share	102	0.270	0.340	0	1	Share of the county overlaying a non-alluvial aquifer (USGS 2003)
Average Soil Suitability	102	2.423	0.796	2	5.947	County's spatial average of gridded soil suitability data, binned 1-8 (USDA 2006)
Elevation	102	184.1	37.16	111.7	266.3	Spatial average of elevation for the county (USGS 2006)
Average Slope	102	12.28	4.525	8	35	Spatial average of the county slope, calculated from the elevation
Slope Range	102	17.05	11.62	0	39	Spatial range of the slope within the county
Longitude	102	–89.18	0.926	–91.19	–87.73	Longitidude of the county centroid
Latitude	102	39.84	1.452	37.19	42.37	Latituted of the county centroid
Farm Value per Acre (1940)	102	180.9	96.20	43.96	595.1	Farm value per farm acre in 1940 (Haines et al. 2018)
Corn Yield per Acre (1940)	102	46.19	11.96	20.65	63.29	Corn yield ber acre in 1940 (Haines et al. 2018)
Ave. Farm Acreage (1940)	102	147.5	32.60	57.45	229.9	Average farm size in 1940 (Haines et al. 2018)
Total Population (1940)	102	77423.9	400170.4	5289	4063342	Total county population in 1940 (Haines et al. 2018)

Table 4A.2 **Irrigation uptake**

	Fraction Irrigated					
	(1)	(2)	(3)	(4)	(5)	(6)
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

Note: 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 include 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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