Irrigation Water Demand: Price Elasticities and Climatic Determinants in the Great Lakes Region

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This article explores the environmental and market determinants of irrigation management in a five-state Great Lakes region. We found evidence that corn, soybean, and potato irrigators respond to the cost of water at the intensive margin. Evidence of a water-cost effect at the extensive margin was mixed. This article is unique in its geographic focus and its consideration of various temperature effects. We found evidence of a long-run average temperature effect on crop acreage allocation decisions and a short-run extreme heat effect on water application rates.

Key words: agriculture, climate, Great Lakes, irrigation, natural resources

Introduction

A significant body of research explores the effects of climate change on agricultural yields. Deschénes and Greenstone (2007) found that climate change is likely to have a net positive effect on agricultural output and profit. In a conflicting result, Schlenker and Roberts (2009) found that yields are likely to diminish significantly before the end of the century due to the damaging effects of heat and water stress on rental rates for non-irrigated land. Hendricks (2018) predicts significant losses: 33 percent by mid-century under Intergovernmental Panel on Climate Change (IPCC) greenhouse gas Representative Concentration Pathway (RCP) 4.5. Broadly, the literature has established important nonlinear effects of climate and weather conditions on agriculture in the United States (U. S.). Despite the apparent relationships between heat stress, precipitation, and irrigation water use, the consideration of these effects exists only to a limited degree in the irrigation water demand literature.

The approach typically taken in the irrigation demand literature includes estimation of straightforward linear temperature and precipitation effects, which fails to capture any important nonlinearities similar to those captured in the adjacent literature on agricultural yield. Olen, Wu, and Langpap (2016) moved beyond typical irrigation demand studies by including an indicator for counties that are historically drought prone in their model of irrigation

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application rates. The literature has otherwise not addressed the effect of extreme heat or precipitation variability on water application rates. This study introduces measures of extreme heat. This study also introduces concerns about irrigation water demand and water availability in the Great Lakes Region of the U.S.

Aquifers in the Great Lakes Region tend to be shallow and connected to surface water resources, leading to sensitivity of surface water systems to groundwater withdrawals (Wallander 2017). Importantly, Mubako, Ruddell, and Mayer (2013, p. 678) found that in the Kalamazoo River watershed in Southwest Michigan "most instream water scarcity is caused by localized consumptive uses of water in late summer months at small spatial scales." These intense localized withdrawals caused scarcity impacts that reverberated through downstream segments, including the main river stem. The Mubako study noted further that irrigation withdrawals are particularly important drivers of scarcity because they are most heavily concentrated during summer months, coinciding with seasonal lows in in-stream water flow. Further, unlike other consumptive withdrawals, irrigation withdrawals are often located in small-scale upland agricultural watersheds that are vulnerable to seasonal change. A number of studies (Luukkonen et al. 2004; Zorn, Seelbach, and Rutherford 2012; Mubako, Ruddell, and Mayer 2013; Watson, Mayer, and Reeves 2014) have similarly concluded that adaptive management of water scarcity in water-rich regions like the Great Lakes Region must address the sensitivity of aquatic ecosystems within localized scales of space and time.

The Great Lakes – St. Lawrence River Basin Water Resources Compact (Great Lakes Compact), ratified in 2008, requires basin states to protect aquatic ecosystems from adverse effects of large-quantity (100,000 gallons per day or more) groundwater and surface water withdrawals. To meet this obligation, states have implemented programs that limit the water available for irrigators and other large-quantity users, a novel approach for these riparian doctrine states. In some areas, these programs introduce binding constraints on water withdrawals and introduce competition for irrigation water resources where neither was experienced previously. Understanding the determinants of irrigation water use is particularly important in the context of these developing institutions. An improved understanding of the conditions that drive irrigation decisions will enable resource managers to anticipate water-use conflicts and may serve as a guide for estimating the marginal value product of increasingly scarce irrigation water in the Great Lakes Region.

This article reports estimates of the water-use response of irrigators in water abundant regions to various climatological, environmental, and price conditions. The study was conducted using secondary data sources, including the Farm and Ranch Irrigation Survey and public weather and climatological data sources. The research focused on the response of irrigators across water application and irrigated acreage decisions. The intensive margin estimation addresses the annual irrigation water application rate per acre. The extensive margin estimation explores allocation of irrigated acreage among crop types. The combined results of the crop acreage and water application models can be evaluated to produce generalized expectations of long-run changes in water use.

Irrigation Water Demand

The majority of the existing literature on irrigation demand in the U.S. is confined to water-scarce western states. A national-scale meta-analysis of irrigation demand, including studies dating from 1963 to 2004, did not include a single study east of the Mississippi; over a third of the studies used data from California irrigators (Scheierling, Loomis, and Young 2006). In recent years, the focus on irrigation in the western U.S. has continued. Notable studies evaluated the effect of energy prices on agricultural groundwater extraction from the high plains aquifer and the effects of water scarcity and climate conditions on irrigation decisions in the western U.S. (Olen, Wu, and Langpap 2016; Hendricks and Peterson, 2012; Pfeiffer and Lin 2014).

A small number of irrigation demand studies have evaluated irrigation management decisions in the relatively water abundant eastern regions of the U.S. This geographical imbalance is likely due to a number of factors: water scarcity and heightened water concern in western states, limitations in data availability, and a general assumption that the low cost of water in eastern states would lead to a near zero price elasticity for irrigation water. Alternatively, the availability of irrigation substitutes (i.e., precipitation) might provide additional flexibility in water application decisions and thus increase the expected price elasticity for irrigation water in eastern states.

With evidence from Georgia, Gonzalez-Alvarez, Keeler, and Mullen (2006) concluded that even outside of the water scarce west, the cost of irrigation water is an important factor in farm irrigation decisions. Gonzalez-Alvarez, Keeler, and Mullen noted that a number of management choices might be influenced by the cost of irrigation water: "Irrigation efficiency can be improved, crops can be irrigated less, and farmers can pay closer attention to soil moisture and irrigation timing" (Gonzalez-Alvarez, Keeler, and Mullen 2006, p. 311). Another of the few irrigation management studies considering firms east of the Mississippi found that irrigation water demand is "modestly affected by water price (with elasticities between -0.01 and -0.17) but more so by crop price (with elasticities between 0.5 and 0.82)" (Mullen, Yu, and Hoogenboom 2009, 1421). These studies used pump and well characteristics to generate a proxy measure of the marginal cost of irrigation.

In contrast to agricultural inputs purchased in competitive markets, measuring an own-price elasticity for irrigation water demand in areas like the southeastern U.S. and the Great Lakes Region is uniquely challenging. Crop irrigators often receive irrigation water from unpriced sources, most

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often on-site groundwater wells and occasionally nearby surface water. Efforts to circumvent the lack of an explicit unit price through the use of imputed irrigation costs suffer from bias due to unobserved variables (Mieno and Brozović 2016). These issues can be avoided when data on direct irrigation expenditures are available.

Theoretical Model

This analysis focuses on firm irrigation management decisions across a decision framework that includes allocation of irrigated land among crop choices and water application decisions. The firm's maximization problem is rooted in a simple total profit function for a multi-output irrigating firm (equation 1).

$$\Pi(\boldsymbol{p},\ b,\ N, \boldsymbol{x}) \tag{1}$$

Where $\boldsymbol{p}$ is a vector of crop prices, b is the cost of irrigation water, N is the land constraint, and $\boldsymbol{x}$ is a vector of other exogenous environmental variables (climate, weather, soil quality).

To develop a theoretical framework for the crop allocation decision, the total profit function is decomposed into a set of individual irrigated crop profit functions, where i indicates a particular crop:

$$\pi_i(p_{\boldsymbol{i}},\ b,\ n_i^*, \boldsymbol{x}) \tag{2}$$

The optimization can be restated as a choice of irrigated acreage allocation for the individual crops, constrained by the total acreage under irrigation N_{irr}^*.

$$\Pi(\boldsymbol{p},\ b,\ N, \boldsymbol{x}) = \max_{n_1 \ldots n_m} \left\{ \sum_{i=1}^{m} \pi_i(p_{\boldsymbol{i}},\ b,\ n_i^*, \boldsymbol{x}) : \sum_{i=1}^{m} n_i = N_{irr}^* \right\} \tag{3}$$

The estimable forms for the crop allocation and water application decisions are derived from the crop level model of a multi-output irrigating firm. At the intensive margin, the specific management behavior of interest is the volume of water applied to a particular crop—corn, soybeans, or potatoes—given that a firm is growing the crop on a field with irrigation infrastructure in place.

