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

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Selected Paper prepared for presentation at the 2022 Agricultural & Applied Economics Association

Annual Meeting, Anaheim, CA; July 31-August 2

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Abstract

This work quantifies the soil salinity sensitivity of specific crop choices at the field level by econometrically estimating the response of crop choice by using the Multinomial Logit Model with Fixed Effects. We use high-resolution remote-sensing data of saline soils and crop-specific land cover for 2007-2016 in California's Western San Joaquin Valley and measure growing-degree days to accommodate the effects of climate change. Our 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 our estimates may have some endogeneity bias. Crop choice affects the amount of water applied which could affect salinity. Unfortunately, we 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.

Keywords: California, crop choice, salinity, irrigation

1. Introduction

Soil salinization, as one of the primary causes of land degradation[1], is the process of the accumulation of soluble salts in the root zone through the evapotranspiration of irrigated water. 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 specifically ion toxicity and upset of the nutritional balance in crops (Wong et al. 2006; Jahknwa et al. 2014). Continuous salt accumulation may threaten the sustainability of agricultural 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 in the United States of America[2].

Salinization challenges are generally more pronounced in semiarid and arid regions than compared to humid regions, which is attributed to the former's restriction in terms of the supply of sufficient rainfall to dissipate the salts out of the root zone. Also, ongoing climate change affects the frequency and severity of extreme weather events, including heatwaves and droughts, which can disrupt effective dissipation. That is, the increased evapotranspiration and the reduced precipitation caused an instant decline in both surface water runoff and groundwater recharge, which lessens water availability to dilute existing levels of saline groundwater discharge and leach the salts out of the root zone. Increasing irrigated agriculture has been considered a critical adaptation to meet growing food demands, due to the world's growing population in arid and

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

[2] 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.

semiarid regions. In the case of irrigated areas, the intensive local pumping needed by irrigated agriculture is certainly inducing the water table to decline (i.e., the surface of the saturated part of the aquifer), thus leading to an increased upward movement of the saltwater into the freshwater.

A particular concern for the saline regions is that soil salinization would induce supply shortages of foods, ushering in an increase in prices. Most of the existing studies have focused on agricultural productivity, particularly in terms of yield change of a specific crop in response to soil salinity with linked climate, agronomic, and hydrologic models (e.g., Maas 1993; Van Genuchten 1993; Horticulturae 1998). Additionally, 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 the changes in productivity or revenues of crops; there needs to be an inclusion of farmers' reactions, management adjustments, and the product of those changes in practices in response to salinity. For instance, as soil salinity levels increase, 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. This is an instantaneous and relatively easy adaptation compared to other possible alternatives, while still allowing cultivation even though it is on less profitable land due to salinity. In other responses, leaving the land fallow is often the 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 often triggers an intensification of water consumption rendering a high irrigation cost. The NRCS-USDA (2009), for example, reports that the larger irrigation systems requiring permanent pumps and pipelines increase the production cost of land from \$1800/ha to \$2500/ha. Regarding such high costs, it is challenging to alter irrigation systems without government subsidies or incentives.

Despite the abundant literature on irrigated crop choices[3], changes in crops cultivated as farmers' response to soil salinity in arid and semiarid settings have not been investigated without agronomic field experiments. Ayars (2003) carries out two field experiments in California with saline soils and saline groundwater, respectively, but 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. Likewise, Beare and Heaney (2002) examine land-use activity choices including different crop types in connection with soil salinity. But they merely consider the choices in the context of the net return based on the revenue from crop yields and cost increases caused by incremental irrigation salinity. They also do not estimate how farmers' cropping patterns change in response to higher salinity.

To address this gap in the literature, we 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. We use high-resolution remote-sensed soil salinity and remote-sensed crop data during 2007-2016 to capture fine-scale spatial variations in agricultural settings, controlling for other soil properties and climate conditions on irrigated lands at each field. Our estimates show that as the level of soil salinity increases, the

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[3] 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).

probability that salt-tolerant crops will be selected for cultivation increases, which suggests that farmers adapt corresponding to the degree of salinity. However, it is necessary to note that our estimates may have some endogeneity bias. Crop choice affects the amount of water applied which could affect salinity. Unfortunately, we 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.

