Adapting to Climate Change Through Tile Drainage: A Structural Ricardian Analysis

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Abstract

This paper provides the first estimates of the effects of climate change on agriculture while explicitly modeling tile drainage. We show in a simple conceptual model that the value of precipitation should differ between drained and non-drained land, implying that pooling these lands could bias estimates of the effects of climate change on land values. We test this hypothesis by estimating a Structural Ricardian model for U.S. counties east of the 100th meridian. Consistent with our theoretical model, our estimates show that the value of precipitation is higher on non-drained lands.

JEL codes: Q10, Q15, Q51, Q54

Keywords: Climate change; adaptation; agriculture; climate impacts; tile drainage

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"Look at this flower pot. What is the hole at the bottom for? I ask you, because there is a complete agricultural revolution in that hole." - (Klippart, 1861, p. 3)

1 Introduction

Designing efficient policies to address climate change requires accurate damage estimates. Recent studies that quantify the value of climate to agriculture have provided key insights in this area (Fisher et al., 2012; Deschenes and Greenstone, 2007; Schlenker et al., 2006; Mendelsohn et al., 1994). However, much uncertainty still remains regarding the magnitude and distribution of expected damages. One critical piece to this puzzle is the role of adaptation (Burke et al., 2016; Auffhammer and Schlenker, 2014). Specifically, farmers may invest in technologies that mitigate the harmful effects of changes in climate. Understanding this adaptive behavior is fundamental to improving damage estimates.

This paper studies a key adaptive technology available to farmers - subsurface drainage. This type of drainage, also known as tile drainage, reduces excess water stress in crops by lowering the water table, which allows rainfall to move more quickly through poorly drained soils.[1] Tile drainage was introduced to the U.S. in 1835 and quickly experienced wide-spread adoption (Pavelis, 1987, p. 19). From 1855 to 1985, approximately 43 billion dollars was invested in tile drainage infrastructure (Pavelis, 1987, p.122).[2] Today, nearly 48 million acres utilize tile drainage; this land represents approximately a quarter of the total cropland value in the country.[3] Many have argued that U.S. agriculture as we know it today would not exist without this critical piece of infrastructure (Jaynes and James, 2007; Pavelis, 1987).

To assess this important adaptation tool, we develop an economic model of drainage adoption and use newly available data from the 2012 Census of Agriculture to estimate the effects of climate on land values through a Structural Ricardian analysis (Kurukulasuriya et al., 2008; Seo and Mendelsohn, 2008). The original Ricardian method, developed by Mendelsohn et al. (1994), utilizes a cross-sectional regression of farmland values on climate and control variables to recover implicit values for marginal changes in long-run averages of precipitation and temperature. The key insight

[1]Subsurface drainage is often referred to as tile drainage because early drains were constructed from clay tiles. However, most modern drains are constructed from corrugated plastic.

[2]2012 dollars.

[3]Author's estimate based on 2012 Census of Agriculture.

of this method is that long-run climate effects should be capitalized into land values. The estimated coefficients are used in conjunction with climate change scenarios to simulate the impact of climate changes on agriculture.

To help inform our empirical analysis, we develop a theoretical model of drainage adoption. This model illustrates how marginal increases in precipitation on tile drained land are less valuable than on non-tile drained land. Intuitively, and similar to other production models, this result comes from the first order conditions comparing the marginal benefits of tile drainage to its marginal cost. To test our model's predictions, we employ a *Structural* Ricardian model. The Structural Ricardian model builds on the original Ricardian model by explicitly modeling the adaptive choices of farmers.[4] In the first stage of this two-stage model, we estimate the probability of a farm containing tile drainage as a function of exogenous land characteristics and climate. In the second stage, we estimate separate Ricardian functions for tile drained and non-tile drained farms. We apply our estimates from both stages to climate change simulations and combine them to form expected farmland values following climate change. Thus the resulting damage estimates capture changes in farmland values as well as changes in the probability of being on tile drained land. Our preliminary results show that the marginal value of precipitation is higher on non-tile drained land than on tile drained land, supporting our model's prediction.

Our paper builds on a strand of literature which investigates the role of adaptation in Ricardian models. To date, this work has focused almost exclusively on irrigation. As observed by Schlenker et al. (2005), a key assumption of the Ricardian method is that the coefficient on precipitation measures the supply of water for crops. In the Western half of the United States, however, much of the supply of water for crops is obtained through irrigation. Schlenker et al. (2005) show that Ricardian functions are fundamentally different on irrigated and non-irrigated land. We build on this idea by observing that the supply of water for crops on tile drained land is also not equal to precipitation, since excess water is drained away. This implies there may be fundamental differences in tile drained and non-tile drained land as well. While some studies have focused on non-irrigated land, we know of no other Ricardian analysis which accounts for tile drainage, including those based in countries with heavily drained areas such as the U.S. (Burke and Emerick, 2012; Deschenes and

[4] Seo and Mendelsohn (2008) develop a Structural Ricardian model to account for the potential endogeneity of irrigation.

