Essays on the economics of salinity in irrigated agriculture

by

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B.S., Keimyung University, Korea, 2006
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AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

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Abstract

Salinity has become a major concern in irrigated agriculture. Degraded water quality due to salinity threatens agricultural sustainability by limiting agricultural productivity and profitability. The natural intrusion of saltwater into aquifers is one reason for salinity, yet groundwater overpumping for irrigated agriculture, and regional climate and hydrology conditions have compounded such salinity challenges. The sustainability of irrigated agriculture in a saline environment depends on an accurate understanding of the effects of salinity and potential methods of adaptation. This dissertation contains three chapters providing insights into how salinity impacts agricultural decisions and land values. These insights are obtained by analyzing two regions, the High Plains Aquifer in central Kansas and the Central Valley Aquifer in California.

The first chapter examines the impact of groundwater salinity on farmers' main irrigation decisions by estimating the response along the extensive (i.e., irrigated acres), direct intensive (i.e., water application depth), and indirect intensive (i.e., crop choice) margins. Econometrics models are estimated using observed farmer behavior in response to exposure to different groundwater salinity levels using field-level panel data in a region of Kansas during 1991–2014. Results demonstrate that farmers facing salinity adjust their water use through all three margins, but most of the decrease in water use due to higher salinity is through the extensive margin.

The second chapter evaluates the impact of groundwater salinity on agricultural land values with a unique dataset of parcel sale prices during 1988–2015 in a region of Kansas. I estimate hedonic regression models that control for spatial heterogeneity using either county fixed-effects or a nonlinear function of the geographic coordinates. The results demonstrate that

groundwater salinity negatively impacts land values. These estimates can be interpreted as the economic damages from salinity, or equivalently, farmers' willingness-to-pay to offset salinity.

The third chapter quantifies the adaption to soil salinity by farmers in California's Western San Joaquin Valley by econometrically estimating how farmers change crop choices in response to different soil salinity levels. I use high-resolution remotely-sensed soil salinity and crop data during 2007–2016. My estimates show that as the level of salinity increases, the probability of growing salt-tolerant crops increases. This suggests that farmer' adapt to salinity according to the degree of salinity. However, my estimates may have some endogeneity bias since crop choice affects the amount of water applied, which could affect the amount of soil salinity.

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Approved by:

Major Professor
Nathan P. Hendricks

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Dedication

This dissertation is dedicated to the memory of my father, and to my beloved mother, little sister, and my boyfriend, for their unending support and encouragement.

Chapter 1 - Agricultural Decisions in Response to Groundwater Salinity on Irrigated Lands in Kansas

1.1. Introduction

Many of the most productive agricultural areas of the world including the United States depend on groundwater. Dependence on groundwater for irrigation has grown rapidly over the last 20-40 years, even in areas with long dry seasons and/or regular droughts (Llamas and Martínez-Santos 2005). The UN-FAO initiative estimates that more than one-third of the world's 303 million ha irrigated lands are served by groundwater, and the United States uses groundwater for 59% of its irrigated area 26.4 million ha (FAO 2019a).

The value of groundwater depends on the sustainable availability of water that is of a suitable quality and adequate quantity. Much attention has focused on conserving quantity through management strategies to reduce depletion of groundwater (e.g., Gisser and Sánchez 1980; Brozovic et al. 2006; Merrill and Guilfoos 2018; Ashwell, Peterson and Hendricks 2018), yet relatively little attention has been given to suitable quality. The likely reason for this can be attributed to the fact that the degradation of groundwater quality—due to its hydrogeographic position—takes a long time to be visually captured by users. Even if it is noticeable, there exist difficulties in sampling and quantifying the change in quality (Suarez 1989).

Groundwater salinity in irrigated lands is a prominent issue in groundwater quality degradation and closely aligned to an intrusion of saltwater into freshwater aquifers in the process of pumping for agricultural production (Foster et al. 2000; Scanlon et al. 2007; Van Weert, Van der Gun and Reckman 2009; Garduño and Foster 2010). The natural intrusion of saltwater is one reason for salinity, yet excessive groundwater pumping triggers aquifer depletion and may change the intrusion rate or flow patterns of the salinity through alterations in groundwater head (Rubin, Young and Buddemeier 2000).

Many previous studies have found evidence that elevated salinity contamination adversely affects the agricultural potential by reducing the productivity and profitability of crop yields and increasing additional costs for salinity controlled and remediated (e.g., Haw, Cocklin and Mercer 2000; Shani and Dudley 2001; Munns 2002; George, Clarke and English 2008). The majority of existing literature has largely highlighted crop/plant responses to salinity rather than farmers' responses—mainly in terms of reduction of crop yields. These studies presuppose that farmers make no behavioral changes to adjust to losses from groundwater salinity. This assumption, however, might overestimate the damages (Seo and Mendelsohn 2008a). The existing literature has also found that irrigation practice, current local hydrological properties, and the climate were all causes of groundwater salinity (Ma and Sophocleous 1994; Beltran and Martinez 1999; Foster, Brozović and Butler 2017; Foster et al. 2018).

The limited economic literature examining groundwater salinity has focused on analyzing salinity control via improved irrigation efficiency and changing cropping pattern using mathematical programming optimization approaches and calibration of crop-water production functions (e.g., Lee and Howitt 1996; Heaney, Beare and Bell 2001; Schwabe, Kan and Knapp 2006). Some related papers examine crop choice in the context of water/land environment and irrigation technology changes, policy or energy prices changes, and climate changes, yet no single paper is involved in groundwater salinity.[1] There is a lack of econometric studies that

[1] For example, representatively, water/land environment and irrigation technology changes include (Lichtenberg 1989; Wu, Mapp and Bernardo 1994); policy or energy prices changes include (Wu and Segerson 1995; Wu and Adams 2001; Pfeiffer and Lin 2014); and climate changes include (Kurukulasuriya and Mendelsohn 2008; Seo and Mendelsohn 2008a; Fleischer et al. 2011).

estimate how farmers adapt to higher salinity through changes in irrigation decisions with observed behavior.

Unlike prior literature, I estimate econometric models using observed farmer behavior in response to different groundwater salinity levels based on field-level panel data over 23 years in south-central Kansas. I analyze responses in terms of three main agricultural decisions: irrigated acreage, crop choice, and water application. In particular, I observe changes in such decisions in the context of total groundwater use and decompose it into the extensive, indirect intensive, and direct intensive margins effect, in the spirit of Moore, Gollehon and Carey (1994), Schoengold, Sunding and Moreno (2006), and Hendricks and Peterson (2012).

My findings demonstrate that farmers in the face of groundwater salinity change their decisions on irrigated acreage, crop choice, and water application. First, I find that farmers reduce water use along the extensive margin by reducing irrigated acres in response to an increase in groundwater salinity. Second, farmers increase water use along the indirect intensive margin by switching to more salt-tolerant crops that happen to be more water-intensive. Third, farmers decrease water use along the direct intensive margin by reducing the depth of water applied to avoid increasing water salinity. Fourth, the overall impact of an increase in salinity is a decrease in water use, predominantly through changes at the extensive margin.

The empirical findings indicate that it is critical to design effective and efficient management of groundwater so as to minimize costs from ongoing groundwater quality degradation and maximize sustainable agriculture benefits. Understanding the interaction between groundwater salinity and agricultural decision-making is important for such groundwater management.

1.2. Background and Data Description

To understand how groundwater salinity impacts farmers' responses, it is necessary to provide background on the region's environmental setting. I focus on field-level decision making by constructing panel data of 31,293 unique fields during 1991–2014 from the High Plains Aquifer (HPA) in the eastern portion of Big Bend Groundwater Management District No.5 (GMD5) underlying the Great Bend Prairie Aquifer of South-Central Kansas (**Figure 1.1**).

1.2.1. Environmental Setting in GMD5

The eastern portion of GMD5 shows high salinity contamination in groundwater. The source of salinity is ascribed to natural saltwater intrusion from the Permian bedrock into the freshwater aquifer, called the Great Bend Prairie aquifer (see the bottom half of **Figure 1.2**). Since the Great Bend Prairie Aquifer is not effectively separated from the underlying Permian bedrock containing ancient brine (halite)[2], saltwater in the bedrock intrudes freely into the base of the aquifer, then disperses upward in the aquifer with groundwater flow. As a result, the base of the Great Bend Prairie aquifer shows a salinity pattern similar to the Permian bedrock wells (Buddemeier, Sophocleous and Whittemore 1992).

The source of salinity is in the Permian bedrock, but intensive local pumping causes the water table to decline (i.e., the surface of the saturated part of the aquifer), leading to increased upward movement of the saltwater into the base of the aquifer. GMD5 in Kansas, which is using 99% of groundwater pumped for irrigated agriculture (Pfeiffer and Lin 2014), is expected to be particularly vulnerable to salinity during the growing season.

[2] Halite, commonly known as rock salt, is a type of salt, is composed of sodium chloride with mineral form.

The slope of the aquifer and permeability of the aquifer result in greater salinity accumulation in the eastern portion of GMD5. The water table in GMD5 slopes downward from west to east, resulting in a west-to-east flow of the water (see the bold arrow in the upper half of **Figure 1.2**). Thus, the depth to water table (i.e., the distance between the altitude of the land surface and the altitude of the water table) tends to decrease toward the east, thereby the eastern part of GMD5 becomes a discharge area for either saltwater or freshwater (Buddemeier, Sophocleous and Whittemore 1992).

If the aquifer has a confining layer, then saltwater intrusion can be blocked. Nearly all rocks and sediments contain pores of diverse-size. The fraction of the pores through which water can flow relative to the total space is called porosity. Porosity depends on the size of the soil particle determining soil texture and is fairly associated with the permeability of soils (Nimmo 2004). Simply, clay with low porosity by small particles can hold water longer than sand with high porosity, easier-drained soils by large particles. This imparts that GMD5, where soils are sandier than other regions, and more easily drained, is prone to exposure to saltwater intrusion due to the lack of the confining layer acting as a shield from the saltwater (Buchanan et al. 2009).

Indeed, since 1990, the eastern portion of GMD5 has maintained a moratorium on appropriations due to concerns about groundwater quality challenges. This reflects that groundwater salinity is a long-standing concern in the region, and it is quite clear that this concern needs to be managed within the context of the sustainability of both groundwater resources and irrigated agriculture.

1.2.2. Irrigated Acreage, Crop Proportion, Depth of Water

I construct three dependent variables for three agricultural decisions: (i) the number of total irrigated acres during the water-use year (i.e., *acres_irr* in **Table 1.1**), (ii) probability of planting each of the crops, and (iii) depth of water applied conditional on crop choice (i.e., *depth_inches* in **Table 1.1**). Mean and standard deviation for these dependent variables are provided in **Table 1.1**. These dependent variables are from a unique database known as the Water Information Management and Analysis System (WIMAS) administrated by the Kansas Department of Agriculture, Division of Water Resources (KDA-DWR) and the Kansas Geological Survey. WIMAS contains spatially-referenced information on groundwater wells or surface water intakes (i.e., the point of diversion), place of use, authorized quantity, reported water use, crop type, irrigation system type, along with an identification number and information on each farmer and the field. Farmers are required by law to report this information to the KDA-DWR annually.

WIMAS does not report the number of acres planted to each crop nor the water applied to each crop. Because of this, I follow the methodology of Hendricks and Peterson (2012), and simply assume that if k crops were grown, the proportion of the field in each crop was $1/k$, based on the 78 crop reporting codes provided by the KDA-DWR annual report. Based on this methodology, I categorized that the most common irrigated crops grown in the study region are corn, soybeans, multiple crops, other crops, alfalfa, sorghum, and wheat, over the entire sample period. The proportion of these seven crops are obtained by dividing with irrigated acres. Specifically, corn (61.46%), soybeans (20.71%), and multiple crops (16.74%) account for the majority of the seven major crops, while alfalfa (6.79%), sorghum (3.87%), wheat (6.75%), and other crops (3.40%) comprise a relatively small share of the observations.

“Multiple” is defined as double-cropping[3] or more than one type of crop but the specific crops grown were not indicated by farmers. “Other” is defined as the mixed composition of oats, barley, rye, dry beans, sunflowers, orchard grass, golf course, truck farm, and nursery. To constitute a more relevant crop choice, this paper reduces the choice to four field crops by combining alfalfa, sorghum, and wheat into “other” crops. The four field crops include corn, soybeans, multiple, and other.

1.2.3. Groundwater Salinity

Total dissolved solids (so-called TDS), which is literally the sum of all the substances dissolved in water, are generally known as a measure of salinity. However, the regions where the groundwater consists of different chemical types or a certain predominant chemical character such as chloride and sulfate composing the total dissolved solids, either chloride or sulfate concentration can be a better measure of salinity. GMD5 mainly displays chloride-type water and hence I use the level of chloride concentration with four salinity classifications: (i) freshwater (<500 mg/L), (ii) low to moderate salinity (500-1,000 mg/L), (iii) moderate to strong salinity (1,000-5,000 mg/L), and (iv) very strong salinity (>5,000 mg/L). The first level called freshwater is used as the base category. This level appears where there is non-salinity or very slight natural saltwater. This level does not cause the region’s main crops yield loss and thus is referred to as “freshwater[4]” in this study.

The spatial variation of salinity is obtained from the image files displaying maps of chloride contours for the Permian bedrock, the base, and the upper of the unconsolidated aquifer

[3] Double-cropping means planting two different crops in the same field during a single year.

[4] According to the Department of Health and Environment, freshwater has TDS contents less than 500 mg/L and both chloride and sulfate concentrations 250 mg/L.

in the eastern part of GMD5. These maps were updated in 2017 from the map generated from Whittemore (1993) and provided via personal communication. The base, which has a salinity pattern similar to the bedrock, is located at the lower part of the aquifer and has a higher concentration of salt than the upper portion of the aquifer. The base of the aquifer has a greater concentration of salt because groundwater with a greater density due to the salt content naturally sinks towards the bottom.

My key measure of salinity that impacts farmer behavior is the measure of salinity at the base of the aquifer. Even though groundwater wells do not pump water from the base of the aquifer, the salinity in the base should affect farmer decisions. The degree of salinity in the base affects pumping decisions because farmers want to avoid intrusion of the salinity into the upper part of the aquifer. Pumping more water for irrigation increases how much salinity is in the upper portion and thereby affects how much salinity is applied to the cultivated crops and ultimately crop yield. Another key advantage of using the salinity in the base of the aquifer as my measure of salinity is that it is not something the farmer can control (i.e., it is exogenously determined by natural causes). Even though the salinity of the aquifer in the upper portion is a better measure of the salinity of the water actually applied to the crop, I would not want to use it as my measure of salinity in the regression because salinity in the upper portion is endogenous since the amount of pumping causes changes of the salinity of the upper portion.

Based on the map of chloride concentrations for the base of the aquifer, I extract attribute values by georeferencing in ArcGIS and spatially merge the data to points of diversions. **Figure 1.3** illustrates an original image file and a new map by georeferencing for the spatial distribution of chloride concentrations. It is important to note that I only use measures of how salinity varies spatially in this region and do not use measures of how salinity has changed over time.

According to Whittemore (1993), chloride concentrations at some sites remained almost constant, some slightly decreased/increased, some noticeably decreased/increased, while others still fluctuated, but most wells overall show a constant salinity indicating no substantial changes. As such, variations in salinity over time across observed wells are detected in the region, but are not large enough to yield estimates of meaningful agricultural responses over time. Furthermore, the only map of chloride concentrations available from the Kansas Geological Survey was for a single point in time, so data availability constrains me from incorporating changes over time.

1.2.4. Soils, Hydrology, and Weather

I use soil characteristics, hydrological properties, and weather conditions as control variables that affect agricultural decisions. Mean and standard deviation for these explanatory variables are provided in **Table 1.1**.

Soil characteristics include soil organic carbon, bulk density, proportion of cropland with a pH less than 6, proportion of cropland with a pH greater than 7.5, root zone available water storage, and the log of slope and are collected from the Soil Survey Geographic (SSURGO). These variables were selected based on the Soil Quality Indicator Sheets from the USDA's Natural Resources Conservation Service Soils (USDA-NRCS 2019) and are the same variables selected by Hendricks (2018).

Soil organic carbon improves various soil structure or fertility by providing energy sources for soil microorganisms and nutrient availability through mineralization, leading to the promotion of plant growth. High bulk density indicates low soil porosity and soil compaction by restricting root growth and impacting movement of air and water through the soil. Soil pH is an indicator of soil health by measuring soil acidity or alkalinity. Soil pH levels that are too high or too low cause declines in crop yields, suitability, or plant nutrient availability, resulting in deterioration of soil health. For example, if the pH is less than 6 or greater than 7.5, yields for most crops decrease due to limited availability of phosphate to plants. Root zone available water storage[5] is plant-available water holding capacity in the root zoon depth and supports crop yield potential and stability. The slope of the land affects crop productivity in relation to soil loss—for instance soil loss tends to increase with steep slopes (Liu et al. 2000; Kapolka and Dollhopf 2001). I take the log of slope to use a more normally distributed variable.

For hydrology, I use predevelopment saturated thickness. Saturated thickness is the vertical saturated thickness of the aquifer (i.e., the distance from Permian bedrock to the water table in **Figure 1.2**) presenting the amount of water available. As the saturated thickness declines, the depth to the water table increases, which implies upward movement of more salinity and limits the irrigation extensity and intensity. I use predevelopment values rather than the current values to avoid any potential endogeneity issue—current saturated thickness is smaller in areas with larger water use—since predevelopment values are estimated before the withdrawal of significant amounts of groundwater.

Additionally, I construct January-April and May-August growing season precipitations and May-August growing season reference evapotranspiration using daily precipitation, maximum and minimum temperature from the PRISM climate group to represent field-level weather conditions. Reference evapotranspiration (ET_0) is the loss of water from the soil (i.e., evaporation) and from crops (i.e., transpiration) of a grass landcover. Therefore, high evapotranspiration causes the soil and the plant to lose water faster, which impacts water use.

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[5] The information of this variable from the Soil Quality Indicator Sheets is insufficient. See Leenaars et al. (2015) for details.

I do not include temperature as a separate control because temperature is embedded in the calculation of ET_0. With reference to Allen et al. (1998) and Hendricks (2018), in calculating reference ET_0, a reduced-set Penman-Monteith method that requires only maximum and minimum temperature is used as an alternative to the full Penman-Monteith method that demands additional information on solar radiation, vapor pressure, and wind speed, besides minimum and maximum temperature.

1.3. Conceptual Model

Consider a farmer's total water use on a field where S_i is the groundwater salinity. In the conceptual model, I use simple notation by writing the total water use as only a function of the salinity—admittedly, water use depends on several other factors, such as crop prices, other input prices, pumping costs, land quality, or climate conditions—and by treating salinity as a continuous variable for the purpose of decomposing the total margin effect of total water use.

For each field *i* over time *t*, let $IA_{it}(S_i)$ denote the irrigated acreage, let $C_{itj}(S_i)$ denote the proportion of irrigated acreage for each of the possible $j=1,\ldots,J$ crop choices, and let $W_{itj}(S)$ denote the water applications per acre (inches per acre) for each of the possible $j=1,\ldots,J$ crop choices. The summation of $C_{itj}(S_i)$ times $W_{itj}(S_i)$ constitutes the average water applied per acre. Total water use is driven by multiplying the irrigated acreage to the average water applied per acre as follows:

$$\underbrace{TW_{it}}_{tatal\ water\ use} = \underbrace{IA_{it}(S_i)}_{irrigated\ acreage} \times \underbrace{\sum_{j=1}^{J} \underbrace{C_{itj}(S_i)}_{crop\ choice} \underbrace{W_{itj}(S_i)}_{water\ application}}_{average\ water\ applied\ per\ acre} \tag{1}$$

Differentiating each component in equation (1) with respect to S_i and multiplying by $1/TW_{it}$ in order to display the decomposition of the total water use as a percent change in total water use due to the salinity gives:

$$\underbrace{\frac{\partial TW_{it}}{\partial S_i}}_{total\ margin} \frac{1}{TW_{it}} = \left[\underbrace{IA'_{it} \sum_{j=1}^{J} C_{itj}(S_i) W_{itj}(S_i)}_{pure\ extensive\ margin} + \underbrace{IA_{it}(S_i) \sum_{j=1}^{J} C'_{itj} W_{itj}(S_i)}_{indirect\ intensive\ margin} + \underbrace{IA_{it}(S_i) \sum_{j=1}^{J} C_{itj}(S_i) W'_{itj}}_{direct\ intensive\ margin} \right] \frac{1}{TW_{it}} \tag{2}$$

where primes denote first derivatives. The definition of the margin effect terms varies with the existing literature.[6] I refer to the first term in equation (2) as the "pure extensive margin (or more concisely, extensive margin)" effect; the second term as the "indirect intensive margin" effect; and the third term as the "direct intensive margin" effect according to Hendricks and Peterson (2012)'s definitions.

The pure extensive margin effect measures the effect of an incremental expansion in irrigated acreage holding the crop choice decision C_{itj} and water application on the crop W_{itj} constant. The indirect intensive margin effect is a change in water application per acre through a change of crop choice decision, holding total irrigated acres IA_{it} and water application on the crop W_{itj} constant. The direct intensive margin effect captures a change in water applied per acre

[6] Moore et al. (1994), Schoengold et al. (2006), and Brent (2018) describe "indirect intensive margin" defined in this study as "extensive margin", and "direct intensive margin" as "intensive margin".

through changes in the water applied on each crop choice, holding total irrigated acres IA_{it} and the crop choice decision C_{itj} constant.

Table 1.4 gives a summary of the expected sign of each of the marginal effects of an increase in salinity. Excessive pumping causes aquifer depletion that leads to salinity intrusion in the upper parts of the aquifer. Accordingly, an increase in the level of salinity in the base of the aquifer will cause farmers to irrigate fewer acres to avoid saltwater intrusion into the upper regions of the aquifer where water is extracted from. I therefore expect salinity to have a negative impact on irrigated acreage.

I hypothesize that as the salinity increases farmers would switch to more salt-tolerant crop, *ceteris paribus*. Accordingly, salinity will have a negative impact on the probability of planting less salt-tolerant crops. Whether these changes in cropping patterns result in an increase or decrease in water use depends on whether the more salt-tolerant crops are more water intensive crops or not.

First considering the negative case, farmers switch to more salt-tolerant crops that happen to be less water-intensive, leading to reduced pumping. Consequently, this reflects a reduction along the indirect intensive margin. Alternatively, farmers could switch to more salt-tolerant crops that happen to be more water-intensive, leading to increased pumping. Consequently, this reflects an increase in water use along the indirect intensive margin. In summary, the sign of the effect of salinity on the indirect intensive margin is indeterminant (see **Table 1.4**).