Empirical Model

Assuming a normalized quadratic profit function, the estimable empirical functions are linear in the exogenous variables (Lau 1978; Moore and Negri 1992; Moore, Gollehon, and Carey 1994). The equation for n_i^*, acreage allocation for crop i, is presented as a function of crop prices, water cost, total cropland, and environmental conditions with effects varying by crop.

$$(4) \qquad n_i^* = a^i + \sum_{j=1}^{m} \beta_j^i p_j + \delta^i b + \tau^i N + \sum_{s=1}^{t} \eta_s^i x_s \qquad i = 1, \ \ldots, m$$

This function is intended to capture the indirect water use response observed as the change in the allocation of irrigated land among the *m* crops, each of which has unique water requirements and favors certain environmental conditions. In the crop acreage models, the environmental and price variables, $\boldsymbol{x}$ and $\boldsymbol{p}$, include weather and price conditions lagged one year with additional controls for long-run climate conditions. The variables were chosen to reflect the information available to the firm in the winter of the survey year when planting decisions are made.

Application of Hotelling's lemma to the individual crop profit function produces the estimable intensive margin water demand function.

$$(5) \qquad -\frac{\delta\pi_i(p_i, \ b, \ n_i^*, \boldsymbol{x})}{\delta b} = \ w_i(p_i, \ b, \ n_i^*, \boldsymbol{x}) \qquad i = 1, \ \ldots, m$$

$$(6) \qquad w_i = \alpha^i + \beta^i p_i + \delta^i b + \tau^i N + \sum_{s=1}^{t} \eta_s^i x_s \qquad i = 1, \ \ldots, m$$

The general forms for the two estimations are similar, although cross prices do not appear in the empirical function for *w*. The price and environmental variables that appear in the water application models are selected to reflect the relevant information and conditions available to the firm during the irrigation season. The exclusion of cross prices from the water application model reflects an assumption that water application decisions are made independently for each crop.

Data and Hypotheses

Individual response data from the USDA Farm and Ranch Irrigation Survey (FRIS) comprise the foundational data set for this analysis. FRIS contains firm level responses on water application rates, irrigated acreage, irrigation pumping expenditures, and other irrigation management topics. Precipitation and temperature data were obtained from the PRISM Climate Group. Solar radiation, humidity, and wind speed data were obtained from the Department of Energy's National Solar Radiation Database, Physical Solar Model 3.0. Soil quality data was derived from the NRCS STATSGO database. Finally, state level crop price data was obtained using USDA Quick Stats. Due to limitations of the survey data used for this study, each firm is geographically identified at the county level. The climate and soil data characteristics were aggregated and linked to the FRIS response data at the county level.

FRIS

FRIS is a supplement to the Census of Agriculture (COA), a general farm management survey conducted on five-year cycles. The FRIS is collected in the years following the COA from a sample frame of firms that reported having participated in irrigation in the latest COA. The sample used in this article includes major irrigating states in the Great Lakes Region – Illinois, Indiana, Michigan, Minnesota, and Wisconsin, and it includes three survey years – 2003, 2008, and 2013.

In 2013, the national FRIS sample targeted 35,000 farms and obtained responses from 34,966. The targeted farms were selected via a stratification strategy. The major irrigators in each state were assigned to a certainty stratum (i.e., probability = 1). The remaining noncertainty strata (probability < 1) were sampled systematically by acreage. The boundaries of each strata were uniquely defined by state to reflect the distribution of farm size in each state measured as total acres irrigated. Of the survey responses, 2,095 responding farms were from the certainty stratum and the remaining 32,871 farms were from the various noncertainty strata (USDA 2013, Appendix A-1). This sampling strategy was also used for the 2003 and 2008 FRIS (USDA 2003, 2008, 2013, Farm and Ranch Irrigation Survey). The individual response data includes weights that are used to correct for non-randomness in the sample selection strategy.

The selected sample includes corn, soybean, and potato irrigators. These crops compose the majority of the irrigated acreage in the five states. Agricultural irrigation occurred on over 2.5 million acres across the five-state region in 2012. Figure 2 displays these acres by the share in each crop. The relative shares of irrigated acreage for each crop are similar across the states in the region with the exception of Wisconsin, where vegetables contribute a larger share. This study did not consider vegetable irrigation because the data does not allow for distinguishing among vegetable types. Additionally, individual vegetable types are grown by relatively few farms, and management practices are likely to vary by type. Potato irrigation occurs on a larger share of acreage in the northern part of the region, and potatoes are an important crop to evaluate because they generally require greater irrigation volume than corn or soybeans.

Figure 3 displays the spatial distribution of irrigated acres as reported in the COA 2012. The figure highlights the presence of several key irrigation areas within the sample region. Most notably, the largest concentrations of irrigating farms are in Southwest Lower Michigan/Northern Indiana, Central Wisconsin, and Central Minnesota. Table 1 contains the number of farms by year, state, and crop as they appear in the final study sample. The 4,737 farms are relatively evenly distributed over the three sample years and five sample states. Summing the number of firms over the three crops in a given state and year does not sum to the reported total number of firms because many firms irrigate more than one of the studied crops.

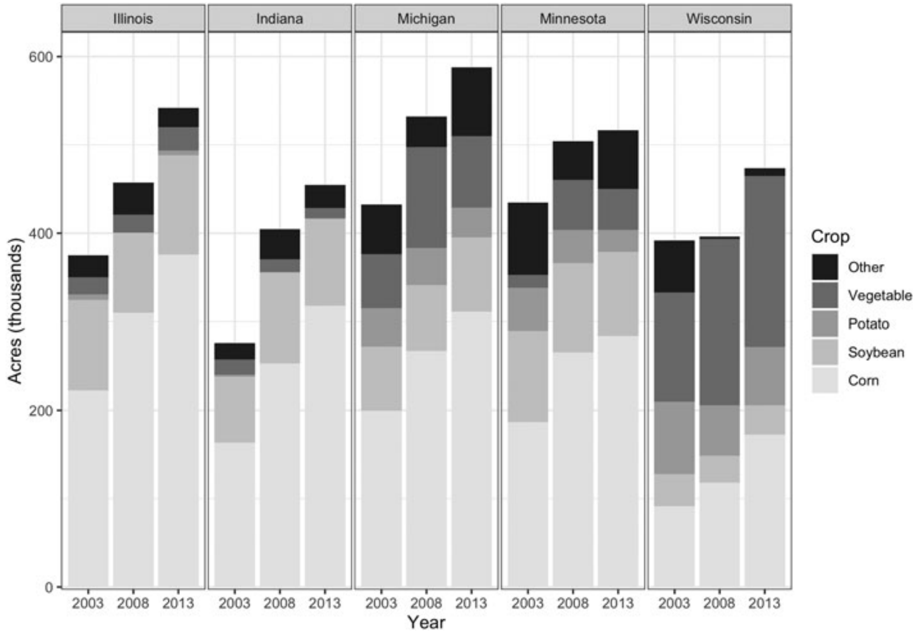

Figure 1. Irrigated Acres of Major Irrigated Crops, by State and Year
Source: FRIS summary reports 2003, 2008, 2013

Some firms appear in multiple survey years. Approximately 10 percent of the total number of surveyed firms appear in all three survey years, comprising 20 percent of the observations in the sample. Approximately 18 percent of unique firms appear in two years of the survey, comprising 25 percent of the observations.

Water Use and Acres Irrigated

The FRIS questionnaire asks firms to report water applications to each irrigated crop as an annual per-acre value. These reported values were used directly as the dependent variable in the water application estimation. Potatoes are the most water intensive of the three crops, receiving an average of 9.6 inches per acre. The difference in water intensity provides the basis for the hypothesized effects of water cost in the crop allocation model. In response to higher water prices, firms are expected to substitute away from potatoes and toward corn and soybeans.