Greenstone, 2007; Schlenker et al., 2006; Mendelsohn et al., 1994), Canada (Reinsborough, 2003), Germany (Chatzopoulos and Lippert, 2015), and the United Kingdom (Fezzi and Bateman, 2007).[5]

This paper also contributes new climate change damage estimates. Our paper uses the most recent data U.S. Census data at the individual farmer level.[6] Combined with zip code level climate data, this should significantly decrease the aggregation bias that has been found in county level estimates (Fezzi and Bateman, 2007). To our knowledge, only Fezzi and Bateman (2007), Schlenker et al. (2007), and Kurukulasuriya et al. (2011) use farm level data in a Ricardian analysis; these studies were based in California, Germany, and Africa, respectively. Our data includes all farmers in the Eastern United States in 2012 - almost 1,000,000 observations. Using micro data across this large geographic region allows us to fully exploit the wide variations in climate, farmland values, and tile drainage across space.

The paper proceeds as follows. Section 2 builds a simple conceptual model of a representative farmer's optimal choice of tile drainage, which generates intuition for the empirical analysis. Section 3 provides a summary of the data, which includes a discussion on the availability and accuracy of the existing universe of tile drainage data. Section 4 describes the econometric model used in this paper, followed by the coefficient estimates in section 5. Section 6 uses these coefficient estimates to simulate the effects of climate change on agriculture, and compare our results with previous estimates. Section 7 provides a brief conclusion.

2 Conceptual Model

This section builds a simple economic model of tile drainage. Although our model uses profits as the outcome variable rather than land rents, profits can be converted into land rents using a capitalization ratio (Schlenker et al., 2006), thus the results can be used to gain intuition on the effect of including tile drainage in a Ricardian analysis. Assume that there is a crop production function, $f(w)$, whose sole input is the amount of water supplied to crops, w. Let this function have an inverted-U shape, reflecting the fact that water is beneficial for crop growth up to a certain amount, $\overline{w}$, but is harmful beyond that point as the soil becomes saturated. This implies $f_w \geq 0$

[5]See Feick et al. (2005) for a digital global map of artificial drainage.

[6]Farm level U.S. Census of Agriculture data is confidential, and our results are still under review by the USDA. Here we include preliminary county level estimates.

when $w \leq \overline{w}$, $f_w \leq 0$ when $w \geq \overline{w}$, and $f_{ww} < 0$ throughout.

The supply of water for crops, $w(D; P)$, is a function of tile drainage, D, and the exogenous level of precipitation, P. Assume $w_D < 0$, since tile drainage is typically used to decrease the amount of water on cropland, and $w_{DD} > 0$, indicating that the amount of water that tile drainage is able to remove decreases as tile drainage increases.[7] Assume that $w_P > 0$, meaning that an increase in precipitation will increase the supply of water to crops. Let p_c and p_d represent the strictly positive, exogenous prices of crops and drainage, respectively. The farmer chooses D in order to maximize their profit:

$$\max_{D \geq 0} \pi = p_c f(w(D; P)) - p_D D \tag{1}$$

This gives the following first order condition:

$$p_c f_w w_D \leq p_D \tag{2}$$

Equation (2) holds with equality when the optimal amount of tile drainage is positive. Given the strictly positive prices, as well as the negative sign on w_D, this implies that tile drainage will only be used on the portion of f where the marginal product of water is negative ($f_w < 0$). In other words, tile drainage will only be installed when the supply of water is so high that it is detrimental to crop growth.

On the other hand, when the optimal amount of tile drainage is zero, equation (2) becomes a strict inequality. This inequality is always satisfied when the available water supply is not harmful to crop growth ($f_w \geq 0$), indicating that farmers will not remove water from their land if it is beneficial to crops. However, depending on the relative prices of crops and tile drainage, it is also possible for the inequality to be satisfied when the amount of water is harmful to crop growth, $f_w < 0$. Specifically, if the marginal cost of tile drainage, p_D, is higher than the value of the marginal product, $p_c f_w w_D$, then farmers would rather accept the damage to their crops (or not

[7] Since our empirical analysis focuses on non-irrigated counties, we do not consider the use of tile drainage to flush excess salts from the soil.

grow crops at all) rather than install tile drainage.

The demand function for tile drainage is a function of the exogenous prices and precipitation, $D^*(\boldsymbol{p}, P)$, where $\boldsymbol{p} = (p_c, p_D)$. Substituting this demand function into equation (1) gives the profit function:

$$\pi = p_c f(w(D^*(\boldsymbol{p}, P), P)) - p_D D^*(\boldsymbol{p}, P) \tag{3}$$

When the optimal amount of tile drainage is zero, this simplifies to:

$$\pi = p_c f(w(0; P)) \tag{4}$$

Taking the derivative of equation (4) with respect to precipitation yields:

$$\frac{\partial \pi}{\partial P}_{D^*=0} = \underset{(+)(+/-)(+)}{p_c f_w w_P} \tag{5}$$

The single term on the right hand side of equation (5) is simply the increase in profits that occur through an increase in crop productivity due to an increase in precipitation. In general, the sign of equation (5) is ambiguous, since optimal tile drainage may be zero even when $f_w < 0$, as noted above. If water is beneficial to crops on the average farm that does not install tile drainage, so that $f_w > 0$ when $D = 0$, then equation (5) predicts that precipitation increases profits on land without tile drainage.

When the optimal amount of tile drainage is positive, the derivative of equation (3) with respect to precipitation is:

$$\frac{\partial \pi}{\partial P}_{D^*>0} = p_c f_w w_D D_p + p_c f_w w_p - p_d D_p$$

Grouping terms by D_p and using the fact that $p_c f_w w_D$ equals p_D when the optimal amount of tile drainage is positive:

$$\begin{aligned} \frac{\partial \pi}{\partial P}_{D^*>0} &= D_p(p_c f_w w_D - p_D) + p_c f_w w_P \\ &= \underset{(+)(-)(+)}{p_c f_w w_P} \end{aligned} \tag{6}$$

Equation (6) shows that an increase in precipitation on tile drained lands will decrease profits. This makes sense, since farmers will either have to accept the crop damages due to an increase in precipitation, or pay the price of installing more tile drainage to mitigate damages.