The impact of groundwater salinity on water application per acre conditional on crop choice is expected to emerge from two different effects. On one hand, if more water is applied then the aquifer is depleted more, and salts move from the lower portions of the aquifer into the higher portions of the aquifer, so that pumping more means that there will be effectively more salinity in the water. Consequently, farmers with greater amounts of salinity in the base of the aquifer would be induced to decrease the irrigation intensity to avoid saline groundwater application, which implies that greater salinity leads to less irrigation intensity (hereafter called "salinity intrusion effect").

On the other hand, lower irrigation intensity would lead to accumulation of salts in the soil over time. In response to this, one might expect farmers to increase their irrigation intensity because if more water is applied then it can flush out the salts in the soils (hereafter called "salinity washing effect"). Consequently, more salinity in the groundwater could lead to greater irrigation intensity. The overall impact of salinity on intensity is indeterminant because it resorts to whether the "salinity intrusion effect" or "salinity washing effect" is larger (see **Table 1.4** for summary).

1.4. Econometric Model

To estimate the decomposition for each margin effect in equation (2), I exploit three different econometric models that enable me to accommodate each agricultural decision in response to groundwater salinity.

In panel data, typically, observations within the panel share similar characteristics, thereby the error is large when considering individual observations. However, due to the clustering nature, there is a tendency to reduce the standard error of the entire data. Not considering this within-cluster dependence can lead to misleadingly narrow confidence intervals, large t-statistics, and low p-values, and can be consequently misleading as a result of reduced standard error even for results that do not actually have statistical significance (Cameron and Miller 2015).

A common way to correct the estimation of the standard error is to assume zero spatial correlation across groups, but allow the within-group spatial correlation (Cameron and Trivedi 2005). I cluster standard errors at the point of diversion and assume observations (i.e., all of the fields) within a point of diversion close to each other are likely to have dependency, but independence across the point of diversions.

1.4.1. Irrigated Acreage Estimation

The regression model for irrigated acreage is as follows:

$$IA_{it} = \alpha_1 + \boldsymbol{\beta}_1 \mathbf{S}_{\mathbf{i}}' + \boldsymbol{\gamma}_{\mathbf{1}} \mathbf{X}_{\mathbf{it}}' + \theta_t + \varepsilon_{it} \tag{3}$$

where IA_{it} are irrigated acres for each field *i* in year *t* and $\mathbf{S}_{\mathbf{i}}$ is a vector of categorical variables to indicate a different levels of salinity for each field *i*. Specifically, the salinity levels are categorized into four levels: (i) freshwater (<500 mg/L) as the base category, (ii) low to moderate salinity (500-1,000 mg/L), (iii) moderate to strong salinity (1,000-5,000 mg/L), and (iv) very strong salinity (>5,000 mg/L). $\mathbf{X}_{\mathbf{it}}$ is a vector of controls including soil organic carbon, proportion of cropland with a pH less than 6, proportion of cropland with a pH greater than 7.5, rootzone available water storage, bulk density, log of slope, saturated thickness, January-April precipitation, May-August precipitation, and May-August evapotranspiration. $\boldsymbol{\beta}_{\mathbf{1}}$ and $\boldsymbol{\gamma}_{\mathbf{1}}$ are vectors of parameters to be estimated. θ_t represent year fixed effects to estimate a separate parameter (i.e., intercept) for each year and captures the effect of macro-level shocks which affect all fields, such as changes in crop prices, energy prices, and other input prices. ε_{it} is an idiosyncratic error term.

1.4.2. Crop Choices Estimation

This section describes the multinomial logit (MNL) model for crop choice, deriving indirect intensive margin effect by salinity. The probability of selecting crop *j* is:

$$Prob(C_{it} = j) = \frac{\exp(\alpha^{j}{}_{2} + \boldsymbol{\beta}_{\mathbf{2}}^{\mathbf{j}}\mathbf{S}_{\mathbf{i}}' + \boldsymbol{\gamma}_{\mathbf{2}}^{\mathbf{j}}\mathbf{X}_{\mathbf{it}}' + \sum_{m} \pi_{m}^{j} C_{it\text{-}1,m})}{\sum_{1} \exp(\alpha^{l}{}_{2} + \boldsymbol{\beta}_{\mathbf{2}}^{\mathbf{l}}\mathbf{S}_{\mathbf{i}}' + \boldsymbol{\gamma}_{\mathbf{2}}^{\mathbf{l}}\mathbf{X}_{\mathbf{it}}' + \sum_{m} \pi_{m}^{l} C_{it\text{-}1,m})} \tag{4}$$

where $Prob(C_{it} = j)$ is the probability that crop *j* is selected at field *i* in year *t*. *j* represents four crop choice decisions with $j = 1,\ 2,\ 3,\ 4$ for corn, soybeans, multiple crops, and other crops, respectively, at different levels of salinity. The descriptive of $\boldsymbol{\beta}_{\mathbf{2}}^{\mathbf{j}}\mathbf{S}_{\mathbf{i}}'$ and $\boldsymbol{\gamma}_{\mathbf{2}}^{\mathbf{j}}\mathbf{X}_{\mathbf{it}}'$ is the same as in equation (3) because the controls used for the estimation for the irrigated acreage decision are likely to have the same effect on the crop choice decision. $C_{it\text{-}1,m}$ is a variable indicating the proportion of the field planted to each crop in the previous year.

In this MNL model, the lagged values of the proportion of each crop choice decision are likely to affect crop choice decision this year due to the crop rotation patterns (Pfeiffer and Lin 2014; Hendricks, Smith and Sumner 2014). The lagged values are used as the instrument variables to address endogeneity of current crop choices for the water application model in the next Section 4.3.

1.4.3. Water Application Estimation

This section estimates the two stage least squares (2SLS) model for water application. In estimating this, one potential econometric issue is that crop choices may be potentially endogenous due to omitted variable bias. Intuitively, potential unobserved factors that cause crop choices can also influence the water application decision. Borrowing Hendricks and Peterson (2012)'s example, even if a farmer cultivating corn uses more water than a farmer cultivating wheat, it cannot be concluded that corn is a more water-intensive crop. Possibly some unobservable characteristics of the farmer and field where corn is grown may have corn be selected more often, thereby more water is applied to corn relative to other crops.

Using the Robust Durbin-Wu-Hausman test for endogeneity of the crop choice variables, I conclude these variables are endogenous by rejecting the null hypothesis that crop choices are exogenous with a significance level of 5% (p-values of 0.01 for the crop choices). To address the omitted variable bias, I use the Instrumental Variable (IV) estimation approach using one-year lagged proportions of each crop choice as IV. The IV should affect the outcome only via its connection with the endogenous variable. I assume that the lagged crop choice affects the current crop choice due to crop rotation incentives, but that that the lagged crop choice does not directly affect water use in the current year.

Additionally, considering a just-identified model with four endogenous variables instrumented by four variables, I incorporate conditional crop choices into the 2SLS estimation with the same controls used in other econometric regression models. The specific 2SLS model is as follows:

$$\left(\begin{array}{ll} W_{it} = \alpha_3 + \mathbf{\beta_3 S'_i} + \mathbf{\gamma_3 X'_{it}} + \sum_j \delta_j \widehat{C_{itj}} + \theta_t + u_{it} & \cdots \text{ 2nd stage} \\ & \qquad \uparrow \\ C_{itj} = \alpha_4 + \mathbf{\beta_4 S'_i} + \mathbf{\gamma_4 X'_{it}} + \sum_m \phi_m C_{it\text{-}1,m} + \theta_t + n_{it} & \cdots \text{ 1st stage} \end{array} \right) \qquad (5)$$

where the first stage estimates the impact of salinity and other controls on each crop choice decision. The predicted probabilities for each crop choice from the first stage are then used to estimate the second stage water application model.

In the first stage crop choice model, C_{itj} represents crop choices, namely what crop is planted for each field *i* in year *t* among four choices (i.e., corn, soybeans, multiple crops, other crops). $\boldsymbol{\beta}_4\mathbf{S}_i'$ and $\boldsymbol{\gamma}_4\mathbf{X}'$ are the same controls applied in other econometric regression models above. $\sum_m \phi_m C_{it\text{-}1,m}$ represents one-year lagged proportions of each crop choice and used as IVs to account for endogeneity at the second stage.

1.5. Results

The following estimation results for the decisions on irrigated acreage, crop choice, and water application support that groundwater salinity causes the change of farmers' decisions.

1.5.1. Irrigated Acreage Results

Table 1.2 shows parameter estimates from the regression model for total irrigated acreage. Increases in the salinity level causes a reduction in irrigated acreage from each field. Irrigated acreage is decreased by 7.8 acres at the low to moderate salinity level compared to freshwater, 18.1 acres at the moderate to strong salinity level, and 10.3 acres at the very strong salinity level. Such results are all statistically significant at either the 5% or 10% levels.

In particular, farmers decrease irrigated acreage by 18.1 acres for moderate to strong salinity (1,000-5,000 mg/L), which is the level at which the major crops in this region begin to be affected by salinity[7], compared to the base category (see Fipps 2003). As the biggest reduction, this result implies that salinity decreases the likelihood of a field being irrigated since salinity-induced water quality degradation may cause yield loss, leading to lower farm profitability.

[7] Crop yields experience a 10% yield loss when salinity concentration of the water applied reaches 605 mg/L for corn and 1,815 mg/L for soybeans.

1.5.2. Crop Choice Results

Table 1.3 reports the marginal effects of all variables on the probability of planting each of the crops from the multinomial logit model. The interpretation of the results presents how a unit change in the independent variables affects the probability of each crop choice instead of choosing other alternatives.

My results at the salinity level with very strong salinity (>5,000 mg/L) conform to expectations, showing that salinity causes a decrease in the acreage allocated to corn by 8.9%, increase in the acreage allocated to soybeans by 3.6% and multiple crops by 7.6%, and decrease in the acreage allocated to other crops by 2.4%. The marginal effects in **Table 1.33** for very strong salinity are statistically significant. These results reflect that farmers facing salinity tend to reduce choices for more salt-sensitive corn and other crops[8], while increase choices for more salt-tolerant soybeans and multiple crops as a response to groundwater salinity.

In **Table 1.33** the coefficient is not statistically significant at all salinity levels. The coefficients in low to moderate salinity level and moderate to strong salinity level are statistically insignificant, indicating that farmers may not be attracted to switching crops because those levels do not significantly affect yield loss, and there is no reason to invest in the crop adjustment cost.

Another interesting result comes from the coefficient on the multiple crops indicated by significant coefficients at all salinity levels, which implies that these multiple crops are more likely to be planted in the presence of salinity, compared to the other crops as the base category. This, in large measure, may show that farmers prefer a change from corn or soybeans with the

[8] Using the abbreviation, Tolerant(T), Moderately Tolerant(MT), Moderately Sensitive(MS) and Sensitive(S), each composition of other crops are: oats(MT); barley(MT); rye(MS); drybeans(S); sunflowers(MS); golf course(MS); truck farm specifically including tomatoes(MS), lettuce(MS), melons(MS), beets(MT), broccoli(MS), celery(MS), radishes(MS), onions(S), cabbage(MS), and strawberries(S). This has referenced from FAO (1992).

single crop composition, to multiple crops with mixed crop composition. That said, the likely reason is that under the existence of risk, to the crop choice decision, farmers tend to lower the risk of salinity by diversifying the crop composition.

The marginal effects of the coefficients on the lagged crop choices are all statistically significant at either the 1% or 5% levels despite their different statistical signs. I find that planting corn the previous year increases the probability of planting corn in the current year by 35.3% and other crops by 4.4%, compared to the case when other crops were planted in the previous year. Planting corn in the previous year also decreases the probability of planting soybeans by 5.9% and multiple crops by 33.8%, compared to previously planting other crops. Planting soybeans in the previous year increases the probability of planting corn in the current year by 37.8% but decreases the acreage allocated to all other alternatives, namely, soybeans by 6.3%, multiple crops by 26.1% and other crops 5.4%.

1.5.3. Water Application Conditional on Crop Choice Results

Table 1.5 presents parameter estimates from 2SLS model for water application. I have hypothesized that there are two potentially opposing effects on water application per acre—intrusion effect and washing effect. The intrusion effect is to lower irrigation intensity to avoid increasing water salinity, while the washing effect is to increase irrigation intensity to wash salinity out of the rootzone.

Reduction in water application is most pronounced at the moderate to strong salinity (1,000-5,000 mg/L). At this level, salinity reduces irrigated groundwater application by 0.4 inches relative to the base category of freshwater. This reflects that the salinity intrusion effect dominates the washing effect. Low to moderate salinity (500-1,000 mg/L) level is not statistically significant, and this may be because there may be a low need for controlling water application for intrusion effect or washing effect by no crop yield loss by salinity. The statistically insignificant very strong salinity level (>5,000 mg/L) may arise because the intrusion and washing effects are roughly the same magnitude at a higher level of salinity.

The coefficients for water demand conditional on the choice of crop indicate that soybeans use the most water in this region, followed by corn and multiple crops. Also, crop choice results in the previous section found that farmers tend to switch from corn to soybeans with more salt-tolerance as salinity increases. Considering these two results together, it implies that farmers switch to more salt-tolerant crops that happen to be more water-intensive, leading to increased pumping.

1.5.4. Marginal Effect Decomposition Results

Table 1.6 reports total margin effect of an increase in the groundwater salinity decomposed into the extensive, direct intensive, and indirect intensive margins measured in acre-inches, acre-feet, and the relative impact. I compute each decomposed component using coefficients and predicted values from each econometric model in **Table 1.2**, **Table 1.3**, and **Table 1.5** according to equation (2).

The extensive margin effect shows that farmers reduce irrigated acres in the face of groundwater salinity and the result is statistically significant. The indirect intensive margin effect shows that farmers increase water use due to groundwater salinity through switching to more salt-tolerant crops that happen to be more water-intensive. Yet, the indirect intensive margin is not statistically significant. The direct intensive margin effect at the level of moderate to strong salinity (1,000-5,000 mg/L) shows a decrease in water use that is statistically significant. This indicates that farmers in the face of groundwater salinity respond by reducing water application to avoid inducing saltwater intrusion.

The estimated total margin effect of salinity at low to moderate salinity level (500-1,000 mg/L) illustrates that salinity of this level reduces total water use by 97.2 acre-inches (8.1 acre-feet) relative to when a field has access to freshwater. Average water use in the sample period was 1357.1 acre-inches (113.1 acre-feet), so the relative impact is a 7.2% decrease in water use compared to freshwater. The total margin effect of salinity at moderate to strong salinity level (1,000-5,000 mg/L) indicates that salinity of this level reduces total water use by 272.7 acre-inches (22.7 acre-feet) relative to when a field has access to freshwater. The relative impact is a 20.1% decrease in water use compared to freshwater. The estimated total margin effect of salinity at very strong salinity (>5,000 mg/L) demonstrates that salinity of this level reduces total water use by 112.3 acre-inches (9.4 acre-feet) relative to when a field has access to freshwater. The relative impact is a 8.3% decrease in water use compared to freshwater.

Farmers facing salinity primarily change their water use through changes at the extensive margin rather than at the intensive margin. At the low to moderate salinity level (500-1,000 mg/L), farmers reduce water use by 7.4% at the extensive margin with a total decrease in water use of 7.2% compared to freshwater. At the moderate to strong salinity level (1,000-5,000 mg/L), farmers reduce water use by 17.0% at the extensive margin with a total decrease in water use of 20.1%. Similarly, the extensive margin dominates the reduction in water use when the groundwater is very strong salinity.

In general, where there are water availability constraints, high water-usage, or water quality degradation, farmers reduce water use by lowering irrigation water applications or irrigated acreage and a shift to less water-intensive crops (Kurt A. Schwabe, Kan and Knapp

2006b; Drysdale and Hendricks 2018; USDA-ERS 2020). Among these mechanisms, reducing irrigated acreage can fundamentally reduce water consumption. That said, the reduction in irrigated acreage reduces the need for irrigation water itself. Foster, Brozović and Butler (2014) support this by finding that farmers reduce irrigated acreage rather than water use intensity once well capacities become sufficiently constraining (i.e., a constraint in water quantity). My estimates show that farmers adjust mostly at the extensive margin to reduce the amount of water extracted to avoid inducing intrusion of salt into the upper aquifer that harms water quality.

1.6. Conclusions

Farmers face difficult decisions such as whether to irrigate and how much, what to plant, and how much water to apply. Multiple factors such as the natural environment, water supply, global markets, and government programs can influence this decision-making. My study tests the hypothesis that groundwater salinity may be an important factor driving farmers' agricultural decision-making. To test this hypothesis, I estimate econometric models using observed farmer behavior in response to different groundwater salinity levels based on field-level panel data in southcentral Kansas over 23 years.

My results support the hypothesis that farmers in the face of groundwater salinity change their decisions on irrigated acreage, crop choice, and water application. I find that farmers reduce water use along the extensive margin by reducing irrigated acres in response to groundwater salinity. Farmers increase water use along the indirect intensive margin by switching to more salt-tolerant crops that happen to be more water-intensive, though the effect is small and statistically insignificant. Farmers decrease water use along the direct intensive margin by reducing water application conditional on the same crops to avoid inducing saltwater intrusion.

This result shows that the salinity intrusion effect dominates the salinity washing effect. The overall impact of an increase in salinity is a decrease in water use, predominantly through changes at the extensive margin.

This study provides useful information on agricultural decisions related to groundwater salinity, which has hitherto been less attempted, to relevant government agencies. As well as, this study provides important insights: Firstly, excessive pumping in locations where natural saltwater intrusion is present, particularly, where vulnerable environment settings are formed, accelerates the degradation of water quality. Secondly, careful water management and assessment are required in considering water application in areas potentially subject to saltwater contamination.

The quality of the groundwater resource is certainly as important as its quantity. The water will be of little value once polluted because it occurs high costs to reverse such contamination. Thus, understanding the interaction between groundwater salinity and agricultural decision-making has important implications for groundwater management, particularly sustainable availability of suitable-quality groundwater

1.7. Tables

Table 1.1. Mean and Standard Deviation for Selected Variables

	Dependent Variables	Mean	SD
Crop choice[a]	Proportion for corn	0.5036	0.4817
	Proportion for soybeans	0.1713	0.3521
	Proportion for multiple crops	0.1379	0.3448
	Proportion for other crops	0.1873	0.3623
Irrigated acreage	Irrigated acres (ac) i.e., acres_irr	105.4714	52.0769
Water application	Volume of water applied measured in acre-feet (ac-ft) i.e., af_used	113.0883	72.3639
	Depth of water applied measured in feet (ft) i.e., depth_feet = (af_used/acres_irr)	1.0694	0.4278
	Depth of water applied measured in inches (in) i.e., depth_inches = (af_used/acres_irr)*12	12.8333	5.1335
	Explanatory Variables	**Mean**	**SD**
Four salinity levels[b]	Freshwater: <500 (mg/L)	0.6324	0.4821
	Low to moderate salinity: 500-1,000 (mg/L)	0.1354	0.3421
	Moderate to strong salinity: 1,000-5,000 (mg/L)	0.1421	0.3492
	Very strong salinity: >5,000 (mg/L)	0.0901	0.2863
Soil characterists	Soil Organic Carbon in 0-150 cm depth (kg/m2)	6541.4460	2653.9180
	pH less than 6	0.0351	0.1466
	pH greater than 7.5	0.1265	0.2431
	Root Zone Available Water Storage (mm)	206.5541	32.4031
	Bulk density (g/cm3)	1.5294	0.0348
	Log of slop (%)	0.5385	1.0110
Hydrological properties	Predevelopment saturated thickness (ft)	128.8869	34.2058
Weather conditions	January-April growing season precipitations (mm)	154.5996	60.5895
	May-August growing season precipitations (mm)	389.0493	123.9330
	May-August growing season evapotranspiration (mm)	655.1060	38.2282

[a]Crop choice is presented in the probability of planting each of the crops.
[b]Four salinity levels measured in chloride concentration. Chloride concentration (<500 mg/L) as the base category means "freshwater".

Table 1.2. Regression Model Estimates of Irrigated Acreage[a]

Variables	Coefficients
Low to moderate salinity: 500-1,000 (mg/L)b	-7.8487
	(3.4783)**
Moderate to strong salinity: 1,000-5,000 (mg/L)b	-18.0520
	(3.7371)***
Very strong salinity: >5,000 (mg/L)b	-10.3458
	(4.2419)**
Soil Organic Carbon in 0-150 cm depth (kg/m2)	-0.0034
	(0.0008)***
pH less than 6	20.8806
	(9.2507)**
pH greater than 7.5	-18.7007
	(7.0542)***
Root Zone Available Water Storage (mm)	0.4026
	(0.0614)***
Bulk density (g/cm3)	-74.3734
	(46.5760)
Predevelopment saturated thickness (ft)	0.2516
	(0.0385)***
Log of slop (%)	2.7761
	(1.2978)**
January-April growing season precipitations (mm)	0.0580
	(0.0277)**
May-August growing season precipitations (mm)	0.0182
	(0.0064)***
May-August growing season evapotranspiration (mm)	0.8025
	(0.1515)***
Constant	-425.4112
	(127.7887)***
Year fixed effects	Yes
R2	0.1073
Observations	27,565

Notes: Asterisks ∗∗∗, ∗∗, and ∗ indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered at the point of diversion level are reported in parentheses.

[a]Dependent variable is irrigated acreage (ac).

[b]Four salinity levels measured in chloride concentration. Chloride concentration (<500 mg/L) as the base category means "freshwater".

Table 1.3. Marginal Effects on the Probability of Crop Choices from the Multinomial Logit Regression Model Estimates[a]

	Marginal Effects[b]			
Variables	Corn	Soybeans	Multiple Crops	Other Crops
Low to moderate Salinity: 500-1,000 (mg/L)c	0.0141	-0.0040	0.0218*	-0.0320**
	(-0.0156)	(-0.0117)	(-0.0107)	(-0.0107)
Moderate to strong Salinity: 1,000-5,000 (mg/L)c	0.0127	-0.0128	0.0244*	-0.0243
	(-0.0185)	(-0.0125)	(-0.0109)	(-0.0134)
Very Strong salinity: >5,000 (mg/L)c	-0.0885***	0.0364*	0.0757***	-0.0236
	(-0.0207)	(-0.0154)	(-0.0169)	(-0.0157)
Soil Organic Carbon in 0-150 cm depth (kg/m2)	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
pH less than 6	0.0520	-0.0272	0.0024	-0.0272
	(-0.0384)	(-0.0275)	(-0.0197)	(-0.0328)
pH greater than 7.5	0.0902**	-0.0138	0.0382*	-0.1146***
	(-0.0322)	(-0.0225)	(-0.0172)	(-0.0271)
Root Zone Available Water Storage (mm)	0.0009**	-0.0004*	-0.0002	-0.0003
	(-0.0003)	(-0.0002)	(-0.0002)	(-0.0002)
Bulk density (g/cm3)	-0.3001	0.1287	0.1155	0.0559
	(-0.2428)	(-0.1597)	(-0.1263)	(-0.1708)
Predevelopment saturated thickness (ft)	0.0041***	-0.0005***	-0.0004***	-0.0006***
	(-0.0002)	(-0.0001)	(-0.0001)	(-0.0001)
Log of slop (%)	0.0053	0.0062	0.0006	-0.0122**
	(-0.0066)	(-0.0048)	(-0.0042)	(-0.0043)
January-April growing season precipitations (mm)	0.0004	-0.0005**	0.0001	0.0001
	(-0.0003)	(-0.0002)	(-0.0002)	(-0.0002)
May-August growing season precipitations (mm)	-0.0001	0.0002***	0.0000	-0.0001
	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0001)
May-August growing season evapotranspiration (mm)	-0.0006	0.0001	0.0007	-0.0002
	(-0.0008)	(-0.0006)	(-0.0005)	(-0.0006)

(Continued)

Table 1.3. Continued

Variables	Marginal Effects[b]			
	Corn	Soybeans	Multiple crops	Other crops
One-year lagged crop choice for corn	0.3528***	-0.0586***	-0.3384***	0.0443**
	(-0.0195)	(-0.0109)	(-0.0116)	(-0.0141)
One-year lagged crop choice for soybeans	0.3784***	-0.0634***	-0.2613***	-0.0536**
	(-0.0201)	(-0.0133)	(-0.0138)	(-0.0188)
One-year lagged crop choice for multiple crops	0.1212***	0.2235***	-0.2410***	-0.1037***
	(-0.0215)	(-0.0120)	(-0.0110)	(-0.0191)
Year fixed effects	Yes	Yes	Yes	Yes
Observations	17,570	17,570	17,570	17,570

Notes: Asterisks ∗∗∗, ∗∗, and ∗ indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered at the point of diversion level are reported in parentheses.