The dependent variables in the crop allocation models are the FRIS reported values for irrigated acreage of the specific crop. The mean irrigated potato acreage is significantly larger than the respective means for corn or soybean, indicating a greater degree of firm concentration in potato production. The

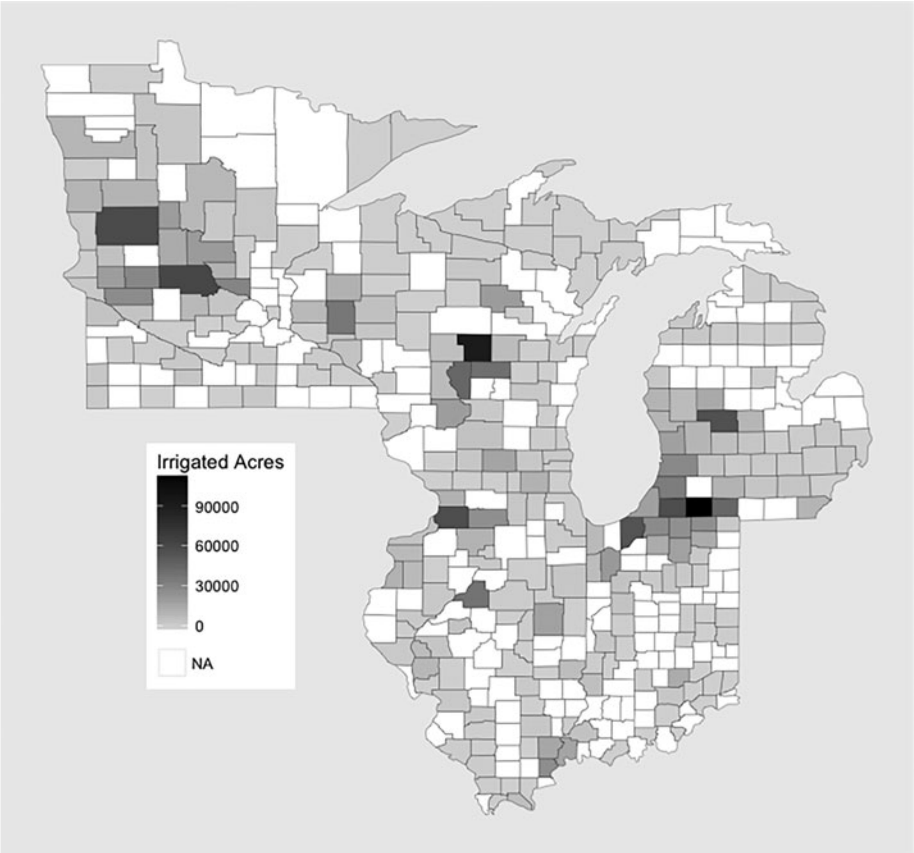

Figure 2. Irrigated acres by county in western Great Lakes states, 2012

Note: NA indicates counties where data was suppressed in published USDA COA summary tables to protect survey respondent confidentiality.

Source: Census of Agriculture, 2012

vast majority of firms irrigated corn or both corn and soybeans in the observed years. This distribution is consistent with typical crop rotations where firms alternate between corn and soybeans on two- or three-year rotations. Similarly, a majority of the potato irrigators in the sample are also irrigating other crops. This is expected, as potatoes are also typically grown on a two- or three-year rotation. Considering the nature of typical crop rotations, it is likely that some, if not all, firms in the sample regularly participate in irrigation of at least two of the studied crops. Thus, substitution effects in the crop allocation parameters are expected to appear primarily as a decision to participate or not participate in growing irrigated potatoes. In the short run, potato production decisions are likely partially constrained by production

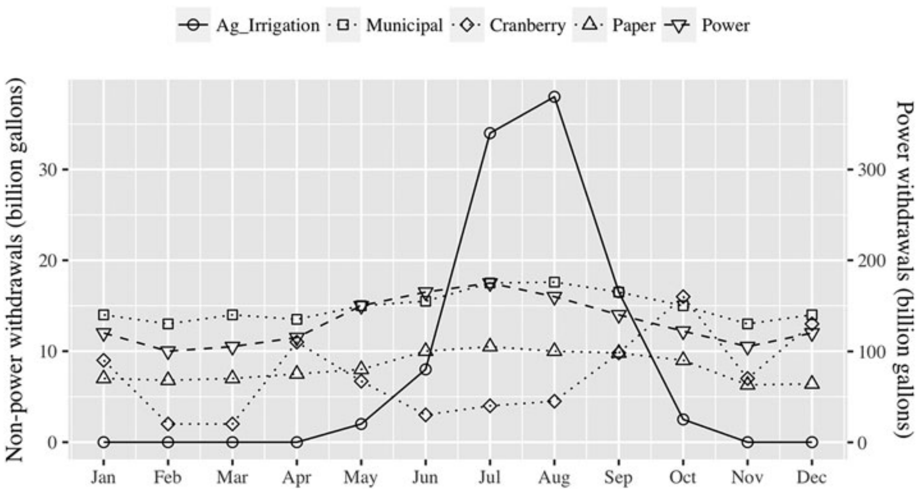

Figure 3. Seasonal Variation in Water Withdrawals in Wisconsin

Source: Wisconsin Water Use Report 2013

http://dnr.wi.gov/topic/WaterUse/documents/WithdrawalReportDetail2013.pdf

Table 1. Number of Farms in Study Sample, by Year, State, and Crop

		STATE					
		IL	IN	MI	MN	WI	Total
2003	All Crops	391	292	233	335	270	1,521
	Corn	372	270	207	299	205	1,353
	Soybean	300	206	138	226	130	1,000
	Potato	*S**	*S**	39	40	91	188
2008	All Crops	335	309	288	361	228	1,521
	Corn	320	289	267	326	182	1,384
	Soybean	199	207	163	230	97	896
	Potato	*S**	*S**	36	33	60	136
2013	All Crops	419	359	291	353	273	1,695
	Corn	391	339	263	323	236	1,552
	Soybean	254	225	177	204	110	970
	Potato	*S**	*S**	38	23	67	144
Total	All Crops	1,145	960	812	1,049	771	4,737
	Corn	1,083	898	737	948	623	4,289
	Soybean	753	638	478	660	337	2,866
	Potato	21	20	113	96	218	468

**S* indicates values that are suppressed according to USDA NASS confidentiality requirements.

contracts, but the FRIS lacks a useable identifier for firms operating with production contracts.

Measuring Water Cost

An explanatory variable of primary interest is the cost of irrigation water. An increase in the cost of water is hypothesized to cause a substitution away from water intensive crops and cause a reduction in water application rates. There are three general approaches to measuring irrigation cost in the irrigation demand literature when water itself is unpriced.

First, the energy price approach relies on variation in local energy prices applied as a proxy for the marginal water cost. Mieno and Brozović (2016) showed that "energy price elasticity is identical to the irrigation cost elasticity of groundwater use when groundwater itself is not priced" (423). The energy price approach is simple in construction, but it does not account for a number of firm technology characteristics that affect the cost of water (e.g., groundwater depth, pumping pressure, total dynamic head). Additionally, this method is only suitable if price varies sufficiently across the sample. In a variation of this approach, direct energy charges may be used rather than prices. When the data are available, this approach is ideal because it accounts for variations in irrigation technology directly. In the context of this study, the available measures of energy price do not provide sufficient variability to use the energy price approach and direct energy charges are not available.

Two general alternatives to the energy price approach, the engineering and average cost approaches, leverage the additional variation between firms with unique water delivery infrastructure. The engineering approach requires data on pump characteristics to impute cost parameters using engineering relationships (Gonzalez-Alvarez, Keeler, and Mullen 2006; Moore, Gollehon, and Carey 1994; Hendricks and Peterson 2012). Common parameters used in the engineering approach include well depth, pump technology, pump system pressure, etc. A number of irrigation demand studies using FRIS data have applied the engineering approach to impute pumping costs (Moore, Gollehon, and Carey 1994; Mullen, Yu, and Hoogenboom 2009; Hendricks and Peterson 2012). However, Mieno and Brozovic (2016) raised concern that correlations between unobserved characteristics of a well or pump can introduce bias. Further, depending on the direction of the correlation, the unobserved variables might introduce amplification bias.