If we assume that, on non-tile drained land, an increase in precipitation does not negatively effect crop productivity, so that $f_w \geq 0$, then:

$$\frac{\partial \pi}{\partial P}_{D^*=0} \geq \frac{\partial \pi}{\partial P}_{D^*>0}$$

To investigate this relationship further, the following section performs a Ricardian analysis which separates observations into tile drained and non-tile drained land. Land values are regressed on a set of explanatory variables, including precipitation. By comparing the coefficients on precipitation we are able to gain further insight into how its value differs between the two subsets.

3 Data

3.1 Land Rents

A Ricardian analysis assumes that current farmland value represents the sum of discounted land rents in equilibrium. As is conventional in the literature, we use reported farmland value as a proxy for land rents. These data are from the 2012 U.S. Census of Agriculture and are reported in dollars per acre at the county level. To focus on the effect of tile drainage, separate from irrigation, we follow Schlenker et al. (2006) and remove all counties West of the 100th meridian. This reduces our sample from 3,072 to 2,466 counties. The spatial distribution of these counties is shown in Appendix B.

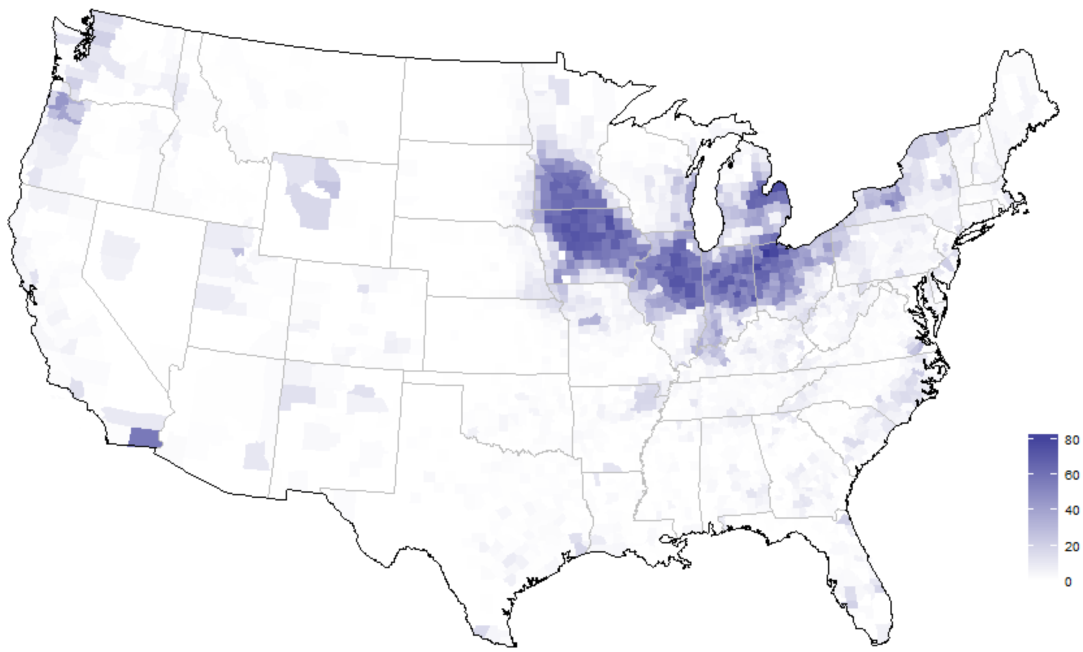


Figure 1: U.S. tile drainage as a percentage of cropland (2012 Census of Agriculture).

3.2 Tile Drainage: Current Estimates

Our main source for tile drainage data is the 2012 U.S. Census of Agriculture, which includes county level data on number of farms with tile drainage as well as the number of acres drained. Theses data represent the first attempt at assessing the extent of tile drainage in the U.S. in over 20 years.

Figure 1 shows the spatial distribution of tile drainage as a percentage of cropland acres across the entire U.S., based on the 2012 Census. Tile drainage is concentrated in the Midwest, with especially high concentrations in Iowa, Illinois, Indiana, Ohio, and southern Minnesota. Many of the counties in these states have tile drainage on over 70% of their cropland, with the highest being Henry, Ohio, with 84%. The map also shows that tile drainage is not exclusively used in the "wet" region of the U.S., as patches of tile drained counties appear throughout the West. However, tile drainage in these areas is primarily used to remove excess salinity from the soil that occurs due to irrigation.[8]

[8]Imperial County, California, for example, shown as the southernmost dark blue county in that state, has tile drainage in over 57% of its cropland, despite being one of the driest counties in the U.S.

3.3 Tile Drainage: Historical Estimates

From 1920 to 1978, estimates of tile drainage were produced through the decennial Census of Drainage and sporadically through the Census of Agriculture. Unfortunately, these estimates are plagued by inconsistent techniques. In addition, tile drainage is inherently difficult to estimate since it is buried underground, sometimes for decades and with no records of installation. These problems combined to create a wide variation in historical drainage estimates. The 1969, 1974, and 1978 estimates from the Census of Agriculture, for example, indicated that the total amount of acres with tile drainage were about 60, 43, and 108 million, respectively.