[a]Dependent variable is probability of planting each of the crops.

[b]Marginal effects from the multinomial logit model for crop choices. The category of "Other crops" is used as the base category. "Multiple" means multiple crops were grown, but not which crops were grown. "Other" are mixed composition of oats, barley, rye, dry beans, sunflowers, golf course, truck farm, orchard, and nursery, wheat.

[c]Four salinity levels measured in chloride concentration. Chloride concentration (<500 mg/L) as the base category means "freshwater" for groundwater.

Table 1.4. Expected Effects on Farmer Behavior in response to Groundwater Salinity

Margin of Adjustment		**Expected Effects**
Irrigated acreage	Extensive (negative sign)	More pumping causes more depletion of the aquifer, thereby increasing saltwater intrusion from the lower portions of the aquifer into the higher portions of the aquifer, leading to greater salinity of water that is extracted from the aquifer. Consequently, farmers seek to reduce irrigated acres to reduce pumping that leads to intrusion.
Crop choice	Indirect Intensive (negative sign)	Farmers switch to more salt-tolerant crops that happen to be less water-intensive, leading to reduced pumping.
	or	
	Indirect Intensive (positive sign)	Farmers switch to more salt-tolerant crops that happen to be more water-intensive, leading to increased pumping.
Water application	Direct Intensive (negative sign) “Salinity intrusion effect”	More pumping causes more depletion of the aquifer, thereby increasing saltwater intrusion from the lower portions of the aquifer into the higher portions of the aquifer. This gives an incentive to reduce water application to avoid increasing water salinity.
	or	
	Direct Intensive (positive sign) “Salinity washing effect”	Increasing irrigation intensity can flush the salts out of the soil and prevent the accumulation of salts in the soil over time.

Table 1.5. Two-Stage Least Squares Regression Model Estimates of Water Application

Variables	Coefficients
Low to moderate salinity: 500-1,000 (mg/L)b	-0.0510
	(0.2067)
Moderate to strong salinity: 1,000-5,000 (mg/L)b	-0.4380
	(0.2067)**
Very strong salinity: >5,000 (mg/L)b	0.1535
	(0.2716)
Soil Organic Carbon in 0-150 cm depth (kg/m2)	-0.0002
	(0.0000)***
pH less than 6	0.0732
	(0.5477)
pH greater than 7.5	0.9202
	(0.3442)***
Root Zone Available Water Storage (mm)	0.0032
	(0.0039)
Bulk density (g/cm3)	-6.0793
	(2.6360)**
Predevelopment saturated thickness (ft)	-0.0021
	(0.0025)
Log of slop (%)	0.2508
	(0.0929)***
January-April growing season precipitations (mm)	-0.0013
	(0.0022)
May-August growing season precipitations (mm)	-0.0078
	(0.0006)***
May-August growing season evapotranspiration (mm)	0.0323
	(0.0085)***
Conditional on crop choice for corn	3.4170
	(0.7109)***
Conditional on crop choice for soybeans	4.4373
	(1.2477)***
Conditional on crop choice for multiple crops	2.3505
	(0.5546)***
Constant	1.5682
	(7.1123)
Year fixed effects	Yes
R2	0.2552
Observations	19,881

Notes: Asterisks ∗∗∗, ∗∗, and ∗ indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered at the point of diversion level are reported in parentheses.

[a]Dependent variables is depth of water applied conditional on crop choice (ac-ft).

[b]Four salinity levels measured in chloride concentration. Chloride concentration (<500 mg/L) as the base category means “freshwater” for groundwater.

Table 1.6. Total Margin Effect and Decomposition into Extensive, Indirect Intensive, and Direct Intensive Margin Effects

Salinity Levels	Margin Effects	Extensive	Indirect Intensive	Direct Intensive	Total
Low to Moderate 500-1,000 (mg/L)	Measured in Inches	-100.4628**	8.6447	-5.3887	-97.2068**
		(42.7553)	(5.3603)	(22.0922)	(49.0433)
	Measured in Acre-Feet	-8.3719**	0.7204	-0.4491	-8.1006**
		(3.5629)	(0.4467)	(1.8410)	(4.0869)
	Measured in Relative Impact	-0.0740**	0.0064	-0.0040	-0.0716**
		(0.0315)	(0.0039)	(0.0163)	(0.0361)
Moderate to Strong 1,000-5,000 (mg/L)	Measured in Inches	-231.0650***	4.6262	-46.2598**	-272.6985***
		(49.5855)	(6.1222)	(21.2415)	(56.2060)
	Measured in Acre-Feet	-19.2554***	0.3855	-3.8550**	-22.7249***
		(4.1321)	(0.5102)	(1.7701)	(4.6838)
	Measured in Relative Impact	-0.1703***	0.0034	-0.0341**	-0.2009***
		(0.0365)	(0.0045)	(0.0157)	(0.0414)
Very Strong >5,000 (mg/L)	Measured in Inches	-132.4258**	3.9298	16.2156	-112.2804*
		(57.9772)	(11.8844)	(27.7702)	(67.4128)
	Measured in Acre-Feet	-11.0355**	0.3275	1.3513	-9.3567*
		(4.8314)	(0.9904)	(2.3142)	(5.6177)
	Measured in Relative Impact	-0.0976**	0.0029	0.0119	-0.0827*
		(0.0427)	(0.0088)	(0.0205)	(0.0497)

Note: Asterisks $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered at the point of diversion level are reported in parentheses. Robust standard errors are estimated using a bootstrap with 400 replications.

1.8. Figures

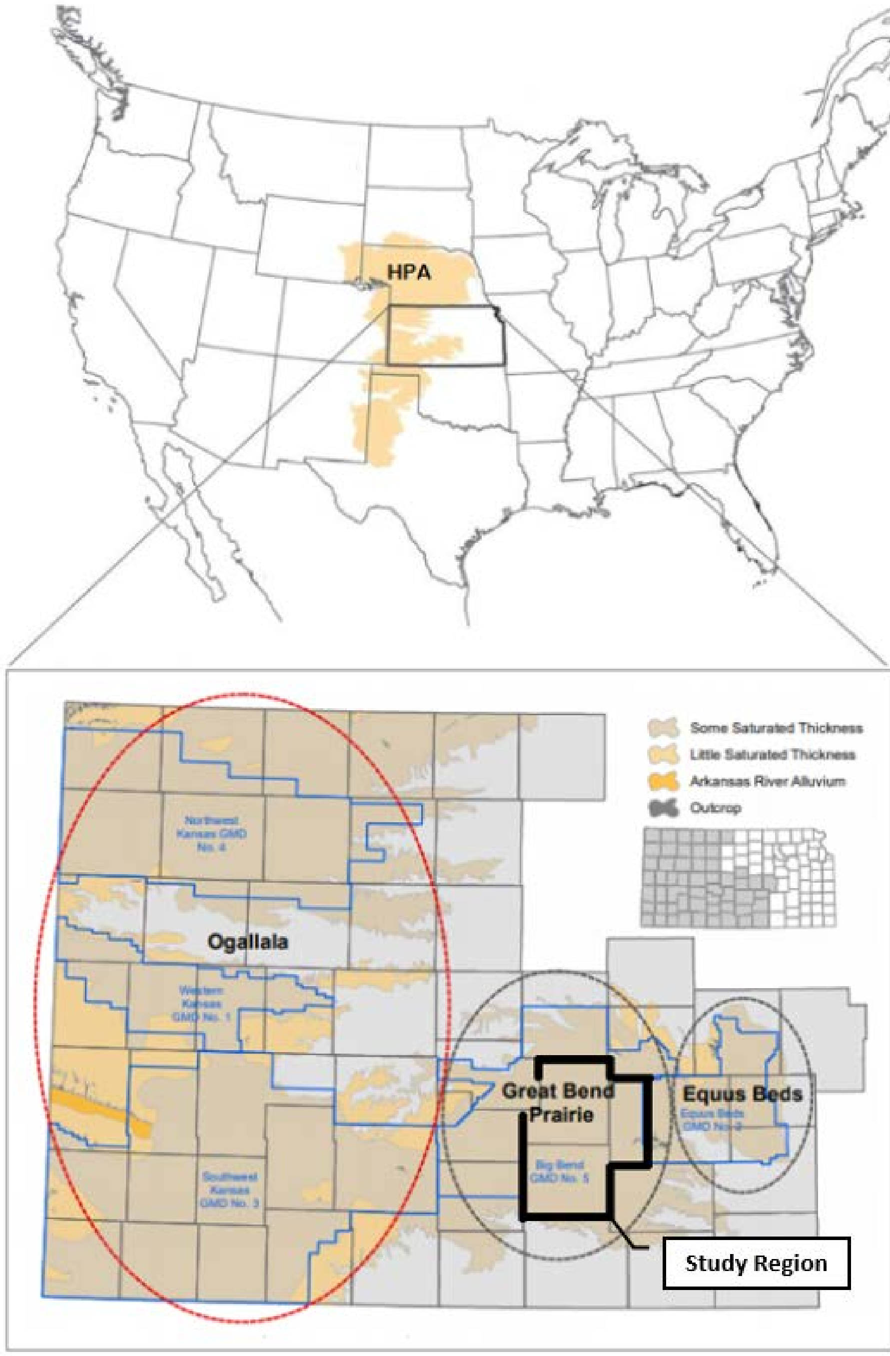


Figure 1.1. Map of the Kansas portion of the High Plains Aquifer (HPA) and study region

Note: Modified from a map provided by the Kansas Department of Agriculture Division of Water Resources, 2017. The thick line is the boundary of the study region.

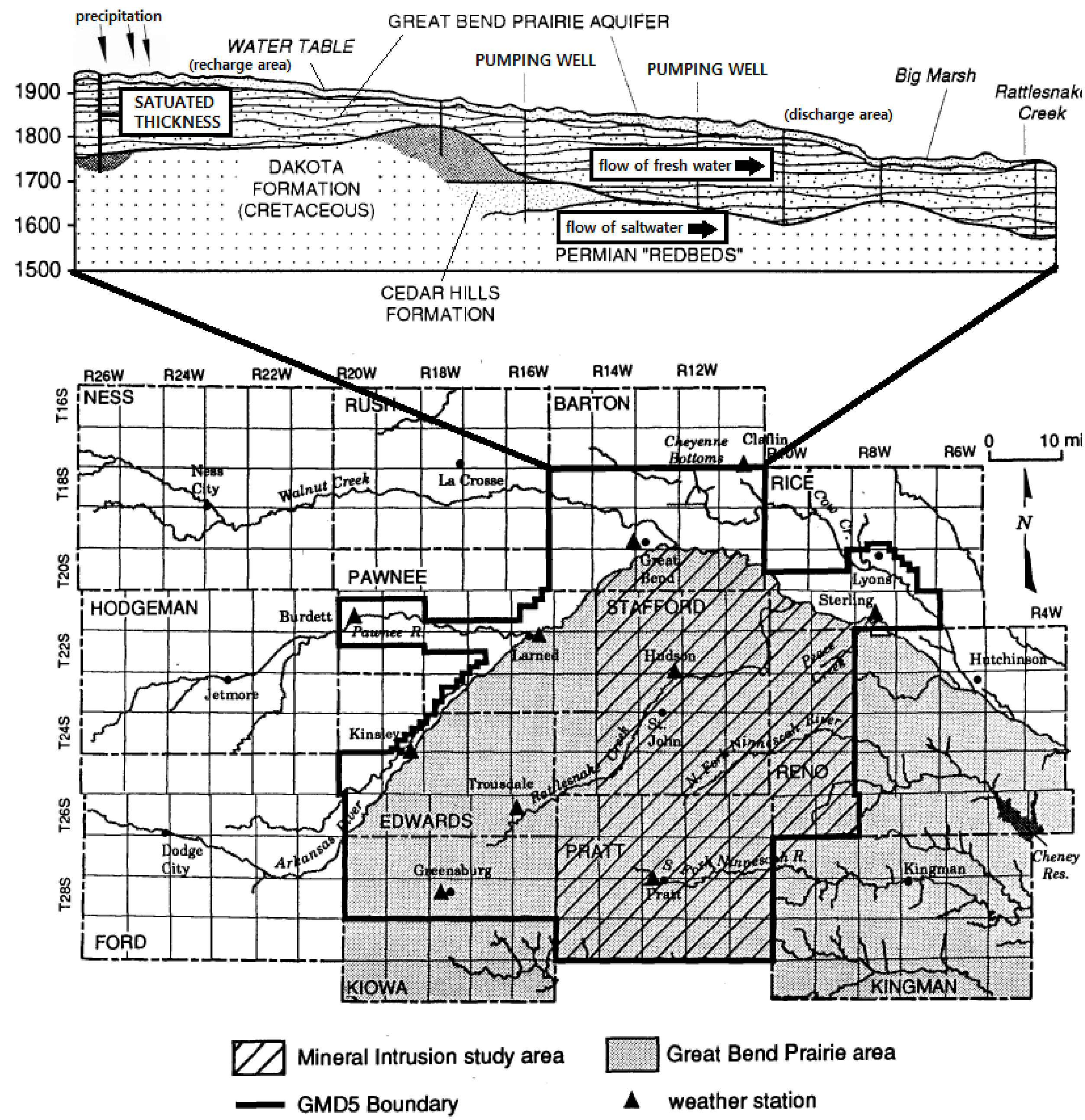
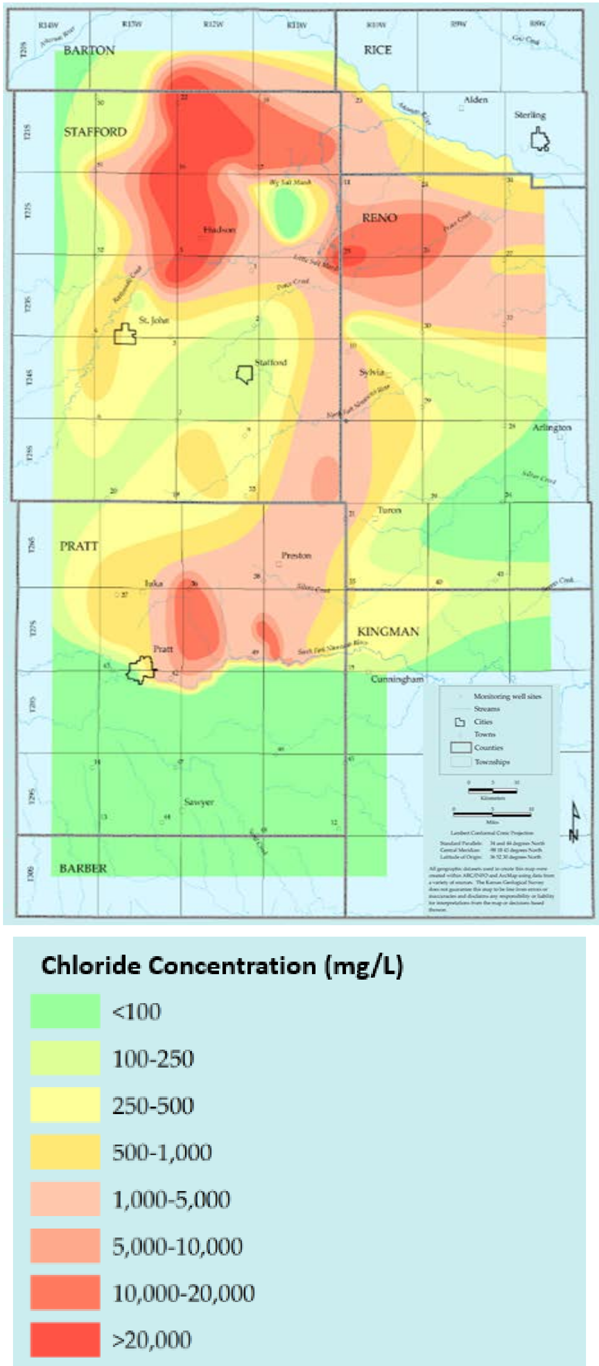


Figure 1.2. Major features in the eastern portion of GMD5 as the primary region

Note: Modified from a map adopted by Whittemore (1993). GMD5 covers part of seven counties: Barber, Barton, Kingman, Pratt, Reno, Rice, and Stafford.

Original colored jpg map	New map by Georeferencing



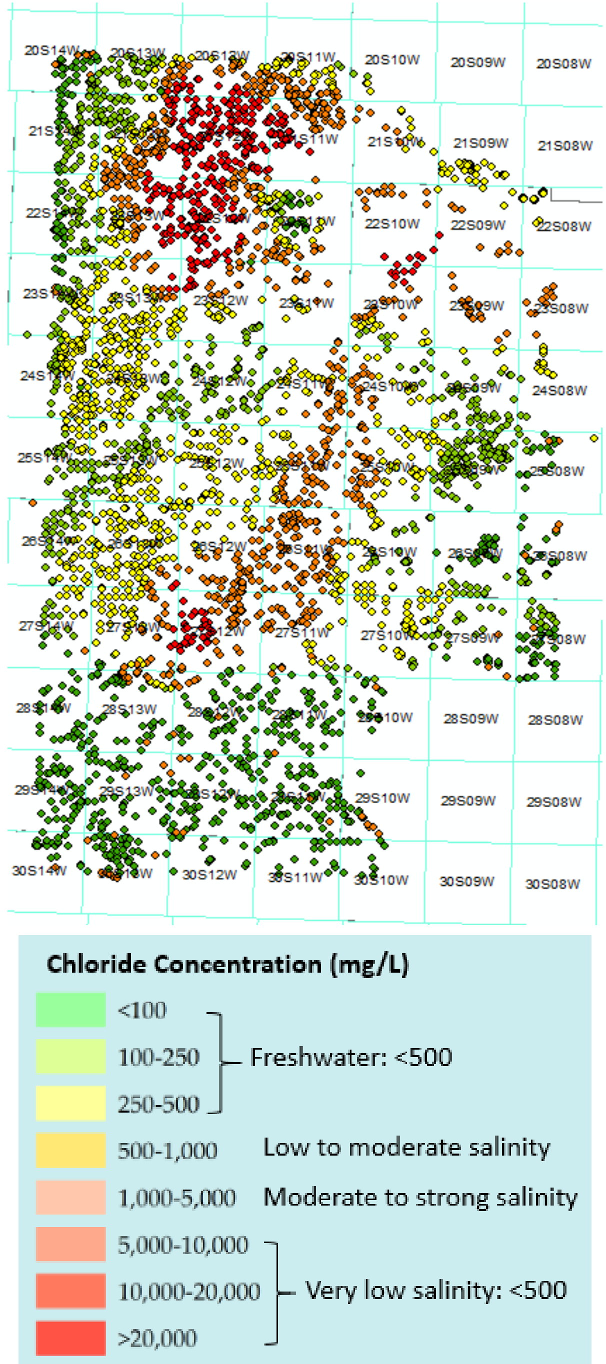


Figure 1.3. Maps displaying chloride contours for the base of the unconsolidated aquifer in the eastern part of GMD5

Notes: Circles on the map denote groundwater points of diversion.

Chapter 2 - The Effect of Groundwater Salinity on Land Values in Kansas

2.1. Introduction

Estimating the value of groundwater used for irrigation is essential for policymakers and agricultural stakeholders throughout arid and semi-arid regions of the world. The value of groundwater depends both on the quantity available and the quality. Most literature assesses the value of groundwater according to the quantity available of groundwater using hedonic methods, but relatively little attention has been given to the impact of groundwater quality on land values. The little literature that does account for water quality is focused on surface water (Shultz and Schmitz 2010; Buck, Auffhammer and Sunding 2014).

Groundwater salinity is the primary form of degradation in groundwater quality, which is closely associated with an intrusion of saltwater into freshwater aquifers in the process of pumping for agricultural production (Foster et al. 2000; Scanlon et al. 2007; Van Weert, Van der Gun and Reckman 2009; Garduño and Foster 2010). Many previous studies have found evidence that elevated salinity contamination adversely affects the agricultural potential by reducing the productivity of crop yields and increasing additional costs for salinity control and remediation (e.g., Haw, Cocklin and Mercer 2000; Shani and Dudley 2001; Munns 2002; George, Clarke and English 2008). Schwabe, Kan and Knapp (2006), Connor et al. (2012), and Mukherjee and Schwabe (2014) find that salinity-induced water quality degradation lowers farm profitability. Therefore, I expect that areas of an aquifer with higher salinity concentrations will have lower land values.

Despite some studies offering valuable contributions to the literature by showing the effects of salinity on agricultural productivity and profitability, there has been relatively little literature using hedonic analysis to estimate the impact of salinity on land values. Schwabe, Kan and Knapp (2006) and Connor et al. (2012) use mathematical programming methods to estimate the impact of groundwater salinity on land values.

There is a large literature that estimates the value of water quantity using hedonic models (Schlenker, Hanemann and Fisher 2007; Shultz and Schmitz 2010; Buck et al. 2014; Sampson, Hendricks and Taylor 2019). However, there is a much smaller literature that estimates the value of water quality with a hedonic model. Koundouri and Pashardes (2002) investigate empirically how sample selection bias affects the hedonic valuation of the effect of groundwater salinity on land values with a small sample size (193 observations). Mukherjee and Schwabe (2014) use a spatial econometric hedonic analysis including groundwater salinity as an explanatory variable in California with farm-level data. In contrast, I estimate hedonic regressions with 5,162 observations using parcel-level market transaction data to focus on the effect of groundwater salinity on land values in Kansas.