Olen, Wu, and Langpap (2016) used FRIS data and applied the average cost approach, which requires individually reported irrigation expenditure data and is distinct from the energy price and engineering approaches in that it may capture some irrigation costs that are fixed over the relevant interval. A profit maximizing firm with complete information would optimize water use as a function of the marginal cost of water, but firms in the context of this article may instead respond to average cost over the time scale of a regular billing cycle. This expectation applies particularly to firms that primarily use electricity as their energy source for pumping.

Findings from Ito (2014) suggest that electricity consumers may not effectively respond to marginal prices due to complicated signals from nonlinear pricing. Many utility rate plans include pricing structures that might obscure an irrigating firm's perception of marginal cost (e.g., demand charges, block rates). Thus, the average cost of water may be more salient than marginal cost for irrigating firms. For irrigators in this study, diesel expenditures composed a large portion of the total pumping expense, but electricity was the majority source in most state-years in the sample.

For this study, firm-level average cost of irrigation water was calculated as the total annual energy expenditures for pumping, E, divided by the total number of acre inches applied (calculated by summing the product of irrigated acreage, n, and water application, w, over m crops).

$$b = \frac{E}{\sum_{i=1}^{m} w_i n_i} \tag{7}$$

The average cost of water variable, b, may approximate the marginal cost of water when there are no significant changes in energy prices during the irrigation season and firms do not conflate fixed and marginal costs. The majority of irrigation activity occurs over a relatively short period of time (see Figure 4), so large variation in within-season energy price is unlikely. The reported average cost might be a poor proxy for the marginal cost if irrigators were able to adjust a system's diesel vs. electric energy mix in response to within-season changes in energy price ratios. A subset of the sampled firms reports expenditures on multiple types of energy, primarily electricity and diesel. These irrigators might be potential candidates for energy switching behavior, except the nature of irrigation pump technology makes this behavior unlikely. Irrigation systems are relatively long-term investments for agricultural firms in the Great Lakes Region, and the presence of redundant pumping systems for energy switching is not a known practice (B. Russell, personal communication, February 1, 2018).

Climate and Weather Data

Precipitation and temperature data were obtained from the PRISM Climate Group. Daily precipitation and temperature records were available at a 4km grid resolution. Current year and lagged year temperature and precipitation variables were derived using daily precipitation, maximum temperature, and minimum temperature data. Additional degree day and precipitation variability measures were produced with modifications to the daily PRISM values. PRISM also publishes 30-year normal climate variables calculated as moving averages. Thirty-year average temperature and precipitation variables have been used in recent literature to estimate climate impacts on long-term irrigation management decisions (Bigelow and Zhang, 2018). These variables were included in the crop allocation models to control for gradual climate impacts on crop substitution decisions.

The specifications for the climate variables used in this article were guided by information from agricultural irrigation extension specialists at Michigan State University (MSU). Specifically, MSU irrigation specialists indicated that May 1st –September 31st is a sufficiently wide growing season window during which environmental conditions would affect irrigation decisions, with July and August being the heaviest irrigation months (S. Miller, personal communication, September 17, 2017). Irrigation would only occur outside the growing season window under exceptional circumstances (e.g., to "water-in" a cover crop). The seasonality of irrigation water demand is also apparent in Wisconsin water use reports presented in Figure 4.

Temperature is hypothesized to have a positive effect, and precipitation volume is hypothesized to have a negative effect on water application. Due to the relative sensitivity of potatoes, higher temperatures are hypothesized to cause a substitution away from potato production. With the growing season calendar in mind, the preferred climate specification includes variables for peak irrigation season precipitation volume and average temperature. Peak irrigation season is defined as the months of July and August. These variables were generated by converting the 4km cells in the raw daily PRISM data to their central points and then taking the mean of all points that fall within the county to generate a county level aggregate. The daily, county-level precipitation data was summed to generate the cumulative values over July and August. The mean of the daily, county-level temperature data gives the average daily max temperature over the same time period.

An additional measure was designed to account for nonlinear temperature effects. The measure, Extreme Heat Degree Days (EHDD), is similar to a growing degree day specification common in the crop yield literature. It was calculated as the count of degrees in excess of an extreme heat threshold (34°C) summed over days in the irrigation season, D. In the following equation, t_i is the maximum temperature on day i.

$$EHDD = \sum_{i}^{D} \max(t_i,\ 34) - 34 \tag{8}$$

The 34°C threshold has been identified as the threshold at which additional heat reduces crop yields (Deschenes and Greenstone 2007; Ritchie and NeSmith 1991). Irrigation applications are hypothesized to be increasing in EHDD because irrigation is a potential strategy to mitigate heat stress.

Predictions of climate-related changes in precipitation in the Great Lakes Region are subject to a greater degree of uncertainty than predictions of climate-related temperature changes. The existing literature indicates that precipitation will become more variable across multiple time scales ranging from daily, to seasonal, annual, and even decadal (Pendergrass et al. 2017; Hatfield et al. 2014). Common precipitation measures in the existing irrigation demand literature include seasonal and annual precipitation volume. These broad measures do not account for the importance of precipitation timing. Simply stated, between two locations that receive the same total precipitation over a given time period (e.g., one month), the location that receives that precipitation distributed most evenly throughout the month is expected to use less irrigation water.

A number of peak irrigation season precipitation variability measures were considered: the standard deviation of daily precipitation, a Shannon index measure of precipitation evenness, a count measure of 10-day drought events, and a count measure of 20-day drought events. The water price and main precipitation coefficients did not change significantly with the inclusion of any precipitation variability measure. None of the considered measures produced statistically significant effects, so they were excluded from the final models.

NRCS Soils Data

Soils data was obtained from the USDA STATSGO database. Variables for this analysis were generated from the Soil Capability Class data layer, which groups soils "according to their limitations for field crops, the risk of damage if they are used for crops, and the way they respond to management." For this analysis, the soil capability class data was converted to create a county level soil quality variable. Soil quality was measured as the percentage of land that falls into either class 1 or class 2 in each county. Capability classes 1 and 2 have few to moderate limitations for crop production. This specification is similar to the approach used by Olen et al. (2016). The expected effect of soil quality on water use at the intensive margin is negative, since higher quality soils that better retain moisture would reduce the need for irrigation. At the extensive margin, soil quality is hypothesized to have a positive effect on acreage allocations of water intensive crops (i.e., potatoes) and a negative effect on acreage allocations of less water-intensive crops (i.e., soybeans). The direction of this effect may be confounded by differences in soil types that are not captured by the capability class soil quality measure. Potato growers are generally expected to prefer sandy soils (or other soils with good drainage) because potatoes require careful control of soil moisture and can be easily damaged in overly wet or overly dry soils. Given this sensitivity, land with few impediments (as measured with the capability class data) may be a necessary, but not sufficient, condition for a typical firm to participate in potato production.

Crop Prices

Price data was obtained from the state-by-state monthly crop price database maintained by the USDA National Agricultural Statistics Service. In the water application estimation, a variable indicating same-year, July price was used to measure firm expectations at the time irrigation decisions are made. Lagged marketing-year prices were included in the crop allocation model to capture price expectations at the time planting and investment decisions are made. Importantly, spatial variation in the state-level price data is limited, so the estimation of price effects relies on variation between years. Corn and soybean prices are highly correlated in the sample ($\rho = 0.97$), so their effects cannot be distinguished in the crop allocation models. To address the correlation between corn and soybean prices, a composite price was calculated as the average of the corn and soybean prices faced by each firm. This composite variable is used in the crop allocation model in place of separate corn and soybean prices.