A separate set of county level estimates were produced in 1982, 1987, and 1992 by the National Resources Inventory (NRI). These were based on statistical sampling techniques and produced more consistent estimates. However, they had some notable drawbacks. For example, it could be difficult for a staff member to identify whether the sampling location contained tile drainage. Even if they did, the survey was limited to only listing three land practices, which means it is possible that tile drainage was omitted in some cases (Sugg, 2007, p.2). A new data set, produced by the World Resources Institute (WRI) in 2007, estimated tile drainage in ten mid-western states based on data on row crops and soil quality. That study assumes that if crops are being grown on poorly drained soil, than they are likely to contain tile drainage (Sugg, 2007, p.3). The resulting estimates were combined with 1992 NRI estimates from the remaining U.S. states.

Through conversations with experts familiar with tile drainage data as well as our own analysis, we believe that the 2012 Census data on tile drainage is a reasonably accurate representation of the existing extent of U.S. tile drainage. However, due to the data limitations of past drainage data, as well as the large gap since the last set of estimates was released, we do not believe it is sensible to combine the data during estimation. In the appendix, however, we repeat the cross-sectional analysis for the 1982 and 1987 NRI data, as well as the WRI estimates based on data from 1992.

3.4 Climate

All of our climate variables are derived from Oregon State's PRISM datasets (Oregon State University, 2016). For each day since 1981, PRISM provides data on maximum and minimum temperatures, plus precipitation, for 481,631 grid cells which cover the contiguous United States, where the size of each grid cell is 2.5 square miles.[9] We use daily data from 1982-2011 to calculate yearly variables, where each year is subset to April through September to approximate the growing season. These yearly weather variables are then averaged over all 30 years to approximate the climate.

Our temperature variables are derived from degree days to capture possible non-linear responses of crop growth to heat (Schlenker and Roberts, 2006).[10] These variables include growing degree days, defined as the number of degree days between 8 and 32°C, and degree days above 34°C, which is a threshold that has been used to indicate temperatures that are harmful to plant growth (Schlenker et al., 2006). These variables, along with daily precipitation, are summed over the growing season.

Vapor pressure deficit is the difference between the amount of moisture in the air and the amount of moisture the air can hold when it is saturated. It is strongly correlated with crop yields (Roberts et al., 2012) and therefore may be important to include in a Ricardian analysis.[11] Following Roberts et al. (2012), we approximate VPD from minimum (T_L) and maximum (T_H) daily temperatures using the following equation:

$$VPD = 0.6107 \left(e^{\left(\frac{17.269 T_H}{237.3+T_H}\right)} - e^{\left(\frac{17.269 T_L}{237.3+T_L}\right)} \right) \tag{7}$$

We then average these daily values of VPD over the growing season. To isolate the effects of the climate variables over cropland within a county, rather than over all land (which can include developed land, water bodies, etc.), we weight each PRISM grid cell by its proportion of land in cropland. We follow the approach of Schlenker et al. (2006) and intersect a shapefile of PRISM grid cells with a 2011 National Land Cover Database (NLCD) satellite image using ArcGIS.[12] We then divide the sum of the areas of the land types classified a either "cropland" or "pasture" by the area of a PRISM grid cell.

[9] Monthly values are available as far back as 1895.

[10] Daily Degree days are derived from daily minimum and maximum temperature using the procedure from Schlenker et al. (2006).

[11] Relative humidity, which is closely related to VPD, was used in a Ricardian analysis of Chinese farmland and had a statistically significant coefficient in all specifications (Zhang et al., 2015).

[12] www.mrlc.gov

3.5 Soil and Demographics

To control for land quality across the U.S., we include a group of variables from the STATSGO soil data set. STATSGO divides the U.S. into over 10,000 "map units" whose soil characteristics are determined through statistically expanding the results of several samples in each unit. The variables taken from STATSGO include measures of water capacity, slope, k-factor, amount of clay, soil class, and saturation. Each variable is calculated as an area weighted average of map units within a county.

Several papers have shown that proximity to urban areas can influence farmland values (Zhang and Nickerson, 2015; Shi et al., 1997). To control for these influences we linearly extrapolate demographic data from the 2010 U.S. Census to 2012. These variables are at the county level, and include population density and income per capita.

3.6 Summary Statistics

Table 1 presents the summary statistics of all the variables used in our estimation.[13] Farmland values have an average value of \$4,047 in 2012 dollars and are skewed towards zero, with a maximum of \$126,087. The percentage of cropland with tile drainage is skewed towards zero, with an average of 9.7%. Growing degree days and precipitation have roughly symmetric distributions, with means of 2,309 and 54.22, respectively. The distribution for degree days above 34°C is skewed towards zero, with a mean of 5.93.

4 Methodology

4.1 Empirical Model

A traditional Ricardian analysis regresses farmland values on climate variables and controls without distinguishing between different adaptive technologies available to farms. To model this adaptation, we use a Structural Ricardian model similar to Kurukulasuriya et al. (2011). This two-stage model, closely related to the Heckman model (Heckman, 1977), explicitly models the choice of tile drainage, as well as changes in farmland values, on both tile drained and non-tile drained land.

[13] Appendix A shows the full distributions of our key variables.