To make an additional contribution to the existing literature on the land value estimation, I exploit differences in parcel sale prices in agricultural land across varying levels of groundwater salinity, using finer-scale field-level data during 1988–2015 with more observations of 5,162 than previous papers and using the hedonic price framework for South-Central Kansas wherein groundwater shows high salt contamination. Specifically, I estimate a series of hedonic regression models that control for spatial heterogeneity using either county fixed-effects or a nonlinear function of the GIS coordinates, together with a specification of standard hedonic regression with no spatial controls.

The hedonic model is used assuming that the price of the market good reflects the level of capitalized environmental value embodied in the good. Based on this assumption, the hedonic model has been adopted extensively to value a full range of environmental factors influencing the market good, mainly real property prices. Examples of these studies include: evaluating ambient air quality and its policies (e.g., Won Kim, Phipps and Anselin 2003; Chay and Greenstone 2005), surface water quality (e.g., Boyle 1998; Gibbs et al. 2002), forest vegetation (Tapsuwan et al. 2014; Polyakov et al. 2015), ambient disamenities (e.g., Farber and Stephen 1998; Hite et al. 2001; Mendelsohn and Olmstead 2009), as well as climate change[9] on agriculture (e.g., Mendelsohn and Dinar 2003; Schlenker, Hanemann and Fisher 2007).

I find a negative impact of groundwater salinity on land values by empirically confirming parcel sale prices decline with groundwater salinity levels. This is because salinity-induced water quality degradation causes yield loss, leading to lower farm profitability, and eventually becoming a lower likelihood of a parcel being irrigated. These negative implicit prices can be interpreted as the economic damages from salinity, or equivalently farmer's WTP to offset salinity. The novelty of my study is the implicit valuation of groundwater salinity while controlling for spatial heterogeneity. My results will provide particularly useful information for farmers who need to make land purchase decisions as well as policymakers who seek to understand the economic damages caused by salinity.

[9] Climate change is a closely related Ricardian approach, which is based on a hedonic regression of land values on historical climate variables.

2.2. Conceptual Model

Considering the theoretical underpinnings of the hedonic price model, Court (1939)[10] was often referred to as the pioneer of the hedonic price model, but theoretical support for its application in property value appraisal was provided by Rosen (1974). In Rosen's (1974) formulation, all goods have differentiated characteristics (or attributes), hedonic prices are defined by a vector, namely set of the implicit prices of these characteristics and are disclosed in the form of prices for goods. Therefore, if a differentiated good containing *n c*haracteristics is represented as a vector, $C = (C_1, C_2, \dots, C_n)$, the set of hedonic prices is revealed as $P(C) = P(C_1, C_2, \dots, C_n)$.

Besides, the presence of price differences of goods means that various alternative sets with differentiated characteristics that enable consumers and producers to make transaction decisions are available. Hence, a transaction in good is equivalent to buying and selling the value on a set of characteristics for the good. In accordance with the principle of market equilibrium, this transaction is made when the demand curve derived from maximizing consumer utility meets the supply curve derived from producer maximization. In this context, hedonic prices can be recognized as equalizing consumers' implicit willingness-to-pay (WTP) and producers' implicit willingness-to-accept (WTA), for their decision regarding sets of characteristics, simultaneously is also market-clearing implicit prices.

In the housing market as the most common example of the hedonic price model, hedonic prices are not only implicit prices that include the characteristics of the structure itself (e.g., number of rooms, plot size, construction year, etc.) and the characteristics of its surrounding environment (e.g., education quality of nearby schools access to services such as transportation

[10] Court (1939) developed a pricing index for advertised automobiles to show the demand for those automobiles based on three variables of car weight, wheelbase, horsepower covering the periods 1920~39 with 5-year intervals.

or green area, air pollution), but also market prices of houses traded where consumers' WTP for the house and the producers' WTA for the house match each other.

The model was applied specifically to agricultural land sale prices by Palmquist (1989, 1991) based on the assumption that producers can differentiate factors of production relating to profits when purchasing agricultural land. Thereafter, the model has been used for numerous natural and environmental resources or social amenities valuations, beyond real estate valuation.

The coefficient estimates of the hedonic regression model represent the implicit prices of the differentiated characteristics embedded in agricultural land. I use this estimation—particularly, estimation on salinity—to confirm groundwater salinity is highly likely to be a key negative characteristic. These negative implicit prices associated with different salinity levels can be interpreted as the economic damages from salinity (i.e., change in chloride concentration or degradation of groundwater quality), or equivalently farmer's WTP to offset salinity.

The hedonic prices of agricultural land *P* are a function of all characteristics of the land that consist of W and Z:

$$P = f(\boldsymbol{W}, \boldsymbol{Z}) \tag{1}$$

where $\boldsymbol{W}$ is a vector of key treatment variables to indicate four groundwater salinity levels as groundwater quality attribute, and $\boldsymbol{Z}$ is a vector of other control variables to indicate hydrological and geographic characteristics.

Among various characteristics defining land values, the location of the land is one of the essential characteristics. The benefit of including the latitude and longitude is to control for other unobserved factors that vary smoothly across space. Spatial heterogeneity in hedonic prices I estimate reflects farmers' demand (or preference) for agriculture land based on the salinity level varied across land location, and also the nearer a land is located to the place with higher salinity level, the lower the values for this land, consequently also the lower farmers' WTP.

2.3. Background and Data Description

I exploit variation in parcel sale prices in agricultural land across varying levels of groundwater salinity using the hedonic model and constructing parcel-level data between 1988 and 2015 from the High Plains Aquifer[11] in the eastern Big Bend Groundwater Management District No.5 (GMD5) underlying the Great Bend Prairie Aquifer of South-Central Kansas (**Figure 2.1**). The overall process of constructing a final dataset is to merge unique data of parcel transaction variable with the data of groundwater salinity variable and other variables such as hydrological and soil characteristics. The following subsections provide information about where these multiple data are obtained and how these variables are predicted to influence land value. Summary statistics for variables used in estimating the hedonic models are listed in **Table 2.1**.

2.3.1. Parcel Sale Prices

A data of parcel sale prices used as an outcome variable in the estimation came from the Property Valuation Division (PVD) of the Kansas Department of Revenue. The PVD data contain information between 1988 and 2015 on the acres of the parcels in each type of use (i.e., irrigated cropland, non-irrigated cropland, native grassland, tame grassland, and total agricultural land), parcel identification number, county code, acres of each soil type, improvement values on

[11] The HPA underlies about 174,000 square miles of the central United States, covering through parts of Colorado, Kansas, Nebraska, New Mexico, Oklahoma, South Dakota, Texas, and Wyoming uses about 95% water pumped from the aquifer for irrigation (Gutentag et al., 1984).

the parcel and location, together with sales-related information such as sales price, sales validity codes, and sale date. The PVD data covering GMD5 includes 5,162 unique parcels about seven counties: Barber, Barton, Kingman, Pratt, Reno, Rice, and Stafford.

From the PVD data, first of all, some parcels were removed due to the inherent characteristics of parcel data, for example (i) parcels with missing parcel identification numbers identifying a parcel's location; (ii) parcels with sales that are classified as non-public sales and forced sales because sales transactions are based on self-interest without external pressures such as government; (iii) parcels less than 35 acres in total because there is little chance of farming in these small parcels; (iv) parcels with abnormal resales that are sold within the same month; (v) parcels with only buildings since I focus on agricultural land values; and (vi) duplicate observations due to record retention issues. In the United States, the values of the land and structural improvements placed on it both are typically reflected in sale prices. Thus, total improvements are subtracted from the parcel sale prices left by the above work according to Guiling, Brorsen and Doye (2009) and Nickerson and Zhang (2014).

For the next, in an attempt to capture parcels selling for crop production purposes in the GMD5, the parcels in other types of use except irrigated and nonirrigated cropland are removed from the data set and for other GMDs. I consider nonirrigated parcels with irrigated parcels for agricultural land purposes since salinity could impact land values by making the land less likely to be irrigated in the first place.

2.3.2. Groundwater Salinity Characteristics

The source of salinity this portion of Kansas stems from natural saltwater intrusion from the Permian bedrock (or redbed) into the freshwater aquifer, called the Great Bend Prairie aquifer (see the bottom half of **Figure 2.2)**. Even though the natural intrusion of saltwater is one reason for salinity, excessive groundwater pumping for irrigated agriculture triggers the water table to decline (i.e., the surface of the saturated part of the aquifer), leading to the increased upward movement of the saltwater into the base of the aquifer.

As GMD5 shows water type with a certain predominant chemical character such as chloride, I measure salinity by chloride concentration (mg/L: milligram/liter) and classify four levels of salinity in this region as: (i) freshwater (<500 mg/L), (ii) low to moderate salinity (500-1,000 mg/L), (iii) moderate to strong salinity (1,000-5,000 mg/L), and (iv) very strong salinity (>5,000 mg/L). The first level, called freshwater, is used as the base category. This level appears where there is non-salinity or very slight natural saltwater. This level does not cause the region's main crops to yield loss and thus is referred to as "freshwater[12]" in this study.

The information on salinity as a key treatment variable is obtained from the maps with image files generated from Whittemore (1993) and was provided via personal communication after being updated in 2017. These maps display maps of chloride contours for the Permian bedrock, the base, and the upper of the unconsolidated aquifer in the eastern part of GMD5. Among these maps, my key measure salinity that impacts farmer behavior is the measure of salinity at the base of the aquifer. Even though the source of salinity is in the Permian bedrock and groundwater wells do not pump water from the base of the aquifer, the salinity in the base should affect farmer decisions since pumping results in depletion that induces saltwater intrusion from the bedrock toward the upper portions of the aquifer where groundwater is extracted.

[12] According to the Department of Health and Environment, freshwater has TDS contents less than 500 mg/L and both chloride and sulfate concentrations 250 mg/L.

Based on the map of the base of the aquifer, I extract attribute values for chloride concentrations by georeferencing in ArcGIS (see **Figure 2.3**). I only use measures of the spatial variation of salinity and do not use measures of the temporal variation of salinity because the only map of chloride concentrations available from Kansas Geological Survey was for a single point in time. Extracted salinity values are merged spatially to the center point of the parcels in terms of a latitude and longitude variable for each parcel to analyze for the effect of salinity on land values.

As salinity contamination gets severe then I expect the profitability from the land to decrease, which will lower parcel prices. This in turn will cause land values to fall.

2.3.3. Hydrological and Soil Characteristics

As other control variables affecting land values, I include one variable for hydrological properties and two variables for soil characteristics. For the hydrological properties, data for saturated thickness is obtained Kansas Geological Survey. Saturated thickness is the vertical the distance from Permian bedrock to the water table (see the upper portion of **Figure 2.2**), which represents the amount of water available. As the saturated thickness declines, the depth to the water table increases, which implies upward movement of more salinity and limits current irrigation intensity and potential irrigation extensity. Thus, I expect to see lower land values in the region with low saturated thickness. I use predevelopment values rather than the current values to avoid any potential endogeneity issue between saturated thickness and water use since predevelopment values are estimated before the withdrawal of significant amounts of groundwater.

For the soil characteristics, I use the average National Commodity Crop Productivity Index (NCCPI)[13] and the slope of the land from the Soil Survey Geographic Database (SSURGO). The NCCPI provides condensed information about average national crop productivity based on the inherent soil properties. Further, the NCCPI incorporates together other factors related to crop production, such as landscape and climate characteristics, and imposes a rating (score) on the production. I expect the NCCPI to have a positive impact on parcel sale prices. I use Corn and Soybeans NCCPI score to reflect the productivity of the main crops in the region.

Even though the slope of the land (i.e., a measure of the change in elevation between two points) is not a direct indicator of soil quality, it can impact involving runoff and erosion which affect crop productivity. Borrowing Wu et al. (2004)'s example, corn is likely to be cultivated in more sloped land compared to soybeans since soybean is a more runoff- and erosion-prone crop. Further, the slope of the land can indirectly impact related to soil loss. For instance, soil loss tends to increase with steep slopes, while decrease with flat slopes (Liu et al. 2000; Kapolka and Dollhopf 2001). Thus, I expect highly sloped parcels to have lower values. I take the log of the slope to use a more normally distributed slope across the parcels, according to Hendricks (2018).

2.4. Econometric Model

The hedonic price model does not impose any theoretical restriction on the function form (Le and Li 2008), albeit the estimated result and its interpretation may vary slightly depending on the form used. The findings of earlier literature (e.g., Taylor 2003; Massetti and Mendelsohn

[13] For more detail of the NCCPI, refer to as Dobos, Sinclair Jr, and Hipple (2008).

2011) support that the semi-log form provides a better fit for hedonic data. The regression coefficients of the continuous variable can be interpreted as a percentage change in the outcome variable for a one-unit change in a given variable, and the dummy variable can be interpreted as a price premium relative to the base category (i.e., a relative change in value), holding all other variables fixed (Gennaro and Nardone 2014).

The hedonic function I estimate is the following:

$$\text{In } P_{it} = f(\boldsymbol{W_i}, \boldsymbol{Z_i}) = \alpha + \boldsymbol{W_i'\beta} + T_i\gamma + I_i\delta + S_i\theta + \tau_t + \varepsilon_{it} \tag{2}$$

where In P_{it} is the log of the transaction price of parcel i in time t=1988–2015. It is needed to note that the dataset of parcel sale prices used in this analysis is not true panel data because this study rarely observes repeat sales of a given parcel.

As mentioned in equation (1), $\boldsymbol{W_i}$ represents a vector of key variables for four groundwater salinity levels measured by chloride concentration: (i) freshwater (<500 mg/L), (ii) low to moderate salinity (500-1,000 mg/L), (iii) moderate to strong salinity (1,000-5,000 mg/L), and (iv) very strong salinity (>5,000 mg/L). A vector of other control variables indicating hydrologic and soil characteristics, $\boldsymbol{Z_i}$ specifically includes predevelopment saturated thickness (i.e., T_i), NCCPI (i.e., I_i) and the slope of the land (i.e., S_i). τ_t represents year-fixed effects to capture the effect of prices, government programs, and other macroeconomic variables. ε_{it} is an random component indicating all unobservable factors affecting the outcome variable.

The coefficients to be estimated and the implicit prices of an additional change in each parcel characteristics are $\alpha, \boldsymbol{\beta}, \gamma, \delta, \theta$. Of particular interest, $\boldsymbol{\beta}$ are the implicit prices of groundwater salinity on the parcel sale prices per acre. This can be regarded as the price differential in agricultural land across varying levels of groundwater salinity while controlling for other features. As aforesaid, I only use measures of salinity for spatial variation in this region and do not use measures of salinity for temporal variation. In GMD5, as a matter of groundwater quality, salinity shows little change over the sample period. Further, the only map of chloride concentrations available from the Kansas Geological Survey was for a single point in time.

A challenge in estimating equation (2) is the potential for omitted variable bias. I avoid such concerns by including controls for major characteristics of the land, such as hydrologic and soil characteristics. Urban pressure is minimal in the area I analyze. To further control for variation in the outcome variable due to time-invariant unobserved factors that could affect land values and be correlated with groundwater salinity, I include specifications that contain county fixed-effects or flexible controls for the GIS coordinates:

$$\text{In } P_{it} = \alpha + \boldsymbol{W_i'\beta} + T_{it}\gamma + I_{it}\delta + S_{it}\theta + \tau_t + \lambda_c + u_{it} \tag{3}$$

where the description of the variables that make up the equation is basically the same as above, county fixed-effects λ_c is added to the regression in equation (3).

To further control for directional heterogeneity in land value, I also use the GIS coordinates as:

$$\text{In } P_{it} = \alpha + \boldsymbol{W_i'\beta} + T_{it}\gamma + I_{it}\delta + S_{it}\theta + \mu_1 x_i + \mu_2 y_i + \mu_3 x_i y_i + \mu_4 x_i^2 + \mu_5 y_i^2 + \tau_t + n_{it} \tag{4}$$

where equation (4) is extended by a polynomial expression of longitude and latitude $\{x_i, y_i\}$ coordinates of up to second-degree. The interaction term between GIS coordinates $\{x_i, y_i\}$ is also used. Given that each parcel has a unique set of GIS coordinates, the parcel sale price on its corresponding location is also unique. Particularly, the polynomial expansion of $\{x_i, y_i\}$ coordinates in the analytical model is intended to incorporate this spatial heterogeneity depending on the location, which is allowed to vary across space nonlinearity.

2.5. Results

I present and compare the three specifications of the hedonic regressions in **Table 2.2**: no spatial controls, county fixed-effects control, and nonlinear function control of the GIS coordinates. As expected, all of the regression results at all levels of salinity reflect that salinity reduces land values. To control for spatial heterogeneity using either county fixed-effects or a nonlinear function of the GIS coordinate shows slightly different results compared to the no spatial controls. Overall, these results provide valuable information regarding the effect of various characteristics on the parcel sale prices and its interpretation, as well as support that inclusion of a nonlinear function of GIS coordinates as controls to reduce omitted variable bias because the coefficients on salinity are substantially different when including the controls.

Considering each hedonic regression result, the first column of **Table 2.2** displays the regression result with no spatial controls. Salinity at all levels decreases the value of parcels. Specifically, low to moderate saline water (500-1,000 mg/L), moderate to strong saline water (1,000-5,000 mg/L), and very strong saline water (>5,000 mg/L) show a 12% per acre, a 33% per acre, and a 31% per acre reduction respectively, relative to freshwater as the base category (<500 mg/L). The salinity effects of the coefficients on the parcel sale prices are statistically significant at either the 5% level for low to moderate saline water or 1% level for moderate to strong saline water and very strong saline water.

The second and third columns of **Table 2.2** present regression results using county fixed-effects and using a nonlinear function of the GIS coordinates as controls, respectively. First, low to moderate saline water (500-1,000 mg/L) dropped the value of parcels in the results of the county fixed-effects, while increased the value of parcels in the nonlinear functions. But neither was statistically significant. Perhaps because this level is close to the natural saline level and does not substantially affect yield loss; accordingly, it is basically less likely that parcel prices will fall, and it would be statistically insignificant. Instead, other attributes affecting land value such as land quality crops grown, or/and weather may have influenced parcel prices positively and negatively.

All salinity coefficients except for the coefficient on low to moderate saline water decrease the value of parcels with statistical significance at the 1% level. The moderate to strong saline water (1,000-5,000 mg/L), which is the level at which the major crops in this region begin to be affected by salinity (see Fipps 2003)[14], decreased parcel sale price by 22% per acre under the county fixed-effects compared to freshwater as the base category (<500 mg/L) and 19% per acre per acre under the nonlinear function of the GIS coordinates relative to freshwater. The very strong saline water (>5,000 mg/L) shows decreased parcel sale price by 18% per acre under the county fixed-effects and 20% per acre under the nonlinear function of the GIS coordinates, respectively, relative to freshwater.

Comparing hedonic regression results to each other, the case of controlling for spatial heterogeneity using either county fixed-effects or a nonlinear function of the GIS coordinate clearly shows that the decrease in land value is smaller than that in the specification with no spatial controls. These results can be attributed to the following possible reasons: county fixed-effects reduce bias from time-invariant unobserved factors that could affect land values, and GIS coordinates reduce omitted variable bias that could affect land values. In particular, the result for the GIS coordinates shows that land value increases from west to east (i.e., longitude), and land value decreases from north to south (i.e., latitude). These results are significant at a 1% level.

[14] For example, crop yields experience a 10% yield loss when salinity concentration of the water applied reaches 605 mg/L for corn and 1,815 mg/L for soybeans.

There are two primary mechanisms by which salinity can affect land values. First, salinity-induced water quality degradation causes yield loss on irrigated land, leading to lower farm profitability. Second, salinity decreases the likelihood of a parcel being irrigated and thus decreases land values because irrigated land values are larger than nonirrigated. Indeed, I confirmed from chapter 1 that farmers in the face of groundwater salinity reduce water use by reducing irrigated acres in response to groundwater salinity.

Regarding other control variables, in the estimation of this study region, an increase of 1-foot saturated thickness increases parcel sale price by 0.1% per acre under both results with no spatial and nonlinear function of the GIS coordinates. The result for no spatial shows statistical significance at the 5% level and the result for the GIS coordinates shows statistical significance at the 1% level. It can be intuitive that increased saturated thickness will raise land value by increasing the amount of water available for irrigation.

Based on the arguments in Section 2.3.3, I expected that the value of parcels tends to be increased due to the higher NCCPI, while decreased due to the higher slopes. The coefficients between the NCCPI variable, which represents the inherent capability of soils and the prices of parcels, show a positive relationship under the regression with the GIS coordinates, but it is not statistically significant. Consequently, there is no real impact of the NCCPI on land value in the study region. Meanwhile, the log of the slope is statistically significant at the 5% level under the regression with the GIS coordinates, which indicates that a large slope decreases the value of parcels by 4.9% per acre.

2.6. Conclusions

I evaluate the impact of groundwater salinity on land values. Using the data of the transaction prices of parcels agricultural land in the eastern GMD5 underlying South-Central Kansas, I confirm evidence that groundwater salinity is a key negative characteristic of the land and an economic bad, which is negatively correlated with land values, through demonstrating empirically decreased implicit parcel sale prices with a series of hedonic regression models.

Using either county fixed-effects or a nonlinear function of the GIS coordinates, I control for the spatial heterogeneity of parameters depending on the location and find that the preferred specification is to use the nonlinear function of the GIS coordinates by comparison with specifications of standard hedonic regression and spatial hedonic regression. Specifically, the estimation for the preferred specification shows decreased parcel sale price by the range with 19~20% per acre at the moderate to strong salinity level or higher, which is the level at which the major crops in this region begin to be affected by salinity. This is due to the fact that salinity-induced water quality degradation causes yield loss, leading to lower farm profitability, and eventually becoming a lower likelihood of a parcel being irrigated.

My main contribution is to provide useful information regarding the effect of salinity on the parcel sale prices in agricultural land. These estimates can be interpreted as the economic damages from salinity, or equivalently farmers' willingness to pay to offset salinity. My estimates also help farmers and investors understand the impact of salinity on agricultural land values when they make land purchasing decisions, as well as policymakers who often face the problem of evaluating how water quality affects a region's economic growth and well-being.

2.7. Tables

Table 2.1. Descriptive Statistics for Selected Variables

Variable	Mean	Std.Dev.	Min	Max
Log of real parcel sale prices for 1988–2015 ($)[a]	7.037	0.958	3.579	10.339
Freshwater: <500 (mg/L)[b]	0.803	0.398	0	1
Low to moderate salinity: 500-1,000 (mg/L)[b]	0.06	0.237	0	1
Moderate to strong salinity: 1,000-5,000 (mg/L)[b]	0.082	0.274	0	1
Very strong salinity: >5,000 (mg/L)[b]	0.055	0.228	0	1
NCCPI corn and soybean	0.33	0.102	0.015	0.707
Predevelopment saturated thickness (ft)	123.679	39.988	10.00	259.61
Log of slop (%)	0.819	0.813	-4.605	2.996
Longitude (x-coordinate)	-98.87	0.344	-99.561	-98.06
Latitude (y-coordinate)	37.963	0.251	37.478	38.515

[a]Parcel sale prices are adjusted to 2015 prices.