Addressing Measurement Error

The distribution of marginal energy cost for the study sample is skewed with a number of extreme values in both tails of the distribution. The outliers with unexpectedly large average water cost values may be attributable to errors in the FRIS responses or data entry errors for either irrigation volume or total energy expenditures. Measurement errors in irrigation volume, w_i, would be especially problematic because that term also appears in the denominator of the formula for constructing the water cost variable. The water cost variable, b, calculated as shown in equation 9, is a primary covariate of interest in both the intensive and extensive margin estimations. Measurement error in w_i would introduce amplification bias in the estimated parameter on b, whereas measurement error in E, total energy expenditures, would introduce attenuation bias.

To test for amplification bias, two approaches for calculating total water use were applied. First, the reported responses for acre-inches applied by crop were aggregated across irrigated acreage, as shown in the denominator of equation 9. Second, FRIS responses on the volume applied by water source—ground water, on-farm surface water, or off-farm water—were aggregated. The first approach is preferable because the crop level questions are more narrowly focused, and their targeted nature reduces the likelihood of recollection error and other sources of survey response error (e.g., lack of clarity in reported units). As expected, the variance of b as calculated using this approach is significantly smaller.

The values of b calculated using the sum of by-crop applications were compared to the values of b calculated using the total of all water sources, and the sample was restricted to the subset of observations that reported consistent total water quantity values (difference between the two values < 5 percent). If measurement error is driving amplification bias in the full sample, the parameter of interest estimated with the reduced sample would be smaller in magnitude. However, when the general model was estimated with the limited sample, the estimated parameter on b was slightly larger in magnitude. This suggests the results are unlikely to be significantly biased by measurement error in w_i.

Energy expenditures, which are summed to produce E, may be misreported for a variety of reasons, including but not limited to a blurred differentiation between irrigation-related expenditures and other non-irrigation energy expenditures. Consider two illustrative examples. First, a firm using primarily electricity for irrigation may receive a single bill for irrigation-related and non-irrigation-related electricity use. A second firm using primarily diesel fuel for irrigation may buy diesel fuel in bulk for numerous uses. When asked to report total energy expenditures by energy source, firms may fail to accurately distinguish between these competing uses. In such cases, firms might underreport or overreport actual irrigation expenditures.

To address the measurement error in the numerator of the equation for b, firms above the 95th percentile and below the 5th percentile for average cost of water, b, were removed from the sample. This change had the expected effect; the magnitude of the estimated coefficient on b increased due to the reduction of attenuation bias from measurement error.

Regression Weights

All regressions are reported using the USDA-provided sample weights to correct for the non-randomness in the sampling method. The probability weights denote the inverse of the probability that a farm in the sample frame has been included in the sample. In a simple sense, probability weights can be interpreted as the number of unobserved firms of a similar size that are represented by a single firm in the sample. In this context, the farms selected into the certainty strata would receive a weight of 1. The farms from the non-certainty strata receive weights greater than 1. All models throughout the article are estimated using the provided weights interpreted in Stata as probability weights. The distribution of the sample weights within the group of observations culled from the sample to address attenuation bias closely mirrors the distribution of weights in the kept sample.

Results

Results of the water application models and crop allocation models are reported in the following sections.

Water Application Estimation

Table 2 contains definitions, mean values, and hypothesized effects of the variables that appear in the water application models. Table 3 contains the

Table 2. Summary of Variables: Water Application Models

Variable	Variable Definition (units)	Mean (sd)	Expected Effect
Dependent			
Corn irrigation	Inches applied per acre	7.0 (3.5)	
Soybean irrigation	Inches applied per acre	6.4 (4.0)	
Potato irrigation	Inches applied per acre	9.6 (4.8)	
Cost / Price			
Cost of Water	Dollar/Acre Inch	4.12 (2.59)	−
Corn Price	July price received ($/bu)	5.13	+
Soybean Price	July price received ($/bu)	12.58	+
Potato Price	July price received ($/cwt)	9.26	+
Environmental			
Precipitation	July-August accumulation (inches)	5.80 (2.26)	−
Temperature	July-August mean daily maximum (°C)	27.83 (1.12)	+
Humidity	July-August mean relative Humidity (%)	76.26 (7.36)	−
EHDD	Extreme Heat Degree Days	1.79 (3.14)	+
Soil Quality	Percent of county area in soil capability class 1 or 2	61.12 (28.51)	−

mean and standard deviation for each variable in the sample conditioned by participation in irrigated production of the particular crop. At the intensive margin, cross prices for the alternative crops are expected to have no effect. They were excluded from the crop-specific models for two reasons. First, in the absence of a firm water constraint, we expect that water application decisions are made independently for each crop. Firm water constraints certainly may exist in some cases, but we expect that it is a minority of cases. Additionally, corn and soybean prices are highly correlated in the sample, so the only opportunity to observe a meaningful cross price effect would be among firms growing both potatoes and either corn or soybeans. This is a small subset of the total number of firms.

Table 4 contains results for the intensive margin specification where crop-specific water application rate (inches/acre) was regressed as a linear function of price and environmental conditions. In this and all subsequent models, standard errors are clustered at the individual firm level. As hypothesized, the relationship between water cost and water application rate is significant and negative across all three crops.

Table 3. Water Application Model Variables: Means and (Standard Deviations) for Full Sample and Conditional on Irrigation of Specific Crop

Variable	Full Sample	Corn	Soybean	Potato
Dependent				
Irrigation	NA	7.0 (3.5)	6.4 (4.0)	9.6 (4.8)
Cost/Price				
Cost of Water	4.12 (2.59)	4.10 (2.55)	3.98 (2.49)	4.70 (2.85)
Crop Price	NA	5.13	12.58	9.26
Environment				
Precipitation	5.80 (2.26)	5.80 (2.30)	5.93 (2.30)	5.46 (1.59)
Temperature	27.83 (1.12)	27.87 (1.11)	27.98 (1.14)	27.11 (1.04)
Humidity	76.26 (7.36)	76.23 (7.35)	75.79 (7.43)	76.52 (6.59)
EHDD	1.79 (3.14)	1.86 (3.17)	2.00 (3.31)	0.60 (1.45)
Soil Quality	61.12 (28.51)	62.29 (27.88)	63.48 (26.27)	33.35 (27.77)
N	4,737	4,289	2,866	468

Precipitation, temperature, and humidity variables were included at a peak irrigation season time scale (aggregated over July and August). The coefficient on precipitation is negative across the three crops and significant for corn. The effect of humidity is negative for all crops and significant across corn and soybean. The effect of temperature is positive for all crops and significant for soybean and potato. EHDD has the expected positive effect and is significant for corn and soybean. The soil quality measure has the expected sign and is significant across all crops. Finally, the coefficient for crop price is not significant across the three crops.

The estimated water-price irrigation demand elasticities are similar across the three crops (see Table 5). These elasticities are within the range of those found in existing literature, although elasticities reported in the literature vary widely (see Table 6). The elasticities estimated in this article are somewhat larger than elasticities estimated in a relatively water abundant context elsewhere (Mullen, Yu, and Hoogenboom 2009).

The model was estimated with state and year fixed effects and separately with county and year fixed effects to control for additional unobserved heterogeneity (see Appendix A). The estimates on water price, precipitation, and EHDD are similar across the two model specifications. The estimates on temperature are somewhat sensitive to the spatial fixed effect specification. Estimates on the crop price variables are not significant across the specifications. This may be explained in part by the limited variation in the crop price data.

Table 4. Water Application Models: Estimated Coefficients

	Corn	Soybean	Potato
Water Cost	−0.502	−0.426	−0.569
	(0.024)**	(0.031)**	(0.083)**
Peak Season			
Precipitation	−0.193	−0.085	−0.036
	(0.039)**	(0.069)*	(0.173)
Temperature	0.088	0.274	0.956
	(0.105)	(0.129)*	(0.329)**
Humidity	−0.039	−0.043	−0.092
	(0.017)*	(0.020)*	(0.081)
EHDD	0.131	0.103	0.204
	(0.034)**	(0.047)*	(0.302)
Soil Quality	−0.013	−0.019	−0.045
	(0.003)**	(0.004)**	(0.011)**
Crop Price	−0.335	0.487	0.237
(own-price)	(0.248)	(0.282)	(0.566)
Constant	11.384	1.082	−10.477
	(2.930)**	(3.795)	(13.973)
R^2	0.20	0.16	0.32
N	4,289	2,866	468

*$p < 0.05$; **$p < 0.01$

Crop Allocation Estimation

Table 7 contains a summary of the variables, mean values, and hypothesized effects for the crop allocation models. Crop allocation decisions are assumed to be driven by long-term climate conditions with adjustments made at the margins in response to updated perceptions of environmental conditions. Table 8 contains the means and standard deviations for the variables that appear in the crop allocation models conditioned on participation in the given crop.