Table 1: Descriptive Statistics for Primary Data Set

	Mean	SD	10th Percentile	90th Percentile
Farmland and tile drainage:				
Farmland value ($/acre)	4,047.23	4,240.73	1,767.00	6,694.80
Percent of cropland tiled	9.68	17.65	0.00	38.42
Climate data:				
Growing degree days (thousands)	2.31	0.53	1.61	3.01
Precipitation (cm)	54.22	8.16	43.33	63.39
Degree days above 34°C	5.93	9.66	0.14	17.56
Vapor pressure deficit	1.98	0.33	1.57	2.40
Soil and land data:				
Slope	8.40	7.15	2.06	17.32
K-factor	0.11	0.12	0.00	0.31
Soil class	55.80	11.77	41.99	72.41
Water capacity	7.75	1.69	5.48	10.00
Soil Permeability	12.39	13.08	0.69	27.16
Percent clay	10.78	11.03	0.00	27.31
Latitude	37.73	4.64	31.43	43.93
Demographic Variables:				
Population density (hundreds per square mile)	1.72	4.13	0.12	3.70
Income per capita (thousand $)	22.97	5.07	17.47	28.80

Notes: Sample consists of 2,438 counties east of the 100th meridian. All dollar values are in 2012 dollars.

The first stage models tile drainage as a dichotomous choice, estimated using a probit regression. Assume that farmers decide whether or not to install tile drainage, Y, conditional on a vector of exogenous local variables X, which includes climate, soil, and land characteristics, and an unobservable error term ϵ_1:

$$\begin{aligned} Y &= \beta X_1 + \epsilon_1, \\ \epsilon_1 &\sim \mathcal{N}(0,1) \end{aligned} \tag{8}$$

where $Y_d = 1$ if the farm contains a positive amount of tile drainage, and 0 otherwise.

The second stage estimates two separate Ricardian functions for tile drained and non-tile drained land (Π_d and Π_n, respectively).

$$\Pi_d = \beta X_2 + \epsilon_2 \tag{9}$$

$$\Pi_n = \beta X_3 + \epsilon_3 \tag{10}$$

$$\epsilon_2 \sim \mathcal{N}(0, \sigma_1) \tag{11}$$

$$\epsilon_3 \sim \mathcal{N}(0, \sigma_2) \tag{12}$$

The unobservable variables that determine the farmer's choice of tile drainage in equation (8) are likely to be correlated with the unobservable variables that determine farmland values in equations (9) and (10):

$$\begin{aligned} \text{corr}(\epsilon_1, \epsilon_2) &= \rho_2 \\ \text{corr}(\epsilon_1, \epsilon_3) &= \rho_3 \end{aligned}$$

To control for the resulting selection bias, we calculate the inverse mills ratio from equation (8) and include it as an additional explanatory variable in the Ricardian equations.

4.2 Functional form

Following convention, we estimate equations (9) and (10) using a semi-log functional form. In all regressions we use robust standard errors, clustered at the zip code level.

Past research has emphasized the non-linear response of crop growth to climate (Schlenker and Roberts, 2009), which necessitates a flexible functional form for these variables. We will do this with two different specifications. The first specification bins growing degree days and precipitation into deciles, assigning a dummy variable for each decile. The second specification (not shown here) approximates the non-linear function for each variable using a cubic spline.

5 Results

This section presents preliminary estimates performed at the county level, as farm level estimates have not yet been approved for public release by the USDA. We suggest caution in viewing these results, as Fezzi and Bateman (2007) show that estimates at the county level may be subject to significant aggregation bias. An important component of the final paper will be analyzing the differences in these estimates and the estimates obtained through farm level data.

Figure 2 displays the probit results for precipitation and growing degree days.[14] These figures display marginal effects, rather than coefficient estimates, to ease interpretation. To avoid collinearity we have excluded the lowest bins for each variable. This means that the marginal effects for precipitation are relative to having less than 46 centimeters, and the marginal effects for growing degree days are relative to having less than 2,670 growing degree days.

As expected, the probability of land containing tile drainage increases with the level of precipitation. As precipitation increases from 46 to 81 centimeters, the probability smoothly increases from about 18 to 35%, except for a sharp increase and subsequent decrease at 59 centimeters. The marginal effects are all significantly different from zero at the 1% significance level.

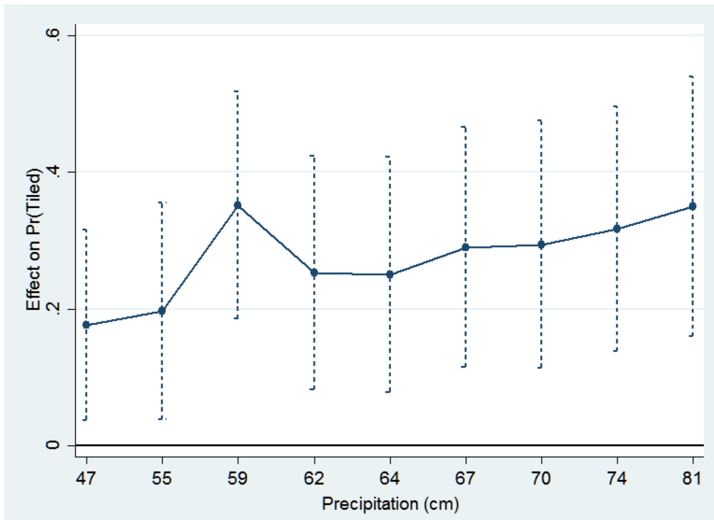
The probability of a county containing tile drainage decreases with the level of growing degree days. At around 2,670 growing degree days, the probability is 22% higher than the reference level. As growing degree days increase, the marginal effect becomes insignificant at 2,600 through 3,150

[14]We have excluded the results for control variables and state fixed effects for simplicity. We will include these results in an appendix in the final version.