[b]Four salinity levels measured in chloride concentration. Chloride concentration (<500 mg/L) as the base category means “freshwater”.

Table 2.2. Hedonic Regression Results with Different Controls (dependent variable = parcel sale prices adjusted to 2015 prices)

Variable	No spatial controls	County fixed-effects	Nonlinear function of the GIS coordinates
Low to moderate salinity: 500-1,000 (mg/L)[a]	-0.124	-0.013	0.020
	(0.053)**	(0.055)	(0.056)
Moderate to strong salinity: 1,000-5,000 (mg/L)[a]	-0.326	-0.220	-0.190
	(0.046)***	(0.048)***	(0.050)***
Very strong salinity: >5,000 (mg/L)[a]	-0.309	-0.177	-0.204
	(0.056)***	(0.059)***	(0.059)***
Predevelopment saturated thickness (ft)	0.001	0.000	0.001
	(0.000)**	(0.000)	(0.000)***
NCCPI corn and soybean	-0.029	-0.000	0.063
	(0.159)	(0.186)	(0.174)
Log of slop (%)	-0.015	-0.032	-0.049
	(0.018)	(0.020)	(0.020)**
Longitude			181.543
			(43.625)***
Longitude^2			0.712
			(0.177)***
Latitude			-198.416
			(46.166)***
Latitude^2			1.201
			(0.335)***
Longitude×Latitude			-1.088
			(0.300)***
Constant	7.080	7.286	12,717.942
	(0.215)***	(0.226)***	(2,861.514)***
Year fixed effects (N_{year} = 30)	Yes	Yes	Yes
County fixed effects (N_{county} = 7)	No	Yes	No
R^2	0.17	0.19	0.19
Observations	5,162	5,162	5,162

Notes: Asterisks ***, **, and *refer to statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are provided in parentheses.
[a]Four salinity levels measured in chloride concentration. Chloride concentration (<500 mg/L) as the base category means "freshwater".

2.8. Figures

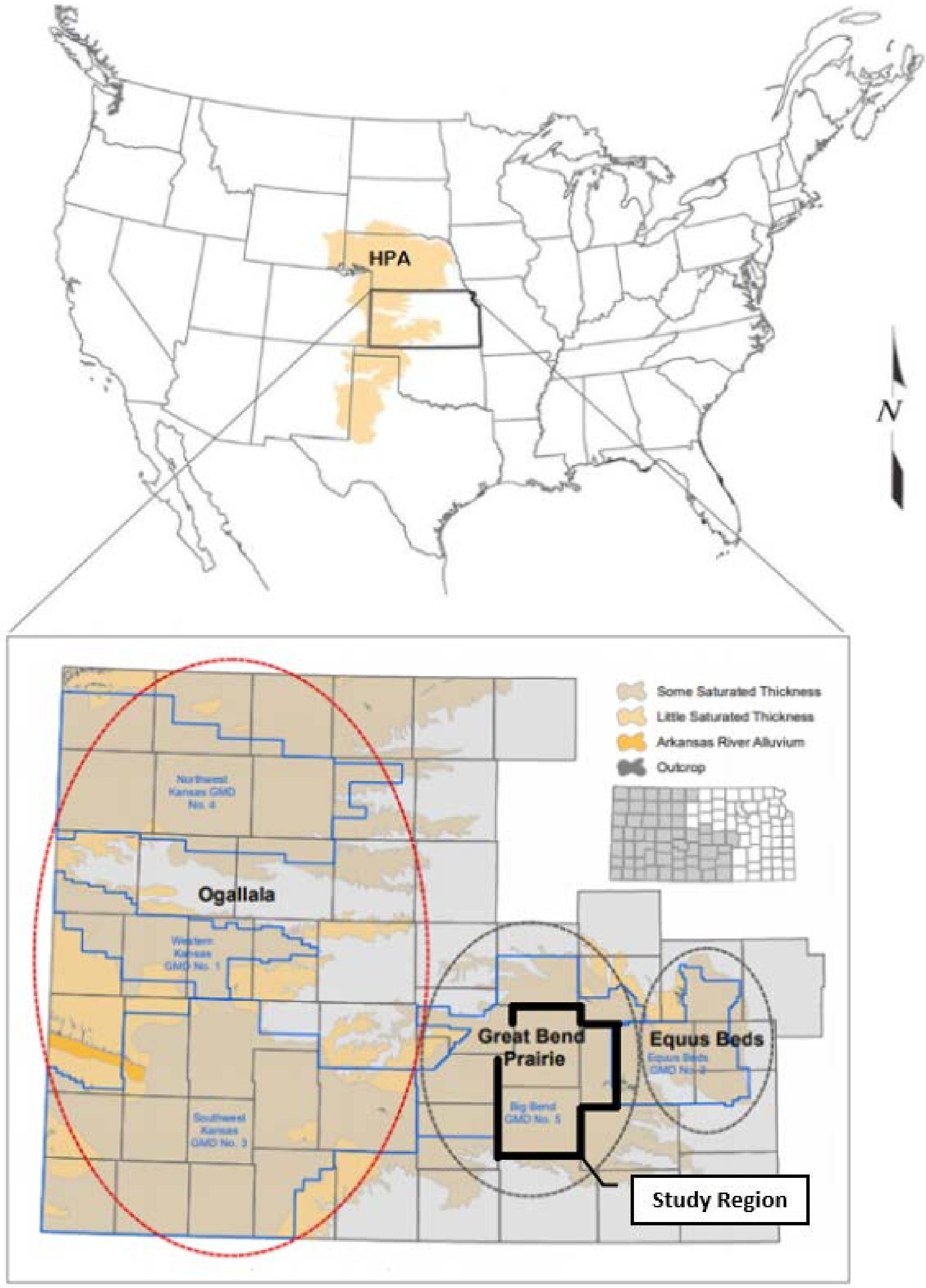


Figure 2.1. Kansas Components of the High Plains Aquifer (HPA) and the eastern portion of GMD5 lied in the Great Bend Prairie Aquifer of South-Central Kansas

Note: Modified from a map provided by the Kansas Department of Agriculture Division of Water Resources, 2017. The thick line is boundary of the study region.

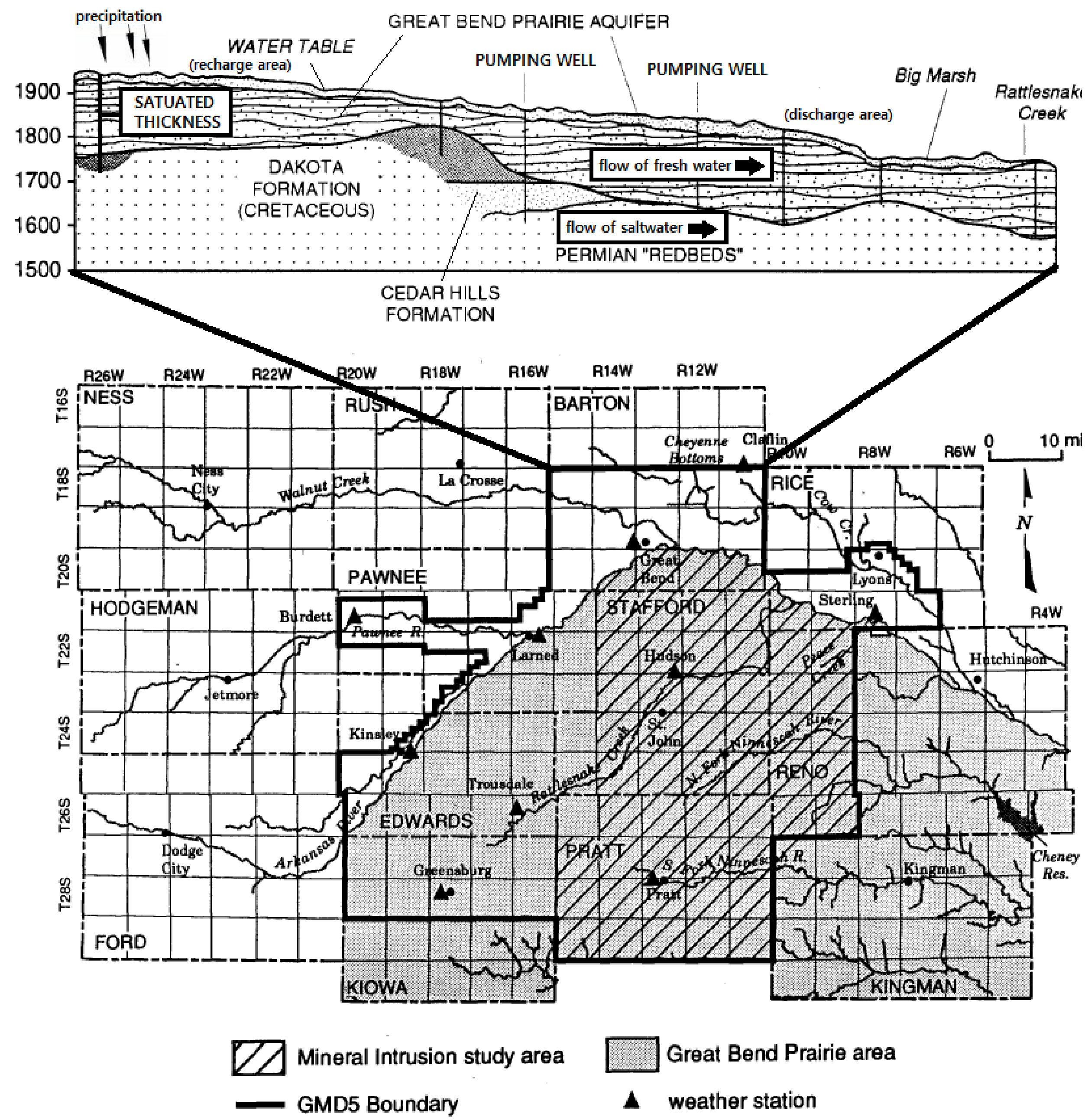


Figure 2.2. Major features in the eastern portion of GMD5 as the primary region

Note: Modified from a map adopted by Whittemore (1993). GMD5 covers part of seven counties: Barber, Barton, Kingman, Pratt, Reno, Rice, and Stafford.

Original colored jpg map	New map by Georeferencing

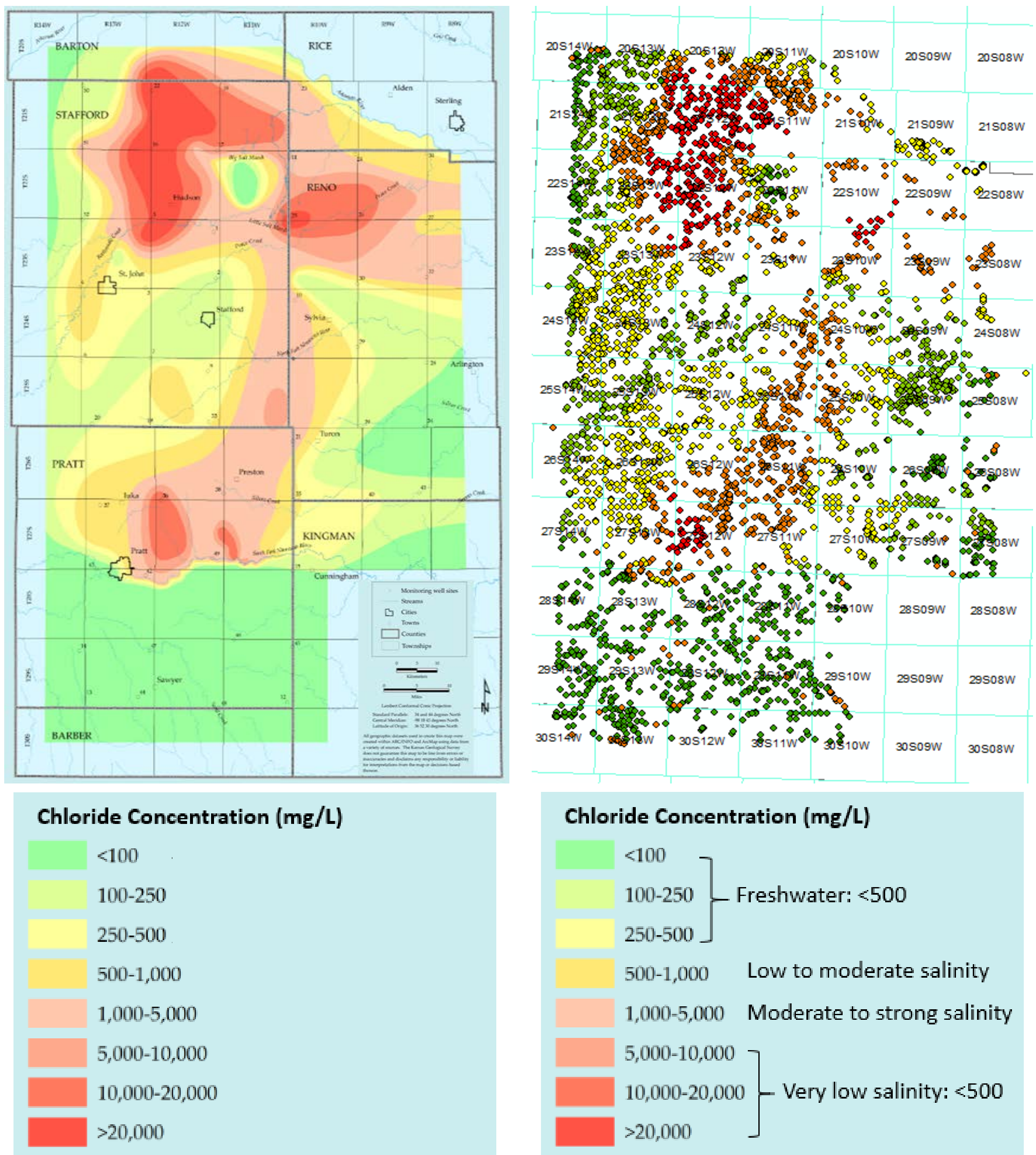


Figure 2.3. Maps displaying chloride contours for the base of the unconsolidated aquifer in the eastern part of GMD5

Notes: Circles on the map denote groundwater points of diversion.

Chapter 3 - Crop Choice Decisions in Response to Soil Salinity on Irrigated Lands in California

3.1. Introduction

Soil salinity is the process of the accumulation of soluble salts in the root zone through the evapotranspiration of irrigated water and is one of the primary causes of land degradation[15]. The high concentration of salts in the soil limits the growth and productivity of crops by adversely affecting soil chemical properties and soil biota, causing specific-ion toxicity or upset the nutritional balance of crops (Wong et al. 2006; Jahknwa et al. 2014). Continuous salt accumulation may threaten the sustainability of agriculture production (Letey 2000; Lobell 2010; Ivits et al. 2013).

It has been estimated that around one-third of the world's 260 million hectares of irrigated land, which accounts for 40% of global food production, are afflicted by salinity (Schwabe et al. 2006). Moreover, the salinized regions are increasing at a rate of 10% annually (Shrivastava and Kumar 2015), and are presently expanding to many countries and states, e.g., Egypt, Pakistan, Australia, China, and California, the United States of America[16].

Salinity challenge is generally more pronounced in regions with semiarid and arid climates than in regions with more humid regions. Albeit salts in soils can be dissipated by rainfall, semiarid and arid climates restrict the supply of sufficient water to wash the salts out of

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[15] Soil erosion is the first primary cause of land degradation, and soil salinity is the second cause of it (Zaman et al. 2018).

[16] Refer to Ghassemi, Jakeman and Nix (1995) and Tanji, Program and Kielen (2002) for Egypt; Qureshi et al. (2008) for Pakistan; (Rengasamy (2006) for Australia; and FAO (2010) for China.

the root zone. Further ongoing climate change growing the frequency and severity of extreme weather events, including heatwaves and droughts, disrupts the dissipating. That is, the increased evapotranspiration and the reduced precipitation cause an instant decline in both surface water runoff and groundwater recharge, and also lessen water availability to dilute existing levels of saline groundwater discharge and to leach the salts out of the root zone.

Salinity challenge occurs in irrigated areas where larger amounts are brought in by the irrigation water than are removed by natural soil drainage process. Increased irrigated agriculture has been considered as a critical adaptation to meet growing food demands due to the world's growing population in arid and semiarid regions. However, such over-irrigated agriculture makes intensive local pumping, causing the water table to decline (i.e., the surface of the saturated part of the aquifer), leading to increased upward movement of the saltwater into the freshwater.

A particular concern for these saline regions with climate and hydrology conditions that are susceptible to salinity was that soil salinity would induce supply shortages for food relative to growing demands for foods, leading to the resultant higher food prices. Despite this concern and some studies offering valuable contributions to the literature, a wide variety of studies on the effects of soil salinity on irrigation agriculture in arid and semiarid setting have not been conducted. Most of the existing studies have focused on agricultural productivity measured in yield change in response to soil salinity for a specific crop with linked climate, agronomic, and hydrologic models (e.g., Maas 1993; Van Genuchten 1993; Horticulturae 1998). Or even the papers linked with economic models have only added economic measurement on agricultural productivity with estimating changes in revenues (e.g., Beare and Heaney 2002; Connor et al. 2012; Welle et al. 2017).

Quantifying the impact of salinity on irrigated agriculture cannot rely solely on how salinity affects changes in yields or revenues. That said, it also needs to include the understanding of how farmers will adjust their management practices to salinity. For instance, as soil salinity levels increases, farmers are likely to switch from salt-sensitive crops to more salt-tolerant crops. Current analysis that overlooks such adjustments may overestimate the welfare losses from soil salinity.

The traditional response to soil salinity is switching crops to more salinity-tolerant crops[17]. This is an instant and relatively easy adaptation compared to other possible alternatives, while continuously cultivating, albeit with a less profitable land use due to salinity. Leaving the land fallow is a last resort when the land cannot be restored from such salinity (Connor et al. 2012). Changing irrigation systems with better control of the distribution and depth of water application can trigger an intensification of water application and a high irrigation cost. The NRCS-USDA (2009), for example, reports that larger irrigation systems requiring pumps and permanent piping incurs cost from \$1800/ha to \$2500/ha. At these high costs, it is not easy to change systems without government subsidies or incentives.

Despite abundant literature on irrigated crop choices[18], crop choice decision as farmers' response to soil salinity in arid and semiarid settings have not been dealt with except in agronomic field experiments. Ayars (2003) carries out two field experiments in California with

[17] Explaining the decline of civilizations in Mesopotamia from 2400 to 1700 BC, Gelburd (1985) reported that ancient farmers responded to the soil salinity due to waterlogging from over-irrigation and poor subsurface drainage, via switching to more salinity-tolerant crops, such as wheat to barley.

[18] In general, studies of crop choice rely either on the link between crop choice and water/land environment and irrigation technology changes (e.g., Lichtenberg 1989; Wu et al. 1994), between crop choice and policy or energy prices changes (e.g., Wu and Segerson 1995; Wu and Adams 2001; Pfeiffer and Lin 2014), or between crop choice and climate change (e.g., Kurukulasuriya and Mendelsohn 2008; Fleischer et al. 2011).

saline soils and saline groundwater, respectively, and demonstrates the type of irrigation systems and management techniques to reduce the adverse effect of salinity to sustain irrigated agriculture in a saline environment. The study only covers current crop choices as a laboratory sampling to show the salinity in the surface layers of the soil profile and the internal drainage of soil under the agronomic approach, not as a farmer response. Not only that, it is much more concerned with the distribution of soil salinity on the different type of irrigation systems. Likewise, Beare and Heaney (2002) also deal with land-use activity choices including different crop type in connection with soil salinity, but they merely consider them in the context of the net return based on the revenue from crop yields and cost increases caused by incremental irrigation salinity, but they do not estimate how farmers' cropping patterns actually change in response to higher salinity.

To address this gap in the literature, I quantify the adaption to soil salinity by farmers in California's Western San Joaquin Valley (WSJV) by econometrically estimating how farmers change crop choices in response to different soil salinity levels. I use high-resolution remote-sensed soil salinity and remote-sensed crop data during 2007–2016 to capture fine-scale spatial variations inherent in agricultural settings, controlling for other soil properties and climate conditions on irrigated lands at each field.

My estimates show that as the level of salinity increases, the probability that salt-tolerant crops will be selected for cultivation increases. Similarly, salt-sensitive crops are less likely to be selected as salinity increases. This suggests that farmers adapt corresponding to the degree of salinity. However, it is necessary to note that it is possible that my estimates have some endogeneity bias. Briefly, crop choice affects the amount of water applied which could affect salinity. Unfortunately, I cannot determine the direction of the endogeneity bias because applying more water can increase or decrease soil salinity depending on the degree of salinity of the water applied.

3.2. Background on Salinity in WSJV

The WSJV is on the west side of the San Joaquin Valley (SJV) in California (**Figure 3.1A**), one of the most productive farming regions in the world. An arid and semiarid region, the SJV cultivates more than 250 unique crops via irrigated agriculture and the annual gross value from such agricultural production is more than $25 billion (U.S. Environmental Protection Agency 2012). The WSJV is challenged by extensive accumulation of soil salinity and such soil contamination has accelerated by regional climate and hydrology conditions. A review of the regional environment setting provides a better understanding of the effect of salinity on farmers' crop choice decisions.

As shown in the **Figure 3.1B**, the WSJV spans across 5,600 square miles and includes two subbasins of the SJV groundwater basin, the Delta–Mendota subbasin where Delta–Mendota Canal passes through and Westside subbasin where California Aqueduct passes through. The WSJV's aquifer system is constituted of late Tertiary to Quaternary age alluvium[19] originated from the Coast Mountain Range to the west and the Sierra Nevada Mountain Range to the east (Fram 2017b).

The alluvial aquifer already contains native levels of soluble salt. That is due to that almost all waters draining from a bedrock of the aquifer naturally possess major mineral components including salts, which were trapped during deposition of the sediment forming the

[19] Alluvium is alluvial deposits consisting mainly of poorly to moderately permeable yellowish-brown gravel, sand, silt, and clay.

bedrock. Specifically, alluvium originating from the Sierra Nevada Mountain Range generally has lower salinity since most surface water from infiltration of precipitation as snowmelt dominates Sierra Nevada Mountain Range. Whereas alluvium originated from the Coast Mountain Range has higher salinity since saline marine sediments from below deep aquifer or the ocean dominate the Coast Ranges Mountain Range.

Irrigation water applied in the WSJV is partially imported as surface water from the Sierra Nevada alluvium and partly pumped as groundwater in the Coast Range alluvium (Dubrovsky et al. 1999). Accordingly, if irrigation water imported from surface water of the Sierra Nevada alluvium is applied, it is likely to be low salinity in soils. Conversely, if irrigation water derived from the Coast Ranges alluvium is applied, the WSJV soils naturally contain high salinity. This implies that the cross-sectional variation of soil salinity across the spatial units can exist depending on which source of adjacent irrigation water is used.