Table 9 contains results for the extensive margin estimation where crop-specific irrigated land allocation (acres) was estimated as a function of price and environmental conditions. The crop-specific allocation models were estimated using the tobit estimation procedure to account for the pool of observations that allocated zero irrigated acres to a particular crop.

The effect of water cost is significant and negative for corn and soybeans. The effect of water cost on potato acreage is positive, significant, and larger in magnitude than for corn or soybeans. These results indicate that increasing water cost causes farms to substitute potato production for corn and soybean

Table 5. Water Application: Point Elasticity Estimates

		Corn	Soybean	Potato
Water Cost	*Coefficient*	−0.50	−0.43	−0.57
	Elasticity	−0.29	−0.26	−0.28

Table 6. Short-Run Water Cost Elasticities in the Literature

	Data Years	Region	Elasticity*
Mieno et al. 2016	2007–09, 2011–12	Nebraska	−0.53
Hendricks et al. 2012	1992–2007	Kansas	−0.10
Mullen et al. 2009	2000	Georgia	−0.095(0.07)
Schoengold et al. 2006	1994–2001	California	−0.30(0.17)
Moore et al. 1994	1984, 1988	Western U.S./Plains	0.01(0.10)
Scheierling et al. 2006	1975	Various West/Plains	−0.48(0.53)

*Where multiple elasticities are reported, values in table are means (standard deviation)

production. This is unexpected due to the water intensity of potato production. However, potatoes are a higher-value crop than corn or soybeans, receiving an estimated $3,900/acre in revenue in 2017 compared to $530 and $400 for corn and soybeans, respectively (USDA Quick Stats 2016). Firms may optimally increase potato production in response to higher water costs because, despite the greater water intensity of potato production, water costs are a smaller percentage of per acre production costs. Relatedly, the marginal value product of irrigation water for potato production is greater than corn or soybean production.

It is possible that unobserved environmental factors that are favorable for potato production are positively correlated with water cost. Alternatively, unobserved heterogeneity in production contract participation may affect the results. Potato producers commonly operate under production contracts that may require a certain level of irrigation capacity. It is possible that potato-producing firms tend to have greater irrigation capacity and subsequently face higher short-run fixed costs of irrigation (e.g., greater fixed electric charges). Unfortunately, the FRIS data does not provide a viable indication of whether a firm operates under a production contract. The results of a mean comparison t-test indicate that potato producers pay higher costs for water (mean difference $= 0.58$, $p < 0.01$).

To check the robustness of the land allocation models to the specification of functional form, the model was estimated with crop-specific linear regression. Among all three crop models, all effects are similar in magnitude and direction

Table 7. Summary of Variables: Crop Allocation Models

Variable	Variable Definition (units)	Mean (sd)	Expected Effect^
Dependent			
Corn Acres	Irrigated Acres	419 (560)	
Soybean Acres	Irrigated Acres	220 (276)	
Potato Acres	Irrigated Acres	724 (1229)	
Cost / Price			
Cost of Water	Dollar/Acre Inch	4.01 (2.47)	–
Composite Price*	Marketing year price received corn soybean average ($/bu)	8.12 (2.35)	–
Potato Price*	Marketing year price received ($/cwt)	8.53 (1.36)	+
Environmental			
30yr Precipitation	30-year normal growing season precipitation	19.28 (1.19)	+
30yr Temperature	30-year normal growing season average daily max temperature	25.47 (1.43)	–
Peak Temperature*	July-August mean maximum daily temperature (°C)	29.17 (1.83)	–
Peak Precipitation*	July August accumulation (inches)	7.67 (3.61)	+
EHDD*	Heating Degree Days	13.87 (22.68)	–
Soil Quality	Percent of county area in soil capability class 1 or 2	61.23 (28.48)	+

*Starred variables are lagged by one year.
^Expected effects indicate substitution toward more (+) or less (–) potato production.

Table 8. Crop Allocation Model Variables: Means (and Standard Deviations) Conditional on Irrigation of Specific Crop

Variable	Corn	Soybean	Potato
Dependent			
Irrigated Acres	419 (560)	220 (276)	724 (1229)
Cost/Price			
Cost of Water	4.08 (2.55)	3.98 (2.49)	4.70 (2.85)
Composite Price	8.14 (2.35)	7.97 (2.37)	7.59 (2.36)
Potato Price	8.54 (1.37)	8.49 (1.37)	8.99 (1.20)
Environment			
30yr Temperature	25.46 (1.43)	25.59 (1.46)	24.16 (1.19)
30yr Precipitation	19.27 (1.20)	19.33 (1.17)	18.76 (1.34)
Peak Temperature	29.16 (1.82)	29.26 (1.87)	27.95 (1.46)
Peak Precipitation	7.67 (3.62)	7.73 (3.60)	7.50 (2.87)
EHDD	13.84 (22.65)	14.60 (23.98)	6.02 (11.83)
Soil Quality	62.30 (27.88)	63.48 (26.28)	33.35 (27.78)
N	4,289	2,866	468

Note: Each column includes the subset of the sample that irrigates the given crop.
Standard deviations appear in parentheses.

to the tobit effects, except for the effects of water cost and potato price in the potato acreage model. This indicates that the effects of water cost and potato price on potato production are sensitive to functional form. The remaining effects in the corn and soybean models are robust to the differing functional forms.

Importantly, long-run average temperature has a large and statistically significant effect across both sets of models. This effect indicates that the acreage allocation to potato production is highly sensitive to average temperature. Long-run average temperature is the most important factor affecting substitution decisions between potatoes and corn/soybeans.

Coefficients for the climate, weather, and price variables generally indicate the expected effects. There is a large, positive, and significant effect of the composite price on corn acreage. The effect of the composite price on soybean acres is negative. It may be that the soybean acreage substitution effect is dominated by the corn effect. Potato price has a large positive and significant effect on potato acreage, but this effect does not persist in the linear specification.

Discussion and Conclusions

Results of the analysis suggest particularly important implications related to climate and weather effects and to water price effects. A discussion of the limitations of this study is also warranted.

Table 9. Crop Acreage Allocation: Tobit Average Partial Effects

	Corn	Soybean	Potato
Water Cost	−10.22	−7.25	40.96
	(1.81)**	(1.74)**	(10.49)**
Total Irrigated Acres	0.39	0.15	0.37
	(0.01)**	(0.02)**	(0.04)**
Composite Price Lag	165.64	51.85	−581.86
	(51.07)**	−48.66	−369.81
Potato Price Lag	−20.83	−12.31	74.46
	−10.84	−11.58	−87.03
Soil Quality	0.82	0.03	−3.3
	(0.17)**	−0.2	(1.28)*
30yr Grow-season Max	52.58	88.6	−412.89
	(15.37)**	(17.08)**	(137.93)**
30yr Grow-season Precipitation	27.69	15.67	10.69
	(5.24)**	(5.38)**	−37.88
Peak Temperature Lag	−38.56	−49.37	183.17
	(15.91)*	(17.16)**	−137.11
Peak Precipitation Lag	2.88	−0.14	−21.29
	−1.65	−1.82	−12.31
EHDD Lag	−0.3	1.22	0.5
	−0.47	(0.46)**	−3.79
N	4,737	4,737	4,737
N Censored	448	1,871	4,269

*$p < 0.05$; **$p < 0.01$

Climate and Weather Effects

Nonlinear effects of temperature and precipitation on crop yields have received some attention in the literature on climate change and agriculture (Hendricks 2018; Zhang, Zhang, and Chen 2017; Schlenker and Roberts 2009; Ritchie and NeSmith 1991), but these effects have been unaddressed in much of the existing irrigation water demand literature. The results of the water application models indicate that extreme heat has an important effect on irrigation water demand. The effect of extreme heat on water application rates indicates that increasing summer temperatures due to changing climate conditions would likely increase water demand throughout the region. The explored measures of precipitation variability do not significantly affect water demand in the context of this study, but future research should explore their effects on water demand in other settings.