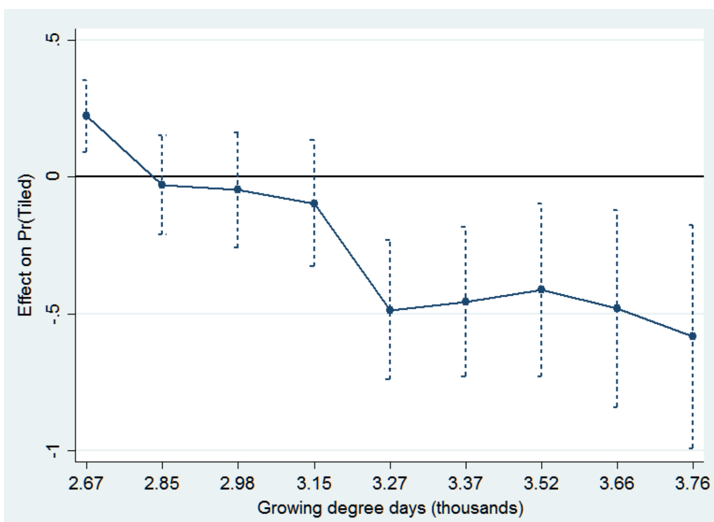
degree days. At 3,270 growing degree days and above, counties are a little over 50% less likely to have tile drainage relative to the reference category.

Figure 2: Marginal effects of precipitation (a) and growing degree days (b).

(a)



(b)

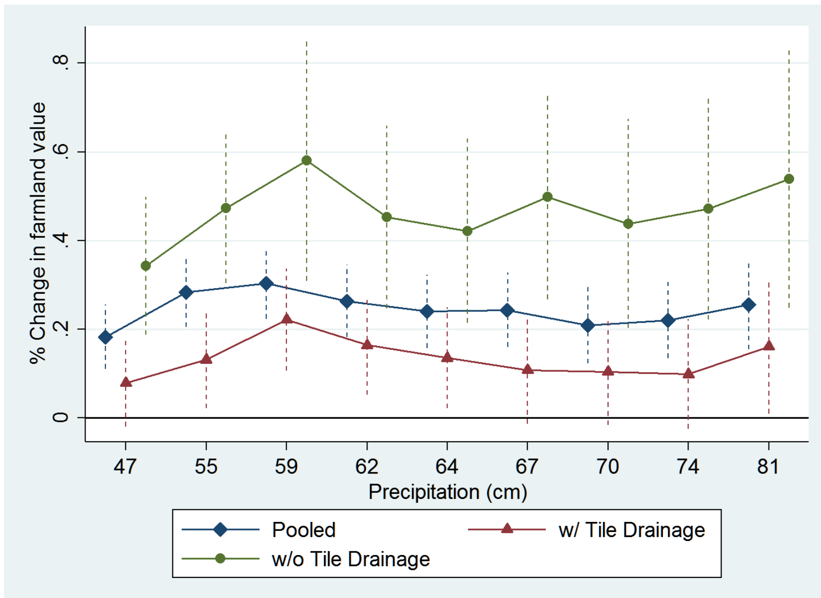


Notes: Dependent variable is a binary indicator for tile drainage. Estimates are from a probit regression which includes soil and demographic control variables, plus state fixed effects. Values are relative to each variable's 10% decile. Vertical lines represent 95% confidence intervals. Calculated with robust standard errors.

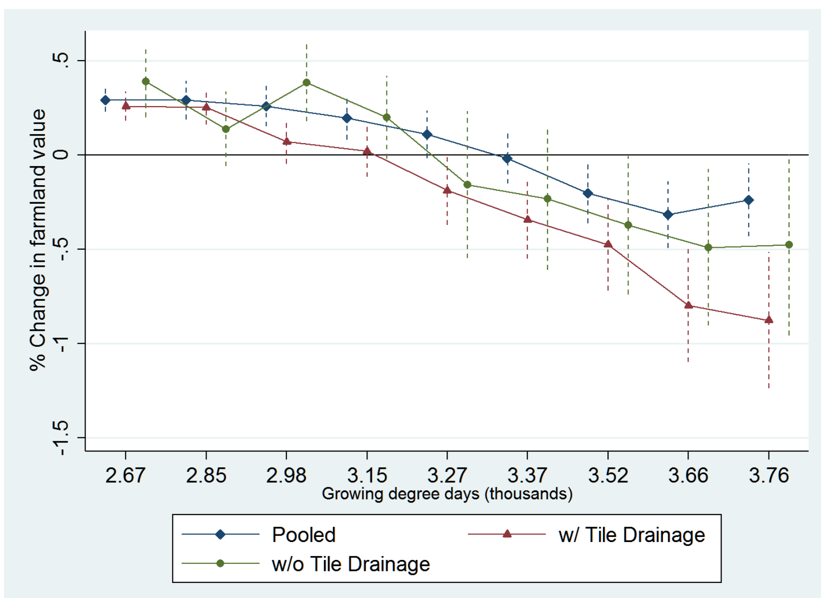
Figure 3 displays the coefficient estimates for three Ricardian models - one estimated on tile drained land, one on non-tile drained land, and one that is estimated when both land types are pooled together. Panel (3a) shows that the marginal value of precipitation is higher on non-tile

Figure 3: Marginal values of precipitation (a) and growing degree days (b).