In essence, the direct source of salinity in WSJV stems from the marine origin of Coastal Range alluvium (Scudiero, Skaggs and Corwin 2014). Due to the geographical location of WSJV more closely adjacent to the Coast Ranges Mountain Range, it is overall susceptible to saline coastal sediments. This vulnerability is compounded by other disturbances, such as the WSJV's climate and hydrology conditions.

First, there is an instant reduction in both surface water runoff and groundwater recharge by arid and semiarid climate and by occasional drought. As a result, reduced freshwater limits the availability of water needed to flush existing salts, and replaces the reduced volume of freshwater with groundwater pumping or groundwater reuse. Second, there is a saltwater inflow by overpumping for irrigated agriculture and by the lack of soil drainage. Once water tables fall by overpumping groundwater, pumping wells need to be drilled deeper to reach the water. In this process, pumping can cause the upward intrusions of saltwater into the fresh aquifer, which ultimately can damage aquifer and contaminate land by exacerbating soil salinity (**Figure 3.2**).

The reality is that there is a substantial delay before a reduction in the effects of water availability is fully reflected in its resultant salt accumulations since natural soil drainage can initially offset the effect (Beare and Heaney 2002). However, the WSJV suffers from a low-permeability soil drainage problem. Indeed, the WSJV's soils are dominated by the finer-textured Corcoran clay[20] sourced from saline alluvium deriving from California's Southern Coast Range (Valley 2009; Scudiero et al. 2014) and is estimated that approximately 60% of the soils were saline by the 1980s due to the influence of soil texture (Scudiero, Skaggs and Corwin 2015).

Possible management practices to mitigate soil salinity include salinity leaching, saline drainage water reuse, land retirement, and changes to salinity-tolerant crops. Salinity leaching is basic and traditional management practice for controlling salinity. This practice is to flush the existing salts below the root zone of crops by applying more water (Fipps 2003; Welle and Mauter 2017). Yet, this practice, unlike some regions wherein average snowpack or rainfall can supply adequate water availability (i.e., the availability of water recharge) for leaching, may be limited in WSJV with limited water availability. Indeed, California's 5-year drought reduced approximately 30% of available surface water in the state of California, and an estimated $600 million in pumping cost occurred to replace the reduced volume with groundwater pumping

[20] Finer-textured Corcoran clay soils usually have weak soil drainage levels by less permeability.

(Lund et al. 2018). These losses[21] were concentrated in the SJV with the inferior climate and hydrology environment and resulted in more pronounced salinity (Scudiero et al. 2015).

The reuse of drainage water to reclaim salt-affected soils can be a useful practice in places wherein irrigation water is scarce in terms of supplementing water needed (FAO 2019b). However, this is only effective when original irrigation water with good-quality is reapplied. It is generally known that drainage water is not as good as the original irrigation water. That is due to that recharge under post-development conditions has inferior water-quality than recharge under pre-development conditions (Fram 2017a). Specifically, under pre-development conditions, groundwater was recharged by infiltration of precipitation, river, and scattered streamflow from the Coast Ranges through alluvial fans and from the San Joaquin and Jings Rivers in the basin, and groundwater was discharged principally by evapotranspiration from crops (Belitz and Heimes 1990; Fram 2017a). Whereas under post-development conditions, groundwater is recharged mostly by infiltration of groundwater and surface water used for irrigation, and groundwater is discharged mostly by pumping for irrigated agriculture, besides evapotranspiration from crops, and engineered drainage (California Department of Water Resources 2006; Faunt 2009). Therefore, salt accumulation aggravates in irrigated areas.

Another management practice is land retirement, namely leaving saline land fallow (Connor et al. 2012). It can often be a difficult decision for farmers concerning economic returns, which is chosen as a last resort when the land cannot be restored from salinity.

Instead, switching crops to more salinity-tolerant crops, as another primary management practice to reduce the negative impacts of soil salinity, is a more popular alternative to fallow

[21] Drought has restricted the availability of irrigation water and thereby leading to reduced irrigated land drastically. Detail information on the economic impacts of the drought, see Howitt et al. (2014, 2015).

lands for farmers. This practice is also an instant and relatively easy adaptation compared to other possible alternatives aforementioned, while continuously allowing to cultivate, albeit the land's productivity is lower due to salinity.

3.3. Data Description

The overall process of constructing the final dataset is to spatially merge the soil salinity data with crop type classification with ArcGIS. By additionally merging other data needed for my empirical analysis on the WSJV with statistical software, I compose a field-level dataset for the period 2007–2016 including 139,060 unique fields, which covers five counties (i.e., Merced, Fresno, Kings, Tulare, and Kern). The final dataset contains records on the crop type classification, five levels of soil salinity measured by the electrical conductivity, other soil properties, and climate conditions at each field. Note that crop type classification is the only variable that changes over time in the dataset. **Table 3.1** presents descriptive statistics for all variables used in the analysis.

3.3.1. Cropland Data Layer

The records of crop-specific land cover data for field-level crop choice decision is derived from the national Cropland Data Layer (CDL) provided by the National Agricultural Statistics Service (NASS) of the National Agricultural Statistics Service (USDA). The CDL is a raster-formatted data with 30m spatial resolution (i.e., one pixel size on the ground is 30m×30m) and produced annually for the conterminous U.S. via satellite imagery from the Landsat 8 OLI/TIRS sensor and the Disaster Monitoring Constellation DEIMOS-1 and UK2 sensors collected based on the current growing season (Boryan et al. 2011, 2012; USDA-NASS 2016; Yan and Roy 2016). In this study, the California CDL data for the years 2007–2016 were obtained through the CropScape. The 2007–2016 CDL data show total crop mapping accuracies[22] range from 89.53% to 97.22% for 247 crop categorization code. Non-agricultural land cover classes, for example, fallow[23], forest, shrubland, barren, water, wetlands, and open space, were excluded from the code, along with missing values (i.e., crop codes 248 and 250). Finally, 72 crops are selected for inclusion in the data.

I select a sample point within each field boundary spatially joined with the Moderate Resolution Imaging Spectroradiometer Irrigated Agriculture Data for the U.S. (MIrAD-US) land cover in Subsection 3.3.2 because I focus on field-level decisions instead of pixel-level[24]. These Common Land Unit (CLU) field points are defined as the centroid of the field. Next, the CDL data are assigned to given the CLU field points using a spatial join tool in ArcGIS (ArcGIS Resource Center 2018) to capture field-level crop choice decision. Based on the spatially joined crop data, I made two crop categories for econometric estimation: (i) five categories (i.e., Field Crops, Forage Crops, Fruit Crops, Vegetable Crops, Other Crops[25]) and soil salinity tolerance level by each crop type followed weighted average in each crop type; as well as (ii) seven categories by selected major crops among 72 crops in the study region according to their share

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[22] The overall accuracies consider only row crops and seasonal fruit and vegetables, not non-agricultural land cover classes.

[23] The reason why fallow was excluded from the crop choice data is that soil salinity on the corresponding fields was not estimated Scudiero et al. (2017).

[24] Refer to the supplementary appendix in Hendricks et al. (2014) for further details on constructing the CDL data. I followed their process with only the study region changed and orchards excluded.

[25] Other crops for five categories by crop type include seed crops, herbs, and double crops.

(i.e., Alfalfa, Cotton, Winter Wheat, Tomato, Corn, Almond, Others[26]) and soil salinity tolerance level by each selected major crop followed crop tolerance index.

3.3.2. Soil Salinity

My key variable of interest that impacts crop choices, soil salinity, was defined as the occurring when dissolved salts in the water are transpired by crops or evaporate to the air, leaving salts behind at the soil surface. I used remote-sensed soil salinity data measured by the electrical conductivity of saturated soil paste extract (EC_e, ds/m: deciSiemens per meter), which is a measure of the concentration of salts in soil. This remote-sensing approach with high-resolution, as Scudiero et al. (2017)[27] asserts, provides a more precise assessment of soil salinity than traditional sampling methods with coarse resolution, allowing capture abrupt changes between neighboring fields. Specifically, I focused on the soil salinity in the root zone (i.e., soil volume down to a depth of about 0 to 4 feet), which is the salinity indicator that gets the most attention in the agricultural evaluation, not salinity on the soil surface (i.e., sometimes visible as salt crusts).

The remote-sensed root zone soil salinity in the WSJV covering the five counties, as shown in **Figure 3.3**, is obtained from Scudiero et al. (2017) via personal communication. **Figure 3.3** shows five levels for root zone salinity quantified as the EC_e classified by Richards (1954) and percentage of at each level in the total area is as follows: 0–2 dS/m nonsaline (433,777 acres, 25%); 2–4 dS/m slightly saline (349,007 acres, 40%); 4–8 dS/m moderately saline (436,476 acres, 25%); 8–16 dS/m strongly saline (374,000 acres, 22%) and >16 dS/m

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[26] Others for seven categories by selected major crops include all remaining crops grown on a small scale except seven major crops.

[27] For additional well-documented papers on the advantages of using the use of remote sensing for assessing and mapping soil salinity, see (Lobell 2010; Allbed and Kumar 2013).

extremely saline (145,070 acres, 8%). This salinity data is assigned to given CLU field points by using spatial join in ArcGIS after the CDLs joined (see **Figure 3.4**).

3.3.3. Irrigation Classification

To identify irrigated agricultural lands in WSJV, I use the MIrAD-US land cover, which is from the U.S. Geological Survey. The MIrAD-US reveals detailed spatial patterns of irrigation change across the nation, including the WSJV and describe. These data are a measure of irrigation status classified from remote sensing at 250m spatial resolution (Brown, Maxwell and Pervez 2009; Boryan et al. 2012; Brown and Pervez 2014). The most recent 2012 MIrAD-US was used as a measure of irrigation status in this application and is spatially joined to the USDA's Farm Service Agency CLU boundary data (Woodard 2016a,b). The CLU boundary data represent field boundaries.

3.3.4. Soil Properties

Data on soil properties such as soil drainage classes and other properties such as bulk density, root zone available water storage, soil organic carbon, soil pH, and the log of slope are from the Soil Survey Geographic provided by the Natural Resource Conservation Service. The soil data are aggregated to the map unit level. Then they are merged to the field by the map unit associated with the point at each field. These soil properties were selected based on the Soil Quality Indicator Sheets from the USDA's Natural Resources Conservation Service (USDA-NRCS 2019).

Soil drainage classes mean the frequency and duration of wet periods during soil formation. It refers to natural soil drainage condition, unlike altered drainage, which is mainly caused by the result of artificial drainage or irrigation; in summary, it is the rate at which water is removed from soils. This natural soil drainage for the WSJV is categorized as four discrete classes as follows: well drained, moderately well drained, somewhat poorly drained, and poorly drained. These soil drainage classes can affect crop choice in terms of accelerating soil salinity but can also directly affect crop choice through other factors than salinity. As aforementioned in Subsection 3.3.1, the clay soils usually have poor drainage levels by less permeability compared to the sand soils with a faster infiltration water rate. This implies that the clay soils may retain essential nutrients that foster crop growth; at the same time, that salinity results in remaining at or near the ground surface since water is removed from the soil so slowly. Thus, the higher the clay percentages, the more severe drainage issues, thereby more remaining salinity, especially in the WSJV with finer-textured Corcoran clay soils.

As other soil properties, bulk density indicates the soil compaction and reflects the movement of air and water through the soil. Bulk density above thresholds means impaired function because high bulk density has low soil compaction and porosity, thereby restricting root growth and impacting the movement of air and water through the soil. Root zone available water storage[28] is the plant-available water volume that the soil can hold within the root zone. This water holding in root zone can be stored and used for crop uptake, and thereby it is a critical variable affecting crop yield potential and yield stability. Soil organic carbon[29] improves various soil structure or fertility by providing energy sources for soil microorganisms and nutrient availability through mineralization, thus affecting plant growth. Soil pH (H_2O)[30] describes the

[28] Further information on this variable beyond the Soil Quality Indicator Sheets, see Leenaars et al. (2015).

[29] Further information on this variable beyond the Soil Quality Indicator Sheets, see Thiele-Bruhn (2016).

[30] Further information on this variable beyond the Soil Quality Indicator Sheets, see Batjes (1995).

degree of acidity, neutral, or alkalinity of a soil sample expressed as a numerical pH value and indicates soil health by affecting various chemical or biological activities in the soils. The pH is measured in a 1:1 soil to water ratio method in this study. Soil pH levels that are too high or too low cause declines in crop yields, suitability, or plant nutrient availability, resulting in deterioration of soil health. The average National Commodity Crop Productivity Index (NCCPI)[31] provides condensed information about average crop productivity based on the inherent soil properties. The NCCPI incorporates together several factors related to crop production, such as landscape and climate characteristics, and imposes a rating (score) on the production.

Elevation indicates height from fixed reference point and slope is degree to which a surface is tilted and is a measure of change in elevation. Although slope is not a direct indicator of soil properties, it affects crop productivity by influencing the distribution of soil moisture near the land surface. For example, steeper slopes generally have lower soil moisture than flatter slopes due to lower infiltration rates, rapid subsurface drainage, and higher surface runoff (Famiglietti, Rudnicki and Rodell 1998). Also, soil loss tends to increase with steep slopes (Liu et al. 2000; Kapolka and Dollhopf 2001). I take the log of slope to use a more normally distributed variable across fields.

3.3.5. Climate Conditions

I measure the climate with precipitation and degree days (DDs) in each field based on the daily weather data (i.e., maximum temperature, minimum temperature, and total precipitation) provided from PRISM Climate Group. I construct long-run average weather variables (i.e.,

[31] For more detail of the NCCPI, refer to as Dobos, Sinclair Jr, and Hipple (2008).

1981–2016) given that long-run average weather (i.e., the climate) is most likely to have an impact on what crop is planted.

For the impact of temperature, I follow the piecewise linear approach, which is applied to prediction of nonlinear temperature effects by referring to Schlenker and Roberts (2009) and Tack, Barkley and Nalley (2015). The piecewise linear model is estimated by including DDs as controls. DDs are a measure of cooling and heating defined as the number of degrees calculated by the sum of degrees above a lower threshold and below an upper threshold during the growing season Fraisse and Brown (2011). DDs are calculated between 0 and 10, 10 and 20, 20 and 30, 30 and 40, and above 40 for a growing season of March 1–September 30. Next, I averaged these DDs and precipitation variables for 36 years of data and then finally merge with field-level CDL data.

3.4. Model

In this section, I explain the conceptual model and empirical model specification underlying farmers' crop choice decisions based on existing studies of crop choice decisions using a multinomial logit model (MNL) (e.g., Wu et al. 2004, Kurukulasuriya and Mendelsohn 2007; Seo and Mendelsohn 2008a,b; Seo et al. 2008; Fleischer, Mendelsohn and Dinar 2011).

3.4.1. Conceptual Model

Each farmer cultivating a field i in year t is assumed to make a crop choice decision to maximize expected profit. Thus, the profit function is composed of $\pi_{itj} = V_j(X_{it}) + \varepsilon_{itj}$ and crop j will be chosen if $\pi_j \geq \pi_k$ for all $j \neq k$. The profit function consists of two parts, the deterministic component V_j and the random component ε_{itj}. The V_j is a function of a vector of explanatory variables X_{it} that include variables to indicate different levels of soil salinity, soil properties, and climate conditions. Typically, the deterministic portion V_j can be assumed in separable linear fashion, the expected profit, π_{itj} can be expressed as:

$$\pi_{itj} = X'_{it}\beta_j + \varepsilon_{itj}. \tag{1}$$

Since V_j is the portion observed by the econometrician and ε_{itj} is the unobserved portion, making the choice in field i in year t to be represented in a probability manner as follows (Baltas and Doyle 2001):

$$Pr(C_{it} = j) = Pr\left(\pi_{itj} \geq \pi_{itk}\right) = Pr\left(X'_{it}\beta_j + \varepsilon_{itj} \geq X'_{it}\beta_k + \varepsilon_{itk}\right) \quad for\ \forall_{j \neq k} \tag{2}$$

Assuming that ε_{itj} follows an independent and identical Gumbel distribution, also known as Type I Extreme Value distribution, then the probability of choosing crop j can be calculated using the familiar MNL as follows (Mcfadden 1981):

$$P_{itj} = Pr(C_{it} = j) = \frac{exp(X'_{it}\beta_j + \varepsilon_{itj})}{\sum_{k=0}^{J-1}(X'_{it}\beta_k + \varepsilon_{itk})}, \quad j = 0,1,2, \ldots, J-1 \tag{3}$$

This method is generally used to predict the probabilities of three or more possible categorical outcomes given a set of explanatory variables.

3.4.2. Econometric Model

I estimate how farmers change crop choices in response to different soil salinity levels with a field-level dataset covering a 9-year period. Given five salinity levels, soil properties, and climate conditions, together with year fixed effects and county fixed effects, the MNL with fixed effects model is specified as follows:

$$P_{itj} = Pr(C_{it} = j|X_{it}) = \frac{exp(X'_{it}\beta_j + \varepsilon_{itj})}{\sum_{k=0}^{J-1}(X'_{it}\beta_k + \varepsilon_{itk})} \tag{4}$$

$$= \frac{exp(\beta_{j1}Salinity_i+\beta_{j2}Soil_i+\beta_{j3}Climate_i+\gamma_j Year_t+\delta_j County_i)}{\sum_{k=0}^{J-1} exp(\beta_{k1}Salinity_i+\beta_{k2}Soil_i+\beta_{k3}Climate_i+\gamma_k Year_t+\delta_k County_i)}$$

where *i* denotes 139,060 unique fields and *t* indexes time period 2007–2016. *j* represents different crop choices and two alternative classifications were used in model estimation: (i) five categories *J*=$\{\text{Other Crops, Field Crops, Forage Crops, Fruit Crops, Vegetable Crops}\}$ and (ii) seven categories *J*=$\{\text{Others, Alfalfa, Cotton, Winter Wheat, Tomato, Corn, Almond}\}$. $P_{itj} = Pr(C_{it} = j|X_{it})$ denotes the probability of observing crop *j* on field i in year t.

Thus, β_j is the coefficient vector including the intercept β_{0j} and β_{kj} are the slope coefficients. Since the probabilities must sum to one, I restrict $\beta_j = 0$ for one of the alternatives used as the base category. Consequently, only 4 (*J-1*) for and 6 (*J-1*) are estimates for five categories and seven categories, respectively. In this study, I apply “other crops” as the base category for five categories and “other” as the base category for seven categories.

$Salinity_i$ has 5 salinity levels: 0–2 dS/m, nonsaline; 2–4 dS/m, slightly saline; 4–8 dS/m, moderately saline; 8–16 dS/m, strongly saline; and >16 dS/m, extremely saline. $Soil_i$ contains soil drainage classes, bulk density, root zone available water storage, soil organic carbon, soil pH, and the log of slope of field i. $Climate_i$ includes precipitation and DDs of field i. $Year_t$ are year fixed-effects to capture the effect of macro-level shocks which affect all fields, such as changes in crop prices, energy prices, and other input prices. $County_i$ are county fixed-effects to capture differences across counties. Robust standard errors are clustered at the county level to allow error correlation for a given field over time as well as spatial correlation within a county. I allow fields within a county to be spatially correlated, but independent across the counties.

The coefficients obtained from the above MNL model are difficult to interpret directly unlike the slope coefficients of the Ordinary Least Squares regression model (Greene, William

2012; Wulff 2015). In particular, simply with the positive coefficients, the increase in the explanatory variable does not necessarily mean an increase in the selection probability of a particular outcome. Instead, the marginal effects (MEs) of the explanatory variables for the categories are calculated as:

$$ME_{itj} = \frac{\partial P_{itj}}{\partial X_{it}} = \frac{\partial Pr(C_{it} = j|X_{it})}{\partial X_{it}} = P_{itj}(\beta_j - \overline{\beta_\iota}), \text{ where } \overline{\beta_\iota} = \sum_k Pr(C_{it} = k|X_{it})\beta_k \quad (5)$$

Here, X_{it} is the explanatory variables including the soil salinity variable as a key treatment variable, and $\overline{\beta_\iota}$ is a probability-weighted average of the coefficients for other alternative combinations.

The MEs are nonlinear since they depend on the probabilities varying across all explanatory variables in the model. This implies that the MEs are not constant as well as they may be positive for some values of explanatory variables or they can be negative for others. The MEs are often calculated at the means (MEM) of the explanatory variables as follows:

$$\text{MEM} = \bar{P}_j(\beta_{kj} - \overline{\beta_\iota}) \quad (6)$$

where $\bar{P}_{jt}$ computed by holding X_{it} at their mean values. In this study, I evaluated the MEM. Another way, average marginal effects (AME)[32] based on actual values of the explanatory variables can be used. While MEM and AME yield different estimates, there is no consensus as to which of the two is the most representative (Greene, William 2012; Wulff 2015), both can be utilized to get MEs.

Equation (6) represents MEM for continuous variables. Yet, I have categorical variables, such as five soil salinity levels and four soil drainage classes. In such case, taking the difference of estimated probabilities between the different levels of the categorical variable is suitable in

[32] AME $= \frac{1}{n}\sum_{i=1}^{n} P_{itj}(\beta_{kj} - \overline{\beta_\iota})$

analyzing the MEM. If, say, x denote the dummy explanatory variable to capture the categorical effect and X^*denote the other explanatory variables at their means. The effect due to the discrete change for categorical variable, x on the predicted probabilities of $C_{it} = j$ is

$$\text{ME} = Pr[C_{it} = j|x = 1, X_{it}^*] - Pr[C_{it} = j|x = 0, X_{it}^*]. \tag{7}$$

3.5. Results

The results in **Table 3.3** and **Table 3.4** present the marginal effects of all variables from the MNL regression models in five categories and seven categories by selected major crops, respectively. The interpretation of the marginal effects on continuous variables represents the change in predicted probabilities of choosing a particular alternative due to a one-unit change in a particular variable. The interpretation of the marginal effects on categorical variables (such as five soil salinity levels and four drainage classes) represents the difference in predicted probabilities of choosing a particular alternative due to a variable taking that particular level compared to the base category. The results of particular interest are the marginal effects of different soil salinity levels on crop choices as a key variable. The marginal effects of the levels inform about how the change in salinity encourages or discourages the probability of a particular crop being grown on a given field.

Table 3.3 indicates the marginal effects in five categories. Overall, at all levels for soil salinity except for slightly saline soil level, the marginal effects of field crops, forage crops, fruit crops, and vegetable crops show signs that match expectations in the light of the relative salinity tolerance index for those crops. They are also statistically significant.