Long-run climate conditions are significantly predictive of crop allocation decisions. Potato production is particularly sensitive to temperature. This result indicates that increasing summer temperatures may reduce the favorability for potato production in the region and may cause producers to substitute toward corn, soybeans, or other crops not addressed in this study.

The following hypothetical scenarios are illustrative examples of potential effects of climate change on irrigation demand. First, consider an increase in long-run average temperature. Hayhoe et al. (2010) concluded that average temperatures in the Great Lakes Region are likely to increase by at least 1.3°C under lower and up to 4°C under higher emissions scenarios by mid-century (2040–2069). All else being equal, the projected increase in average temperature is likely to cause firms to substitute away from potato production. This effect is expected to reduce per-acre water applications by approximately 25 percent. The average potato producer would use 424 fewer acre-inches (35 acre-feet) farm-wide per year after switching all potato acreage to corn and soybeans. This effect is particularly important in the northern part of the region (MI, MN, WI) where potato irrigation contributes a larger share of all irrigation activity. However, in most of the region, this effect would likely be outweighed by a second important temperature effect.

A second major effect is the increase in water applications due to extreme heat events. Vavrus and Van Dorn (2010) concluded that the number of extreme days (daily max temperature $>$ 32°C) is likely to increase from 15 days/year in the late 20th century to 36 days under low or 72 days under high emission scenarios by the end of this century. Using a conservative estimate of an additional eight days exceeding the threshold for extreme heat (measured here as daily maximum temperature $>$ 34°C) by one degree, firms are expected to increase water applications on corn and soybeans by 14.5 percent. For the average firm, this would amount to 315 acre-inches (26.3 acre feet) farm-wide.

To understand the total combined effects of extreme heat and average temperature, we constructed, for each state, a hypothetical firm statistically representative of the state's irrigation activity. Within each state, the representative firms' irrigated acreages were calculated as the mean irrigated acreage for each crop among all irrigating firms in the sample. Table 10 contains estimated temperature effects for a statistically representative firm in each state and the region as a whole. All else being equal, this firm is expected to respond to the hypothetical mid-century temperature scenario by increasing water applications by 9 percent overall. The effect in each state varies primarily due to differences in the share of irrigated acreage in potato production. The states in the southern part of the region—IL and IN—are expected to experience somewhat larger impacts, 14 percent and 16 percent, respectively, because they have a smaller share of irrigated acreage in potato

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Table 10. Expected Temperature Effects* on Mid-Century Water Applications for Statistically Representative Firms

			IL	IN	MI	MN	WI	Region
Current	Irrigated Acres	*Corn*	267.2	222.2	311.7	194.9	176.5	235.8
		Soybean	94.0	85.0	91.6	78.6	57.2	82.7
		Potato	5.2	1.1	63.0	48.9	134.5	44.2
	Application Rate (inches per acre)	*Corn*	7.3	6.2	6.4	7.4	7.7	7
		Soybean	7.1	5.6	5.4	6.9	6.8	6.4
		Potato	7.9	8.1	9.1	9.3	10.2	9.6
	Applications (acre inches)	*Corn*	1950	1378	1995	1442	1359	1651
		Soybean	668	476	495	542	389	530
		Potato	41	9	574	454	1372	424
		Total	2659	1862	3064	2439	3120	2605
Mid-Century Expectation	Irrigated Acres	*Corn*	270.8	223.0	355.8	229.1	270.6	266.8
		Soybean	95.6	85.3	110.6	93.2	97.6	96.0
		Potato	0.0	0.0	0.0	0.0	0.0	0.0
	Application Rate (inches per acre)	*Corn*	8.3	7.2	7.4	8.4	8.7	8.0
		Soybean	7.9	6.4	6.2	7.7	7.6	7.2
		Potato	9.5	9.7	10.7	10.9	11.8	11.2
	Applications (acre inches)	*Corn*	2261	1616	2650	1936	2367	2147
		Soybean	758	548	688	720	744	694
		Potato	0	0	0	0	0	0
		Total	3018	2164	3338	2656	3111	2840
Change	Applications	*Acre-Inches*	359	302	275	217	−9	236
		% change	14%	16%	9%	9%	0%	9%

*Effects estimated assuming a 2.65°C increase in average temperature and an additional 8 extreme heat degree days (EHDD threshold = 34°C) by midcentury.

production. In WI, the combined effects negate each other, resulting in approximately zero net effect.

In regions where the spatial distribution of such increases in water demand aligns with the spatial distribution of limited water availability, including areas where total withdrawals are restricted as a result of Great Lake Compact implementation, there is a heightened likelihood of conflict over water access. Other regions, where potato production is highly concentrated, may experience net reductions in water applications if the observed substitution effect persists.

In sum, agricultural activity and irrigation practices in the region are likely to be affected by changes in both long-run average climate conditions and short-run weather events. The results discussed here provide evidence that temperature is an important determinant of irrigation water demand both in terms of long-run average conditions and short-run extreme heat events. At watershed scales, the net water use effects depend on regional production patterns.

Price Effects

Firms respond to the cost of water by adjusting water application rates at the intensive margin. In the Great Lakes Region, the intensive margin response to water cost dominates the extensive crop allocation response. This result aligns with the conclusions of Mullen, Yu, and Hoogenboom (2009), who found that the intra-seasonal water application effect dominates the crop allocation effect in the southeastern U.S. This appears to be a distinction between water-abundant and water-scarce regions where crop allocation decisions appear to dominate the response to water cost (Moore, Gollehon, and Carey 1994). Firms in the sample are somewhat less responsive to crop prices than firms in the southeastern U.S. (Mullen, Yu, and Hoogenboom 2009).

Limitations

The results of this study should be understood in the context of the relevant limitations of the models and underlying data. Importantly, observations are spatially identified at the county level. Some firms that operate in multiple counties are identified by their primary county. This spatial proxy for firm location introduces some error in all environmental and price variables which may attenuate the resulting effects. Additionally, general equilibrium effects and development of new adaptation strategies may confound the expected effects over longer time periods. For example, development of drought-resistant crop varieties might reduce water applications and reduce crop substitution effects. The net effect of such changes is ambiguous, depending on the magnitude of each effect. Additionally, this study is limited in the degree that it explores spatial variation in effects across the Great Lakes Region. There is an opportunity for future studies to explore how the average regional effects identified in this study might vary for specific subregions.

The FRIS questionnaire distinguishes between sweet corn, corn for silage or green-chop, and corn for grain or seed. Production for grain or seed was included in this article because the majority of the region's irrigated corn acreage is in this category. This grouping, however, does not allow for identification of seed vs. grain producers. There may be significant differences in management practices between these two types of producers. Seed producers commonly operate under production contracts that are likely to affect firm expectations of crop price and may change irrigation management decisions. Production contracts are also unidentified for potato producers. Future research might explore the effects of tournament style or other production contract structures on irrigation incentives.

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Conflicts of Interest

None

Transparency and Openness Promotion Statement

Due to confidentiality restrictions, the USDA Farm and Ranch Irrigation Survey respondent level data is only accessible via limited agreement between researchers and USDA.

References

Bigelow, D.P., and H. Zhang. 2018. "Supplemental Irrigation Water Rights and Climate Change Adaptation." *Ecological Economics*, Volume 154, 2018.

Deschenes, O., and M. Greenstone. 2007. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather." *American Economic Review* 97(1): 354–385.

Gonzalez-Alvarez, Y., A.G. Keeler, and J.D. Mullen. 2006. "Farm-Level Irrigation and the Marginal Cost of Water Use: Evidence from Georgia." *Journal of Environmental Management* 80(4): 311–17. https://doi.org/10.1016/j.jenvman.2005.09.012.