(a)



(b)



Notes: Dependent variable is the log of farmland value. Model includes soil and demographic controls, plus state fixed effects. Coefficient values are relative to each variable's 10% decile. Vertical lines represent 95% confidence intervals. Calculated with robust standard errors.

drained land than on tile-drained land, as our theoretical model predicts. It is statistically significant for non-tile drained land throughout the domain, while for tile drainage it is statistically significant between 55 and 64 centimeters. The marginal value for both land types peaks at around 59 centimeters of precipitation. The pooled estimates lie between the two other estimates throughout the entire domain.

Panel (3b) shows the corresponding results for growing degree days. These results show that the value of growing degree days is roughly similar on tile drained and non-tile drained land, as the confidence intervals for the two land types overlap at every bin. The marginal value begins positive but crosses zero at around 3,270 growing degree days. Afterwards it continues to decline- at 3,670 growing degree days the value of farmland is 24% to 48% percent less than the reference category, depending on the model.

The following section applies these estimates to climate change simulations to estimate the damages to agriculture through climate change.

6 Climate Change Simulations

Data on climate change was derived from four global climate models (GCM's) used in the most recent IPCC report, which produced daily weather simulations through 2100.[15] These data have been down scaled through NASA's NEX project to 25 by 25 km grid cells.[16] Climate normals for each grid cell were calculated for two thirty year periods: 2020-2049 and 2070-2099. These normals were averaged across the four GCM's to reduce the influence of any one model. We then calculate the climate normals for each PRISM grid cell that covers the U.S. by taking a weighted average of the five closest NEX grid cells, using the inverse of the distances between centroids as weights. To find the projected climate normals for each county, we average the PRISM grid cells over the portions of the county that contained cropland, using the same method described in the data section. We repeat this process for both the moderate and severe climate change scenarios (also known as RCP 4.5 and RCP 8.5, respectively).

Climate change will affect both the estimated probability of a land containing tile drainage, as well as the value of that land. We combine these two changes to get an estimate of the expected

[15]The models used were: CCSM4, MIROC-ESM, MIROC5, and GFDL-CM3

[16]https://cds.nccs.nasa.gov/nex-gddp/

value, denoted EV, of climate change for county i :

$$EV_i = P(\widehat{Y_i = 1})(\widehat{\Pi_d}) + P(\widehat{Y_i = 0})(\widehat{\Pi_n}),$$

The predicted farmland values for both tile drained and non-tile drained land are found by summing the percentage change in farmland values across all climate variables and applying this change to the 2012 farmland value. The expected damages from climate change is the difference between the expected value and the 2012 value. Total expected damages from climate change are found by summing these expected damages across counties.

7 Conclusion

This paper studies how climate variables are capitalized into farmland values while explicitly accounting for an important adaptation technology, tile drainage. We build intuition for the empirical analysis by formulating a simple profit maximization model that includes the farmer's choice of tile drainage. The model predicts that the marginal value of precipitation is higher in non-tile drained land versus tile drained land. We test this result by estimating a Structural Ricardian model, which accounts for the farmer's choice of tile drainage through a probit regression. Our initial, county level results show that the marginal value of precipitation is higher on non-tile drained land, providing evidence for our theoretical model's predictions. In a future draft we will present farm level estimates, compare them to our county level estimates, and provide complete damage estimates for several climate change scenarios and time periods.