Specifically, the probability that a field is planted to field crops is 3.16% smaller and to vegetable crops is 5.31% smaller if it has slightly saline soils (i.e., EC_e 2-4 dS/m) rather than nonsaline soils (i.e., EC_e 2-4 dS/m). These results are statistically significant at the 1% level of significance. Meanwhile, the probability that a field is planted to forage crops is 5.98% larger if it has slightly saline soils rather than nonsaline soils, and its result is statistically significant at the 1% level. These results are in contradiction with my expectation, based on the relative salt tolerance index for those crops. Perhaps because this level is close to the natural saline level and does not substantially affect yield loss.

At the slightly saline soils or higher, the probability that a field is planted to fruit crops is 2.24% larger, while to vegetable crops is 9.38% smaller if it has moderately saline soils (i.e., EC_e -8 dS/m) rather than nonsaline soils. These results are both statistically significant at the 1% level. The probability that a field is planted to forage crops is 5.98% larger if it has slightly saline soils rather than nonsaline soils, and its result is statistically at the 1% level. The probability that a field is planted to field crops is 17.26% larger and to fruit crops is 8.32% smaller if it has strongly saline soils (i.e., EC_e 8-16 dS/m) rather than nonsaline soils. The results of field and fruit crops show statistical significance at the 5% and 1% levels, respectively. While, the probability that a field is planted to vegetable crops is 16.33% smaller if it has strongly saline soils rather than nonsaline soils, and its result is statistically significant at the 1% level. The probability that a field is planted to field crops is 25.84% larger and to fruit crops is 11.62% larger if it has extremely saline soils (i.e., ECe >16 dS/m) rather than nonsaline soils. The results of field and fruit crops show statistical significance at the 5% and 1% levels, respectively. While, the probability that a field is planted to forage crops is 16.48% smaller and to vegetable crops is 15.72% smaller if it has extremely saline soils (i.e., ECe >16 dS/m) rather than nonsaline soils. The results of field and fruit crops show statistical significance at the 10% and 1% levels, respectively.

As the level of salinity increases, the probability that salt-tolerant crops will be selected for cultivation increases gradually. In contrast, salt-sensitive crops are incrementally less likely to be selected as cultivated crops. This suggests that the extent of farmers' adaptations to salinity change correspondingly to the degree of salinity.

One notable result comes from fruit crops with all positive and statistically significant marginal effect results at the slightly saline soils or higher. In the light of the relative salinity tolerance index, I anticipated that the choice probability of salt-sensitive fruit crops being grown on a given field would decrease. Possibly this result may be due to that most crops composing fruit crops grow perennially in all locations of the study region. Especially almonds, which account for the largest portion of fruit crops, are representative of perennial crops and crop rotation[33] will not be applicable to perennial crops like almonds. That said, almond trees generally live for 25 to 30 years, depending on the growing conditions. They begin to decline slowly after reaching their maximum yields for about 15 years and given the roughly seven years for the almond tree to reach the point where they can launch for commercial production, the peak production is only for the remaining seven years (Almond Board of California 2016; Ternus-Bellamy 2019). Given the long time and other input costs compared to annual crops (i.e., involving relatively higher sunk costs than the other crops), a slight increase in soil salinity is unlikely to be an incentive to induce an immediate change of choice to different crops.

It is possible that my estimates have some endogeneity bias. For example, if the crop chosen uses much water, and if that water contains much salinity, then water will potentially

[33] Crop rotation is to plant different crops more than two sequentially on the same plot of land for growing season to improve soil health by preventing soil diseases or pests and by optimizing nutrients in the soil (Dufour 2015). However, crop rotation has not confirmed to be an entirely adequate control practice for almond trees (Micke 1997).

increase soil salinity. Alternatively, the farmer could want to grow a crop that uses more water to try to flush the salinity out of the soil and soil salinity will decrease on fields with water intensive crops. Therefore, crop choice depends on how much salinity is in the water being applied and the amount of water applied by crop could affect salinity. Unfortunately, I cannot determine the direction of the endogeneity bias.

Table 3.4 indicates the marginal effects in seven categories by selected major crops in the WSJV according to their share. Overall, except for cotton and almond, the marginal effects of alfalfa, winter wheat, tomato, and corn show signs that match expectations in the light of the relative salinity tolerance index for those crops, at all levels for soil salinity except for slightly saline soil level. They are also statistically significant.

Specifically, the probability that a field is planted to alfalfa is 5.39% larger if it has slightly saline soils (i.e., EC_e 2-4 dS/m) rather than nonsaline soils (i.e., EC_e 2-4 dS/m). This result is statistically significant at the 1% level. Meanwhile, the probability that a field is planted to cotton is 5.65% smaller and to tomato is also 2.20% smaller if it has slightly saline soils rather than nonsaline soils. Both results are statistically significant at the 1% level. Likewise, the result of the five categories above, these all results are in contradiction with my expectation, based on the relative salt tolerance index for those crops.

At the slightly saline soils or higher, the probability that a field is planted to winter wheat is 6.77% larger and almond is 1.05% larger if it has moderately saline soils (i.e., ECe -8 dS/m) rather than nonsaline soils. The results of winter wheat and almond show statistical significance at the 5% and 1% levels, respectively. While the probability that a field is planted to cotton is 8.76% smaller and to tomato is 4.35% smaller if it has moderately saline soils rather than nonsaline soils. Both results show statistical significance at the 10% and 1% levels. Meanwhile, the probability that a field is planted to alfalfa is 10.97% smaller and to corn is 3.02% smaller if it has strongly saline soils rather than nonsaline soils. The results of alfalfa and corn crops show statistical significance at the 5% and 1% levels, respectively. The probability that a field is planted to winter wheat is 17.80% larger and to almond is 4.60% larger if it has extremely saline soils (i.e., ECe >16 dS/m) rather than nonsaline soils. These results show statistical significance at the 1% levels. Whereas, the probability that a field is planted to alfalfa is 17.50% smaller, to cotton is 24.10% smaller, to tomato is 11.67% smaller, and corn is 2.94% smaller if it has extremely saline soils rather than nonsaline soils. The results of alfalfa, cotton, tomato, and corn show statistical significance at the 5%, 1%, 1% , and 5% levels, respectively.

Notable results in the seven categories are for cotton (a field crop) and almonds (a fruit crop). Cotton was expected to be highly selected for farmers facing more salinity because it was a salt-tolerant crop. Its sign is expected to be positive and consistent with the results of field crops in the five categories shown earlier. However, the result was opposite to expectations, and also statistically significant. This may stem from cotton's water use intensity (see **Table 3.2**). Even though cotton is the salt-tolerant crop, farmers are willing to be less likely to choose cotton, due to its high-water use intensity (i.e., average water need: 1000mm/growing period). This high-water need offsets the impact of salinity on the likelihood of choosing a salt-tolerant crop.

Almond, like cotton, has a different statistical sign than expected. The possible reasons for this result are the same as the fruit crops in the five categories shown above. In other words, due to the relatively higher sunk costs than the other crops, no matter how much almonds are salt-sensitive, farmers will not be able to leave from almond cultivation immediately. Moreover, almonds (600mm/growing period) use less water than either walnut in the same fruit crop category or corn and cotton; thus, the effect of salinity on farmers' almond selection also has the potential to increase.

Conversely, winter wheat and corn are field crops as well and showed signs that matched their relative salinity tolerance indices and statistical significance. Moderately salt-tolerant winter wheat is also the best choice for farmers facing salinity because water use intensity (i.e., average water need: 550mm/growing period) is not only resistant to salinity to some extent but also lower water use intensity compared to cotton. Indeed, farmers in the region facing salinity show a high tendency to choose winter wheat. On the other hand, farmers in this region reduce the choice of moderately salt-sensitive corn, as in the case of cotton, but because the corn uses less water than cotton, the magnitude of the decrease is small compared to cotton.

Soil properties and climate conditions also affect crop choice. In **Table 3.3**, as the soil drainage classes are poorly, it decreases the likelihood of selecting moderately salinity sensitive fruit crops. The effect of soil drainage class could partly capture some soil salinity effects because poor drainage can increase soil salinity. This can be seen from field crops and fruit crops. The probability that a field is planted to salt-tolerant field crops is larger if it has more poorly drained soil class relative to a well drained soil class as the base category. Conversely, the probability that a field is planted to salt-sensitive fruit crops is smaller if it has more poorly drained soil class relative to a well drained soil class as the base category. Likewise, seven categories by selected major crops in **Table 3.4** can be interpreted in the same way for the soil drainage classes. In summary, as the soil drainage classes are poorly, it encourages the likelihood of choosing salt-tolerant cotton, while discourages the likelihood of selecting salt-sensitive almond. The results for cotton and almond are matched to the results for field crops and fruit crops, respectively. However, it also possible that the soil drainage class captures other aspects of the soil that affect plant growth so the soil drainage class could be capturing other aspects than soil salinity.

Soil properties such as bulk density and soil pH do not significantly affect crop choice in five crop categories. The seven crop categories are not significantly impacted by bulk density and soil organic carbon. Precipitation has significant effects on all crop categories, and in the case of DDs, between 10°C and 20°C has the most significant impact on crop choice.

3.6. Conclusions

Soil salinity has threatened the agricultural productivity and sustainability in the WSJV, one of the highest crop productivity regions in the United States. The source of salinity in WSJV stems from saline Coastal Range alluvium, yet the lack of freshwater availability by regional climate conditions and saltwater inflow by excessive irrigated agriculture and regional hydrology conditions compound such salinity challenges.

A robust literature examines the effect of salinity in terms of the productivity and crop yields, however, less examines changes in cropping patterns as an adaptation strategy to salinity. I quantify the adaption to soil salinity by farmers in the WSJV by econometrically estimating how farmers change crop choices in response to different soil salinity levels. I use high-resolution remote-sensed soil salinity and remote-sensed crop data during 2007–2016 to capture fine-scale spatial variations inherent in agricultural settings, controlling for other soil properties and climate conditions on irrigated lands at each field. For robust estimation for farmers' crop choices, I estimate the multinomial logit model with fixed effects for two crop classifications: five categories and seven categories by selected major crops in the study region.

My estimated total marginal effect shows that basically, as the salinity level increases, the probability of choosing a salt-tolerant crop increases. This chapter has focused on changes in cropping decisions, which is likely to be more substantial in California than Kansas because California has a more diverse range of crops that farmers choose from. Unfortunately, I do not have access to water use data in California. Future research could quantify the extensive and intensive margin changes in water use In California if data were available and compare to the results for Kansas in Chapter 1.

My results provide useful information for farmers and policymakers on how farmers adjust cropping choices in response to soil salinity in irrigated lands. This information could be used in deriving a reasonable picture of adaptation to it when they make agricultural decisions under more complex environments due to a variety of factors threatening agricultural production and sustainability. Specifically, my work makes an additional contribution to a much broader literature in the WSJV, confined to assessing, sampling or mapping soil salinity at regional and state levels.

3.7. Tables

Table 3.1. Descriptive Statistics

Outcome Variables	Obs	Mean	Std.Dev.	Min	Max
Five categories by crop type					
Field Crops	139807	0.44	0.14	0.04	0.93
Forage Crops	139807	0.27	0.13	0.00	0.70
Fruit Crops	139807	0.08	0.10	0.00	0.94
Vegetable Crops	139807	0.13	0.14	0.00	0.81
Other Crops	139807	0.08	0.06	0.00	0.42
Seven categories by selected major crops					
Alfalfa	139807	0.26	0.13	0.00	0.69
Cotton	139807	0.20	0.12	0.00	0.82
Winter Wheat	139807	0.13	0.09	0.01	0.68
Tomato	139807	0.09	0.10	0.00	0.70
Corn	139807	0.05	0.05	0.00	0.47
Almond	139807	0.03	0.05	0.00	0.65
Others	139807	0.25	0.12	0.01	0.80
Explanatory Variables	Obs	Mean	Std.Dev.	Min	Max
Soil Salinity					
Nonsaline: 0–2 (dS/m)	139807	0.35	0.48	0.00	1.00
Slightly saline: 2–4 (dS/m)[a]	139807	0.30	0.46	0.00	1.00
Moderately saline: 4–8 (dS/m)[a]	139807	0.26	0.44	0.00	1.00
Strongly saline: 8–16 (dS/m)[a]	139807	0.08	0.27	0.00	1.00
Extremely saline: >16 (dS/m)[a]	139807	0.01	0.11	0.00	1.00
Soil Properties Variables					
Moderately well drained[b]	139753	0.13	0.34	0	1
Somewhat poorly drained[b]	139753	0.2	0.4	0	1
Poorly drained[b]	139753	0.27	0.44	0	1
Bulk density (g/cm3)	139165	1.44	0.10	1	1.65
Root Zone Available Water Storage (mm)	139666	190.32	51.40	0	270
Soil Organic Carbon in 0–150cm depth (kg/m2)	139577	6815.35	3349.72	92.44	27709.79
Soil pH	139165	8.09	0.42	4.83	9.80
National Commodity Crop Productivity Index	139595	0.10	0.05	0	0.44
Log of slop (%)	139753	0.83	0.59	0	12
Climate Conditions Variables					
Precipitation (mm)	139807	214.71	40.83	140.57	302.77
Degree days between 0°C and 10°C	139807	6406.58	210.73	5945.26	6822.23
Degree days between 10°C and 20°C	139807	3076.06	195.18	2669.43	3443.63
Degree days between 20 °C and 30°C	139807	998.3	111.37	767.02	1213.49
Degree days between 30°C and 40°C	139807	163.22	34.37	83.18	238.61
Degree days greater than 40°C	139807	0.67	0.42	0.01	2.59

[a]Five soil salinity levels measured by the electrical conductivity of saturated soil paste extract (EC_e) and the base category is “Nonsaline: 0–2 (dS/m)”.
[b]The base category for four soil drainage classes is “Well drained”.

Table 3.2. Soil Salinity Tolerance Indexes and Water Use Intensity

Crop Code	Crop Name	Crop Type	Salinity Tolerance	0% Yield Loss (ECe, dS/m)	50% Yield Loss (ECe, dS/m)	Share (%)	Growing Period (days)	Average Growing Period (days)	Water Need (mm/growing period)	Average Water Need (mm/growing period)
1	**Corn**	**Field**	**MS**	**1.7**	**5.9**	**4.94**	**125-180**	**152.5**	**500-800**	**650**
2	**Cotton**	**Field**	**T**	**7.7**	**17.0**	**19.82**	**180-195**	**187.5**	**700-1300**	**1000**
3	Rice	Field	S	3.0	7.2	0.15	90-150	120	450-700	575
4	Sorghum	Field	MT	4.0	11.0	0.28	120-130	125	450-650	550
12	Sweet Corn	Vegetable	MS	1.7	5.9	0.06	80-110	95	500-800	-
21	Barley	Field	T	8.0	18.0	1.56	120-150	135	450-650	550
22	Durum Wheat	Field	T	5.9	13.0	1.11	120-150	135	450-650	550
23	Spring Wheat	Field	T	6.0	13.0	0.01	120-150	135	450-650	550
24	**Winter Wheat**	**Field**	**T**	**6.0**	**13.0**	**12.55**	**120-150**	**135**	**450-650**	**550**
27	Rye	Forage	MT	5.6	12.2	0.07	-	-	-	-
28	Oats	Field	T	2.0	-	2.62	120-150	135	450-650	550
33	Flaxseed	Others	MS	1.7	5.9	1	150-220	185	450-900	675
36	**Alfalfa**	**Forage**	**MS**	**2.0**	**8.8**	**25.64**	**100-365**	**232.5**	**800-1600**	**1200**
37	Other Hay/Non Alfalfa	Forage	MT	6.0	13.0	0.73	-	-	-	-
38	Camelina	Forage	T	-	-	0.02	-	-	-	-
41	Sugarbeets	Field	T	7.0	15.0	0.06	160-230	195	550-750	650
42	Dry Beans	Vegetable	S	1.0	3.6	0.28	95-110	102.5	300-500	400
43	Potatoes	Vegetable	MS	1.7	5.9	0.40	105-145	125	500-700	600
44	Other Crops	Field	-	-	-	0.02	-	-	-	-
46	Sweet Potatoes	Vegetable	MS	1.5	6.0	0.03	-	-	-	-
47	Misc Vegs & Fruits	Others	-	-	-	0.04	-	-	-	-
48	Watermelons	Fruit	MS	-	-	0.27	120-160	140	400-600	500
49	Onions	Vegetable	S	1.2	4.3	1.09	150-210	82.5	350-550	450
50	Cucumbers	Vegetable	MS	2.5	6.3	0.01	105-130	117.5	350-500	425
53	Peas	Vegetable	MS	3.4	-	0.11	90-110	95	350-500	425
54	**Tomatoes**	**Vegetable**	**MS**	**2.5**	**7.6**	**8.68**	**135-180**	**157.5**	**400-800**	**600**
57	Herbs	Others	-	-	-	0.08	-	-	-	-
58	Clover/Wildflowers	Forage	MS	1.5	5.7	0.03	125-130	127.5	579-1320	949.5
59	Sod/Grass Seed	Others	-	-	-	0.01	-	-	-	-
66	Cherries	Fruit	S	1.7	-	0.07	-	-	-	-
67	Peaches	Fruit	S	1.1	1.4	0.04	-	-	-	-
68	Apples	Fruit	S	1.7	4.8	0	-	-	-	-
69	Grapes	Fruit	MS	1.5	6.7	1.68	-	-	-	-
71	Other Tree Crops	Others	-	-	-	0.02	-	-	-	-
72	Citrus	Fruit	S	1.7	4.8	0.03	240-365	302.5	900-1200	1050
74	Pecans	Fruit	MS	-	-	0	-	-	-	-
75	**Almonds**	**Fruit**	**S**	**1.5**	**4.1**	**3.29**	**180-240**	**210**	**500-700**	**600**
76	Walnuts	Fruit	S	1.7	4.8	0.27	130-140	135	700-1000	850

(Continued)

Table 3.2. Continued

Crop Code	Crop Name	Crop Type	Salinity Tolerance	0% Yield Loss (ECe, dS/m)	50% Yield Loss (ECe, dS/m)	Share (%)	Growing Period (days)	Average Growing Period (days)	Water Need (mm/growing period)	Average Water Need (mm/growing period)
204	Pistachios	Fruit	MS	-	-	1.68	-	-	-	-
205	Triticale	Field	T	6.1	14.0	0.68	-	-	-	-
206	Carrots	Vegetable	S	1.0	4.6	0.69	100-150	125	350-500	425
207	Asparagus	Vegetable	T	4.1	18.0	0.13	-	-	-	-
208	Garlic	Vegetable	MS	3.9	6.0	0.69	-	-	-	-
209	Cantaloupes	Vegetable	MS	2.2	9.1	0.78	-	-	-	-
210	Prunes	Fruit	MS	1.5	4.3	0.01	75-95	85	300-600	450
211	Olives	Fruit	MT	2.7	8.4	0.01	150-180	165	600-1000	800
212	Oranges	Fruit	S	1.3	4.8	0.33	240-365	302.5	900-1200	1050
213	Honeydew Melons	Fruit	MS	1.0	-	0.17	120-160	140	400-600	500
214	Broccoli	Vegetable	MS	2.8	8.2	0.03	100-150	125	250-500	375
216	Peppers	Vegetable	MS	1.5	5.1	0.13	120-210	165	600-900	750
217	Pomegranates	Fruit	MS	2.7	8.4	0.28	120-130	125	280-600	440
218	Nectarines	Fruit	S	1.7	4.1	0.01	-	-	-	-
219	Greens	Vegetable	MS	0.9	-	0.01	-	-	250-500	375
220	Plums	Fruit	S	1.5	4.3	0.02	-	-	-	-
222	Squash	Vegetable	MT	4.9	-	0	95-120	107.5	500-650	600
223	Apricots	Fruit	S	1.6	3.7	0.01	-	-	-	-
224	Vetch	Forage	MS	3.0	-	0.06	-	-	-	-
225	Dbl Crop WinWht/Corn	Others	-	-	-	3.90	-	-	-	-
226	Dbl Crop Oats/Corn	Others	-	-	-	1.95	-	-	-	-
227	Lettuce	Vegetable	MS	1.3	5.2	0.33	75-140	107.5	400-600	500
231	Dbl Crop Lettuce/Cantaloupe	Others	-	-	-	0	-	-	-	-
232	Dbl Crop Lettuce/Cotton	Others	-	-	-	0	-	-	-	-
234	Dbl Crop Durum Wht/Sorghum	Others	-	-	-	0	-	-	-	-
235	Dbl Crop Barley/Sorghum	Others	-	-	-	0.03	-	-	-	-
236	Dbl Crop WinWht/Sorghum	Others	-	-	-	0.95	-	-	-	-
237	Dbl Crop Barley/Corn	Others	-	-	-	0.02	-	-	-	-
238	Dbl Crop WinWht/Cotton	Others	-	-	-	0.03	-	-	-	-
242	Blueberries	Fruit	S	2.0	-	0	-	-	-	-
243	Cabbage	Vegetable	MS	1.8	7.0	0.01	120-140	130	350-500	425
246	Radishes	Vegetable	MS	1.2	5.0	0	35-45	40	300-400	350
247	Turnips	Vegetable	MS	0.9	-	0	-	-	-	-

Notes: Compiled from various sources

Table 3.3. Marginal Effects of the Probabilities to Choose Alternative Crops in Five Categories

	Tolerant	Moderately Sensitive	Moderately Sensitive	Moderately Sensitive	Moderately Sensitive
Variables	Field crops	Forage crops	Fruit crops	Vegetable crops	Other crops[c]
Slightly saline: 2–4 (dS/m)[a]	-0.0316***	0.0598***	0.0006	-0.0531***	0.0255***
	(0.0072)	(0.0108)	(0.0016)	(0.0074)	(0.0025)
Moderately saline: 4–8 (dS/m)[a]	0.0153	0.0286	0.0224***	-0.0938***	0.0275***
	(0.0337)	(0.0347)	(0.0038)	(0.0069)	(0.0054)
Strongly saline: 8–16 (dS/m)[a]	0.1726**	-0.0775	0.0832***	-0.1633***	-0.0151
	(0.0869)	(0.0500)	(0.0096)	(0.0369)	(0.0124)
Extremely saline: >16 (dS/m)[a]	0.2584**	-0.1648*	0.1162***	-0.1572**	-0.0525***
	(0.1043)	(0.0886)	(0.0083)	(0.0619)	(0.0119)
Moderately well drained[b]	0.1222***	-0.0433	-0.0494***	0.0132	-0.0427***
	(0.0239)	(0.0294)	(0.0068)	(0.0288)	(0.0102)
Somewhat poorly drained[b]	0.1300***	0.0169	-0.0683***	-0.0528	-0.0259**
	(0.0280)	(0.0347)	(0.0067)	(0.0406)	(0.0088)
Poorly drained[b]	0.1714***	0.0200	-0.0808***	-0.0165	-0.0940***
	(0.0183)	(0.0609)	(0.0084)	(0.0509)	(0.0140)
Bulk density (g/cm3)	-0.3155	0.2176	0.0707	-0.0205	0.0477
	(0.2659)	(0.2135)	(0.0840)	(0.0639)	(0.0552)
Root Zone Available Water Storage (mm)	-0.0006**	-0.0001	0.0003***	0.0003***	0.0001
	(0.0002)	(0.0003)	(0.0000)	(0.0001)	(0.0001)
Soil Organic Carbon in 0-150 cm depth (kg/m2)	-0.0000	-0.0000	0.0000*	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Soil pH	-0.0193	0.0384**	-0.0093**	-0.0153**	0.0055
	(0.0168)	(0.0153)	(0.0038)	(0.0065)	(0.0060)

(Continued)

3.3. Continued

Variables	Tolerant Field crops	Moderately Sensitive Forage crops	Moderately Sensitive Fruit crops	Moderately Sensitive Vegetable crops	Moderately Sensitive Other crops[c]
National Commodity Crop Productivity Index	0.7635***	0.2296	-0.3532***	-0.2666*	-0.3733***
	(0.1548)	(0.2675)	(0.0710)	(0.1593)	(0.0682)
Log of slop (%)	0.0668**	-0.0774***	0.0198**	0.0097	-0.0188
	(0.0215)	(0.0206)	(0.0100)	(0.0068)	(0.0158)
Precipitations (mm)	-0.0021**	0.0029***	-0.0003	-0.0012***	0.0007
	(0.0009)	(0.0007)	(0.0002)	(0.0003)	(0.0005)
Degree days between 0°C and 10°C	-0.0005	-0.0026	0.0007**	0.0024**	-0.0000
	(0.0023)	(0.0024)	(0.0003)	(0.0010)	(0.0010)
Degree days between 10°C and 20°C	0.0002	0.0061**	-0.0015**	-0.0052***	0.0004
	(0.0028)	(0.0026)	0.0005)	(0.0012)	(0.0014)
Degree days between 20 °C and 30°C	0.0018	-0.0091	0.0017	0.0071**	-0.0014
	(0.0028)	(0.0061)	(0.0013)	(0.0025)	(0.0015)
Degree days between 30°C and 40°C	-0.0035	0.0120	-0.0024	-0.0107*	0.0045
	(0.0104)	(0.0159)	(0.0024)	(0.0056)	(0.0031)
Degree days greater than 40°C	-0.0574	-0.0658	0.0526*	0.1713**	-0.1008**
	(0.1979)	(0.2286)	(0.0307)	(0.0628)	(0.0350)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	139,060	139,060	139,060	139,060	139,060

Notes: Asterisks ∗∗∗, ∗∗, and ∗ indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered at the county level are reported in parentheses.