Hatfield, J.L., D. Brown, J.A. Andresen, D. Bidwell, and J.A. Winkler. 2014. *Climate Change in the Midwest: A Synthesis Report for the National Climate Assessment*. Washington, DC: Island Press.

Hayhoe, K., J. VanDorn, T. Croley, N. Schlegal, and D. Wuebles. 2010. "Regional Climate Change Projections for Chicago and the US Great Lakes." *Journal of Great Lakes Research* 36 (January): 7–21. https://doi.org/10.1016/j.jglr.2010.03.012.

Hendricks, N.P. 2018. "Potential Benefits from Innovations to Reduce Heat and Water Stress in Agriculture." *Journal of the Association of Environmental and Resource Economists* no. 3 (July 2018): 545–576.

Hendricks, N.P., and J.M. Peterson. 2012. "Fixed Effects Estimation of the Intensive and Extensive Margins of Irrigation Water Demand." *Journal of Agricultural and Resource Economics* 37(1): 1–19.

Ito, K. 2014. "Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing." *American Economic Review* 104 (2): 537–563. https://doi.org/10.1257/aer.104.2.537.

Lau, L. 1978. "Applications of Profit Functions." In M. Fuss and D. McFadden, eds., *Production Economics: A Dual Approach to Theory and Applications (I): The Theory of Production*. History of Economic Thought Books, McMaster University Archive for the History of Economic Thought, volume 1.

Luukkonen, C., S. Blumer, T.L. Weaver, and J. Jean. 2004. "Simulation of the Ground-Water-Flow System in the Kalamazoo County Area, Michigan." Scientific Investigations Report 2004–5054. U.S. Department of the Interior, U.S. Geological Survey, Reston, Virginia.

Mieno, T., and N. Brozović. 2016. "Price Elasticity of Groundwater Demand: Attenuation and Amplification Bias due to Incomplete Information." *American Journal of Agricultural Economics*, December, aaw089. https://doi.org/10.1093/ajae/aaw089.

Moore, M.R., N.R. Gollehon, and M.B. Carey. 1994. "Multicrop Production Decisions in Western Irrigated Agriculture: The Role of Water Price." *American Journal of Agricultural Economics* 76 (4): 859. https://doi.org/10.2307/1243747.

Moore, M.R., and D.H. Negri. 1992. "A Multicrop Production Model of Irrigated Agriculture, Applied to Water Allocation Policy of the Bureau of Reclamation." *Journal of Agricultural and Resource Economics*, 29–43.

Mubako, S.T., B.L. Ruddell, and A.S. Mayer. 2013. "Relationship between Water Withdrawals and Freshwater Ecosystem Water Scarcity Quantified at Multiple Scales for a Great Lakes Watershed." *Journal of Water Resources Planning and Management* 139 (6): 671–681.

Mullen, J.D., Y. Yu, and G. Hoogenboom. 2009. "Estimating the Demand for Irrigation Water in a Humid Climate: A Case Study from the Southeastern United States." *Agricultural Water Management* 96 (10): 1421–28. https://doi.org/10.1016/j.agwat.2009.04.003.

Olen, B., J. Wu, and C. Langpap. 2016. "Irrigation Decisions for Major West Coast Crops: Water Scarcity and Climatic Determinants." *American Journal of Agricultural Economics* 98 (1): 254–75. https://doi.org/10.1093/ajae/aav036.

Pendergrass, A.G., R. Knutti, F. Lehner, C. Deser, and B.M. Sanderson. 2017. "Precipitation Variability Increases in a Warmer Climate." *Scientific Reports* 7 (1). https://doi.org/10.1038/s41598-017-17966-y.

Pfeiffer, L., and C.-Y.C. Lin. 2014. "The Effects of Energy Prices on Agricultural Groundwater Extraction from the High Plains Aquifer." *American Journal of Agricultural Economics* 96 (5): 1349–62. https://doi.org/10.1093/ajae/aau020.

Ritchie, J.T., and D. S. NeSmith. 1991. "Temperature and Crop Development." In *Modeling Plant and Soil Systems*, edited by John Hanks and J.T. Ritchie, 5–29. American Society of Agronomy.

Scheierling, S.M., J.B. Loomis, and R.A. Young. 2006. "Irrigation Water Demand: A Meta-Analysis of Price Elasticities." *Water Resources Research* 42 (1): W01411. https://doi.org/10.1029/2005WR004009.

Schlenker, W., and M.J. Roberts. 2009. "Nonlinear Temperature Effects Indicate Severe Damages to US Crop Yields under Climate Change." *Proceedings of the National Academy of Sciences* 106 (37): 15594–15598.

USDA (U.S. Department of Agriculture National Agricultural Statistics Service.). 2003, 2008, 2013. Farm and Ranch Irrigation Survey. USDA (U.S. Department of Agriculture National Agricultural Statistics Service). 2016. Quick Stats. https://www.nass.usda.gov/Quick_Stats/Ag_Overview/stateOverview.php?state=MICHIGAN.

Vavrus, S., and J. Van Dorn. 2010. "Projected Future Temperature and Precipitation Extremes in Chicago." *Journal of Great Lakes Research* 36 (January): 22–32. https://doi.org/10.1016/j.jglr.2009.09.005.

Wallander, S. 2017. "USDA Water Conservation Efforts Reflect Regional Differences." *Choices*, Quarter 4. http://www.choicesmagazine.org/choices-magazine/theme-articles/inducing-water-conservation-in-agriculture-institutional-and-behavioral-drivers/usda-water-conservation-efforts-reflect-regional-differences.
Watson, K.A., A.S. Mayer, and H.W. Reeves. 2014. "Groundwater Availability as Constrained by Hydrogeology and Environmental Flows." *Groundwater* 52 (2): 225–38. https://doi.org/10.1111/gwat.12050.
Zhang, P., J. Zhang, and M. Chen. 2017. "Economic Impacts of Climate Change on Agriculture: The Importance of Additional Climatic Variables Other than Temperature and Precipitation." *Journal of Environmental Economics and Management* 83 (May): 8–31. https://doi.org/10.1016/j.jeem.2016.12.001.
Zorn, T.G., P.W. Seelbach, and Edward S. Rutherford. 2012. "A Regional-Scale Habitat Suitability Model to Assess the Effects of Flow Reduction on Fish Assemblages in Michigan Streams." *JAWRA Journal of the American Water Resources Association* 48 (5): 871–895.

Appendix A County Fixed Effect Models
Water Application Models: Estimated Coefficients

	Corn		**Soybean**		**Potato**	
Fixed Effect	**State**	**County**	**State**	**County**	**State**	**County**
Water Cost	−0.502	−0.495	−0.426	−0.425	−0.569	−0.635
	(0.024)**	(0.024)**	(0.031)**	(0.035)**	(0.083)**	(0.120)**
Peak Season						
Precip.	−0.193	−0.176	−0.085	−0.101	−0.036	−0.061
	(0.039)**	(0.047)**	(0.069)	(0.075)	(0.173)	(0.232)
Temp.	0.088	0.156	0.274	0.064	0.956	−1.29
	(0.105)	(0.313)	(0.129)**	(0.316)	(0.329)**	(1.567)
Humidity	−0.039	−0.053	−0.043	−0.073	−0.092	−0.299
	(0.017)*	(0.025)*	(0.020)*	(0.033)*	(0.081)	(0.102)**
EHDD	0.131	0.094	0.103	0.092	0.204	0.673
	(0.034)**	(0.046)*	(0.047)*	(0.051)	(0.302)	(0.554)
Soil Quality	−0.013	−0.092	−0.019	−0.051	−0.045	−0.079
	(0.003)**	(0.023)**	(0.004)**	(0.022)*	(0.011)**	(0.044)
Crop Price	−0.335	−0.400	0.487	0.467	0.237	0.592
(own-price)	(0.248)	(0.282)	(0.282)	(0.307)	(0.566)	(0.736)
R^2	0.20	0.32	0.16	0.29	0.32	0.60
N	4289	4289	2866	2866	468	468

*$p < 0.05$; **$p < 0.01$