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Appendices

A Data Distributions

B Sample Counties

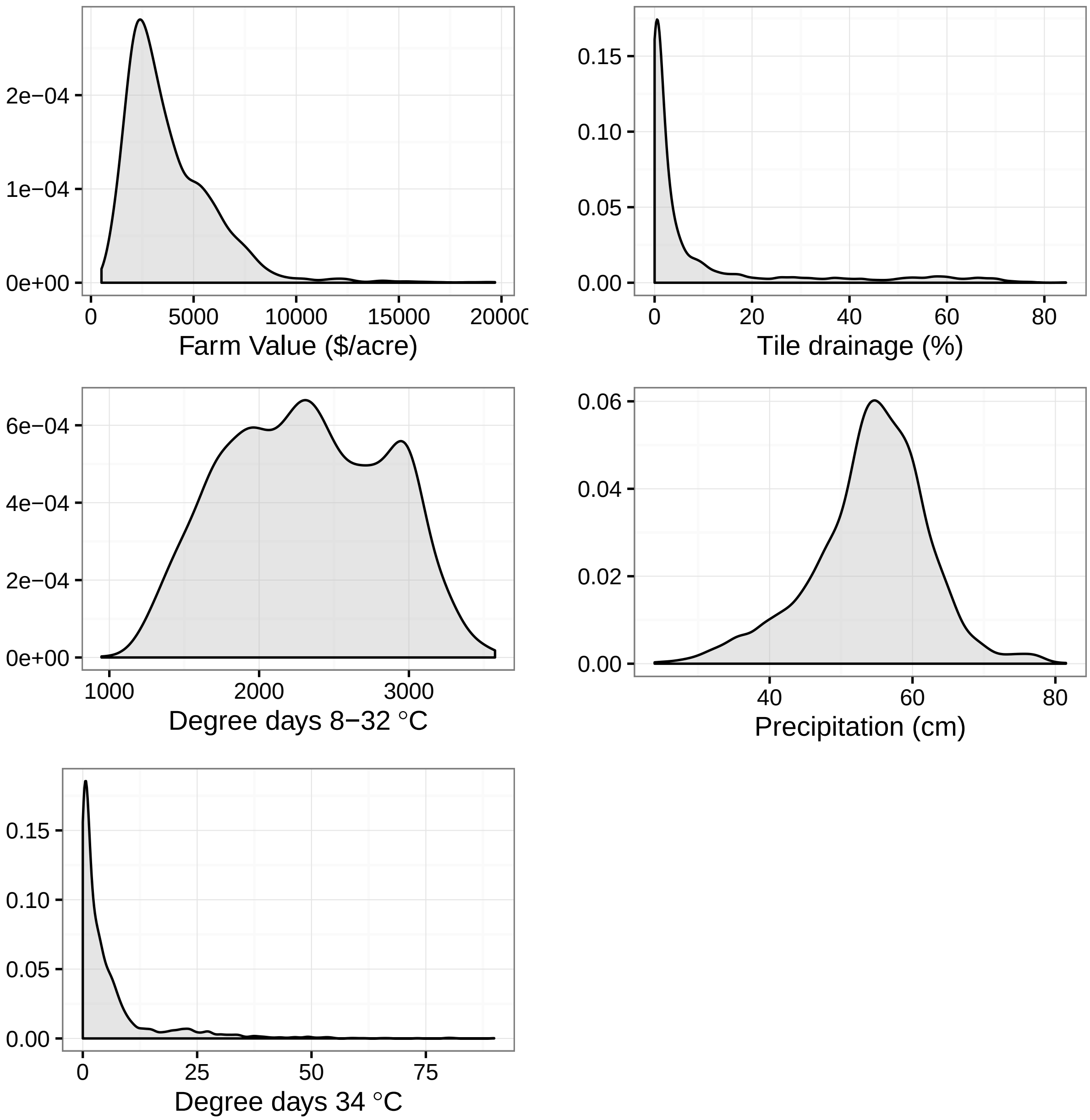

Figure 4: Distributions of key variables.

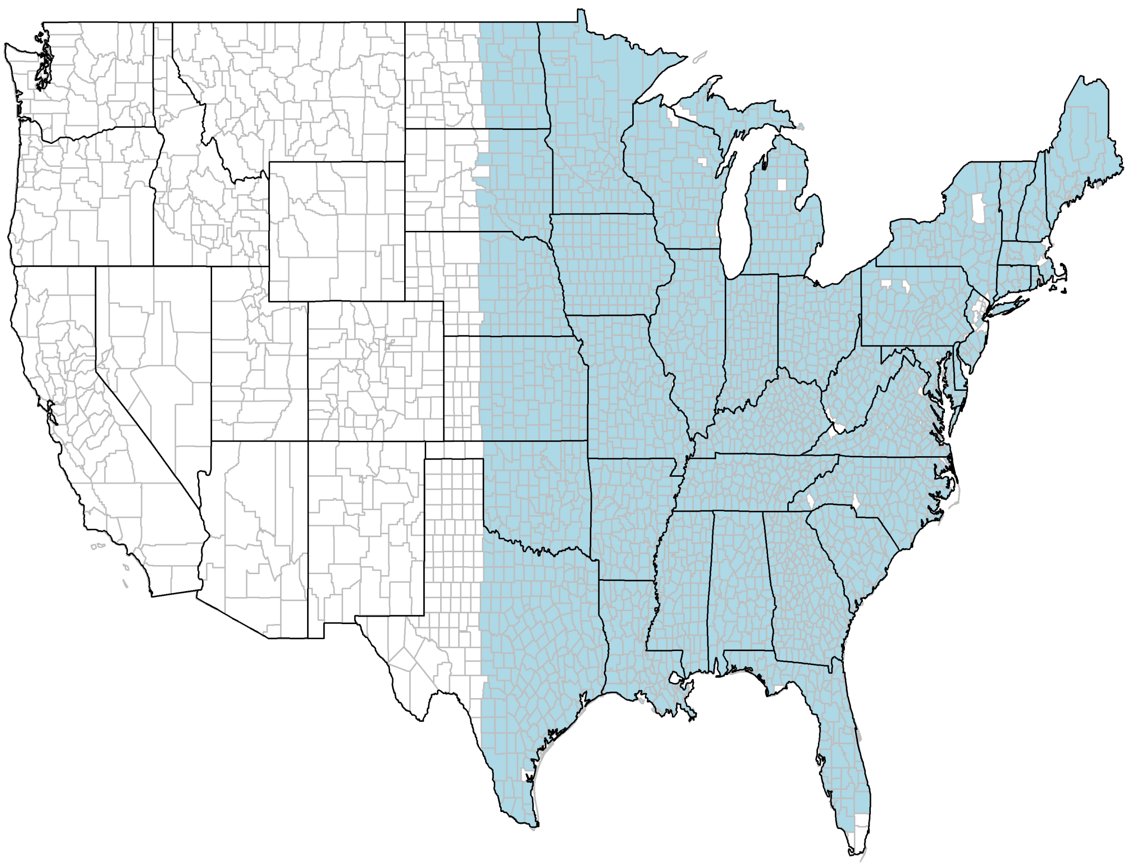

Figure 5: The 2,438 sample counties (in blue).