[a]Five soil salinity levels measured by the electrical conductivity of saturated soil paste extract (EC_e) and the base category is "Nonsaline: 0–2 (dS/m)".

[b]The base category for four soil drainage classes is "Well drained".

[c]Other crops for five categories by crop type include seed crops, herbs, and double crops. Other crops are used as the base category.

Table 3.4. Marginal Effects of the Probabilities to Choose Alternative Crops in Seven Categories by Selected Major Crops

	Moderately Sensitive	Tolerant	Moderately Tolerant	Moderately Sensitive	Moderately Sensitive	Sensitive	Undetermined
Variables	Alfalfa	Cotton	Winter Wheat	Tomato	Corn	Almond	Others[c]
Slightly saline: 2–4 (dS/m)[a]	0.0539*** (0.0103)	-0.0565*** (0.0097)	0.0215 (0.0146)	-0.0220*** (0.0024)	0.0028 (0.0039)	0.0005 (0.0022)	-0.0000 (0.0188)
Moderately saline: 4–8 (dS/m)[a]	0.0068 (0.0257)	-0.0876*** (0.0158)	0.0677** (0.0267)	-0.0435*** (0.0042)	-0.0003 (0.0043)	0.0105*** (0.0027)	0.0463** (0.0177)
Strongly saline: 8–16 (dS/m)[a]	-0.1097** (0.0365)	-0.1682*** (0.0102)	0.1678*** (0.0420)	-0.0724*** (0.0102)	-0.0302*** (0.0048)	0.0382*** (0.0034)	0.1745*** (0.0257)
Extremely saline: >16 (dS/m)[a]	-0.1750** (0.0794)	-0.2410*** (0.0372)	0.1780*** (0.0449)	-0.1167*** (0.0076)	-0.0294** (0.0136)	0.0460*** (0.0067)	0.3381*** (0.0632)
Moderately well drained[b]	-0.0188 (0.0310)	0.1659*** (0.0231)	0.0168 (0.0116)	0.0190 (0.0117)	-0.0115** (0.0055)	-0.0305*** (0.0035)	-0.1410*** (0.0256)
Somewhat poorly drained[b]	0.0273 (0.0392)	0.1723*** (0.0390)	0.0278 (0.0216)	-0.0029 (0.0138)	-0.0161 (0.0117)	-0.0205*** (0.0039)	-0.1879*** (0.0400)
Poorly drained[b]	0.0540 (0.0568)	0.2553*** (0.0250)	-0.0097 (0.0332)	0.0111 (0.0216)	-0.0013 (0.0172)	-0.0277*** (0.0031)	-0.2817*** (0.0374)
Bulk density (g/cm3)	0.1845 (0.1609)	-0.1515 (0.2407)	-0.0617 (0.0844)	0.0025 (0.0401)	0.0254* (0.0138)	0.0442 (0.0405)	-0.0434 (0.1286)
Root Zone Available Water Storage (mm)	-0.0003 (0.0002)	-0.0000 (0.0003)	-0.0003** (0.0002)	0.0001** (0.0000)	-0.0001*** (0.0000)	0.0001** (0.0000)	0.0004** (0.0001)
Soil Organic Carbon in 0-150cm depth (kg/m2)	-0.0000 (0.0000)	0.0000*** (0.0000)	-0.0000** (0.0000)	0.0000 (0.0000)	0.0000*** (0.0000)	-0.0000** (0.0000)	0.0000 (0.0000)
Soil pH	0.0379** (0.0186)	-0.0108 (0.0275)	-0.0153 (0.0152)	-0.0087 (0.0055)	-0.0026 (0.0046)	-0.0125*** (0.0019)	0.0119 (0.0207)

(Continued)

Table 3.4. Continued

Variables	Moderately Sensitive Alfalfa	Tolerant Cotton	Moderately Tolerant Winter Wheat	Moderately Sensitive Tomato	Moderately Sensitive Corn	Sensitive Almond	Undetermined Others[c]
National Commodity Crop Productivity Index	0.6541* (0.3351)	0.6327** (0.3163)	0.2207 (0.2361)	-0.0760 (0.0903)	0.0896** (0.0306)	-0.0789*** (0.0170)	-1.4422** (0.5001)
Log of slop (%)	-0.0803** (0.0326)	-0.0005 (0.0298)	0.0205** (0.0080)	0.0065** (0.0030)	-0.0133 (0.0163)	0.0052*** (0.0014)	0.0619** (0.0295)
Precipitations (mm)	0.0032*** (0.0006)	-0.0015** (0.0005)	-0.0012** (0.0005)	-0.0006*** (0.0002)	0.0016*** (0.0002)	-0.0002* (0.0001)	-0.0014 (0.0011)
Degree days between 0°C and 10°C	-0.0041 (0.0025)	-0.0025** (0.0011)	0.0013** (0.0005)	0.0006 (0.0005)	-0.0025*** (0.0004)	0.0001 (0.0001)	0.0071** (0.0024)
Degree days between 10°C and 20°C	0.0080** (0.0029)	0.0040*** (0.0007)	-0.0028*** (0.0006)	-0.0017** (0.0007)	0.0044*** (0.0009)	-0.0003 (0.0003)	-0.0117*** (0.0029)
Degree days between 20 °C and 30°C	-0.0085 (0.0058)	-0.0018 (0.0052)	0.0033 (0.0031)	0.0032** (0.0013)	-0.0028** (0.0010)	0.0004 (0.0005)	0.0062* (0.0033)
Degree days between 30°C and 40°C	0.0091 (0.0148)	-0.0026 (0.0098)	-0.0039 (0.0063)	-0.0058** (0.0027)	0.0020 (0.0014)	-0.0002 (0.0008)	0.0014 (0.0100)
Degree days greater than 40°C	-0.0661 (0.2127)	0.0292 (0.0547)	0.0387 (0.0631)	0.0896** (0.0289)	-0.0638*** (0.0180)	-0.0066 (0.0102)	-0.0210 (0.1482)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	139,060	139,060	139,060	139,060	139,060	139,060	139,060

Notes: Asterisks ∗∗∗, ∗∗, and ∗ indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered at the county level are reported in parentheses.

[a]Five soil salinity levels measured by the electrical conductivity of saturated soil paste extract (EC_e) and the base category is "Nonsaline: 0–2 (dS/m)".

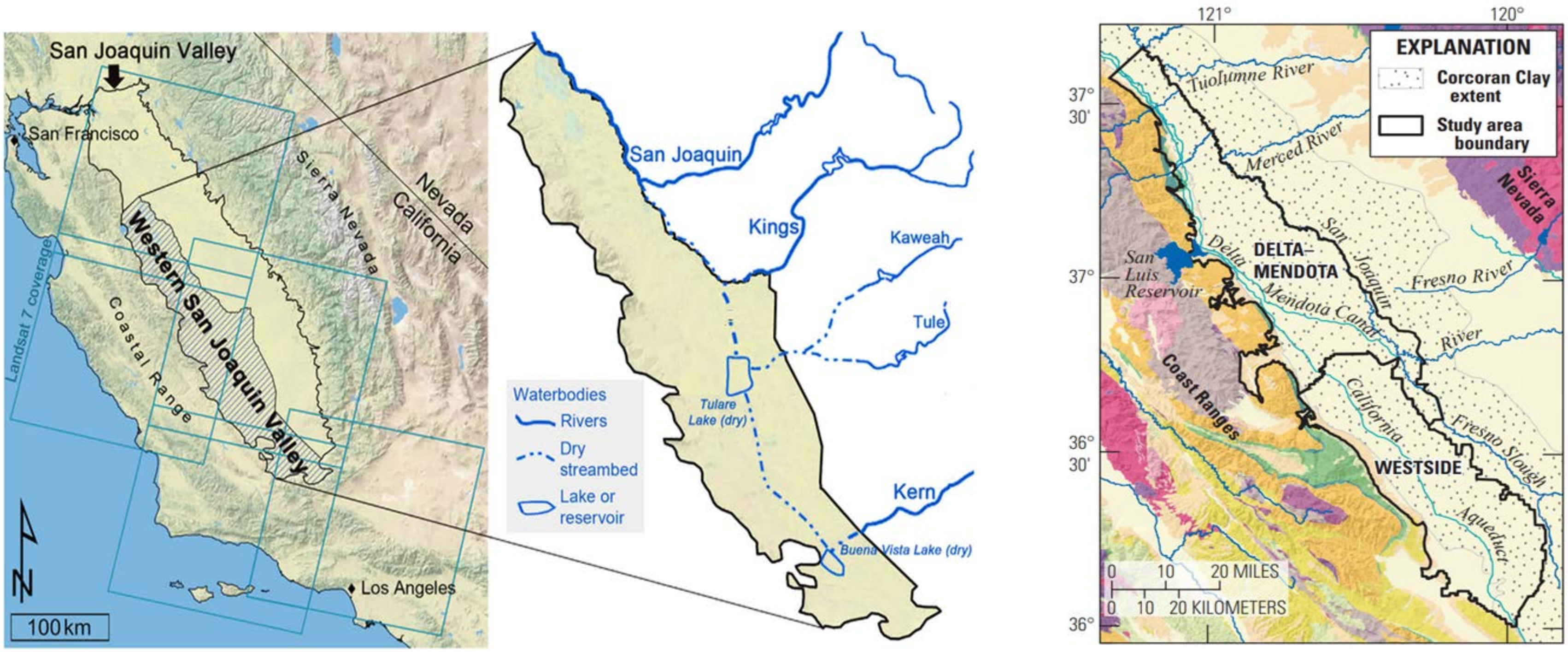
[b]The base category for four soil drainage classes is "Well drained".

[c]Others for seven categories by selected major crops include all remaining crops grown on a small scale except seven major crops. Others are used as the base category.

3.8. Figures

A

B



Note: Modified from Scudiero et al. (2016).

Note: Adapted from Fram (2017a).

Figure 3.1. Overview of the study region: Western San Joaquin Valle California, USA

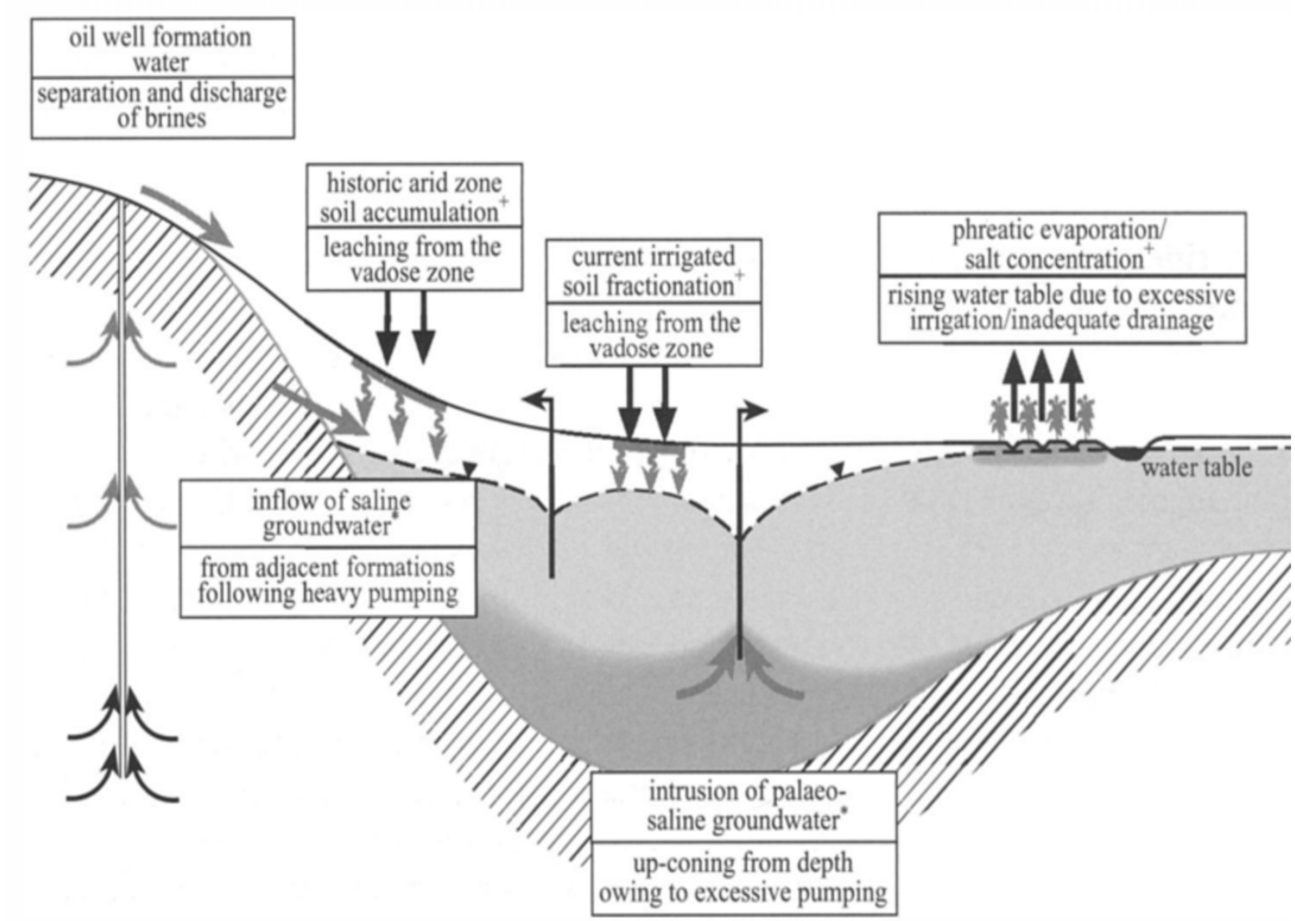


Figure 3.2. Saline water inflow and a subsurface drainage process

Note: Modified from Foster and Chilton (2003). According to the paper, "Those marked with an asterisk are a direct consequence of locally excessive groundwater abstraction but those associated with soil concentration (a plus symbol) are widely distributed. Mid-grey, brackish and saline water; light grey, freshwater".

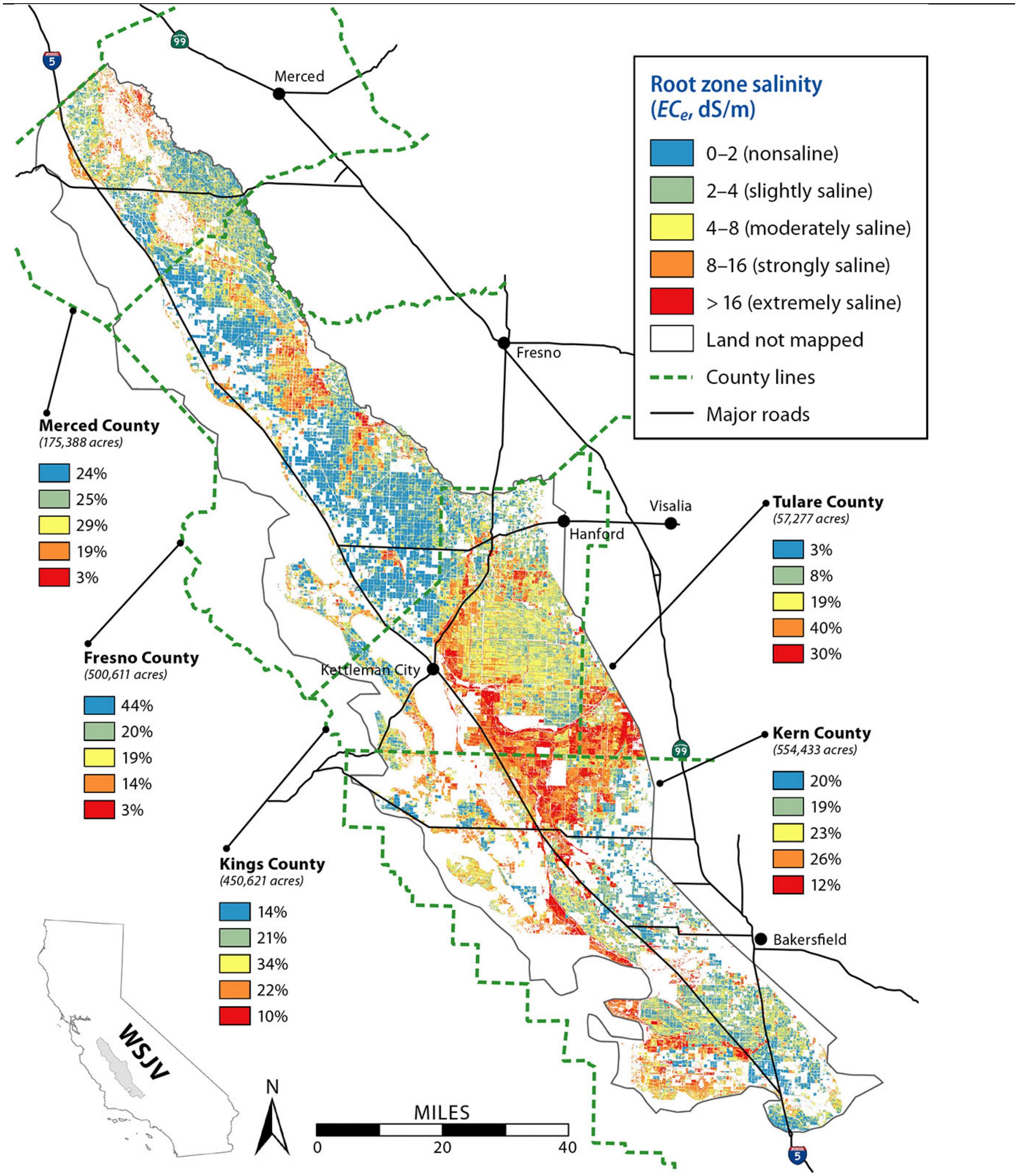


Figure 3.3. Map of remote-sensed root zone soil salinity in the WSJV covering the five counties

Note: Adapted from Scudiero et al. (2017). Boxes indicate the extent (in percentage) of soil salinity.

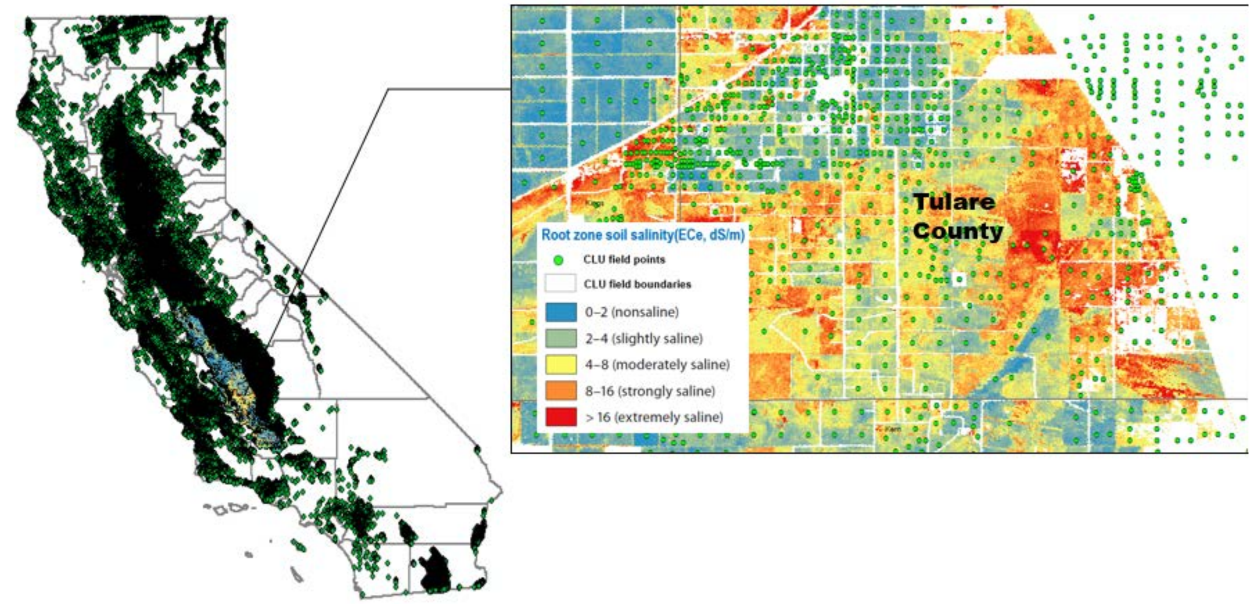


Figure 3.4. Example map of CDLs joined to remote-sensed root zone soil salinity with CLU field boundaries and points used as the unit of analysis for the econometric model

Note: This example targets Tulare County in the WSJV, wherein it shows the most proportion for extreme salinity.

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