2. Background on Soil Salinity in WSJV

The WSJV is located on the west side of the San Joaquin Valley in California, which is one of the most productive farming regions in the world[4] (Figure 1A). The WSJV is often challenged by extensive accumulation of soil salinity and this challenge has been accelerated by the change in regional climate and hydrology conditions.

As shown in Figure 1B, the WSJV spans 5,600 square miles and includes two subbasins of the SJV groundwater basin, one is the Delta–Mendota subbasin where Delta–Mendota Canal passes through, and another is the Westside subbasin where California Aqueduct passes through. The WSJV's aquifer system is constituted of late Tertiary to Quaternary age alluvium[5] which 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 inherent levels of soluble salt. That is because almost all waters draining from a bedrock of the aquifer naturally possess major mineral

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[4] In San Joaquin Valley, there are more than 250 unique crops, which produce an annual gross value greater than $25 billion through irrigated agriculture (U.S. Environmental Protection Agency 2012).

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

components including salts, which were trapped during the deposition of the sediment to form the bedrock. Specifically, alluvium originated from the Sierra Nevada Mountain Range and generally has lower salinity since most surface water from the infiltration of precipitation as snowmelt dominates Sierra Nevada Mountain Range. Whereas alluvium originated from the Coast Mountain Range and has higher salinity since saline marine sediments from the deep aquifer or oceans 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 from 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 have low salinity in the soil. Conversely, if irrigation water derived from the Coast Ranges alluvium is applied, the WSJV soil naturally contains 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 soil 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 adjacent to the Coast Ranges Mountain Range, it is overall susceptible to saline coastal sediments. This vulnerability is also 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 due to the arid and semiarid climate and occasional drought. As a result, the reduced freshwater limits the availability of water to flush the existing salts. Second, there is a saltwater inflow by overpumping for irrigated agriculture and by the lack of soil drainage. Once water tables fall due to overpumping groundwater, pumping wells need to be drilled deeper to reach the water. In this process, pumping can cause the upward intrusion of saltwater into the fresh aquifer, which ultimately can damage the aquifer and contaminate land via increasing soil salinity.

There is a substantial delay before a reduction in water availability is fully attributed to salt accumulations, since natural soil drainage can initially offset soil salinization (Beare and Heaney 2002). However, the WSJV suffers from a low-permeability soil drainage problem. Indeed, the WSJV's soil is dominated by the finer-textured Corcoran clay[6] from saline alluvium which derives from California's Southern Coast Range (Valley 2009; Scudiero et al. 2014). Also, it is estimated that approximately 60% of the soil was 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 shifting 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 where there is inadequate 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 (Lund et al. 2018). These losses[7] were concentrated in the SJV with the inferior climate and hydrology environment and resulted in a more pronounced salinity (Scudiero et al. 2015).

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

[7] 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).

The reuse of drainage water to reclaim salt-affected soil can be a useful practice in places where irrigation water is scarce, to supplement the required water (FAO 2019b). However, this is only effective when original irrigation water of good quality is reapplied. It is generally known that drainage water is not as good as the original irrigation water. That is due to recharge under post-development conditions having inferior water quality than that of the water under pre-development conditions (Fram 2017a). Specifically, under pre-development conditions, groundwater was recharged by the 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 the 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 often aggravates in irrigated areas.

Another management practice is cropland retirement, namely leaving saline land fallow (Connor et al. 2012). It can often be a difficult decision for farmers concerning economic returns, so this practice is chosen as a last resort when the land cannot be restored from salinity by other means. The primary option to allow for soil salinity recovery is to work with the new type of soil by switching vulnerable crops to more salinity-tolerant crops this management practice by farmers is reduce the negative impacts of soil salinity. This practice is also an instant and relatively easy adaptation compared to other possible alternatives aforementioned, while the land's productivity decreases relatively because of soil salinity.

3. Data Description

The overall process of constructing the final dataset is to spatially merge the soil salinity data with crop type classification using ArcGIS. By additionally merging other data needed for our empirical analysis on the WSJV, we compose a field-level dataset for the period 2007-2016 including 139,060 unique fields, which cover 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 1 presents descriptive statistics for all variables used in the analysis.

3.1. Cropland Data Layer

The records of crop-specific land cover data for field-level crop choice decisions are 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., the 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 that are 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 Crop Scape. The 2007-2016 CDL data show total crop mapping accuracies[8] ranging from 89.53% to 97.22% for 247 crop categorization codes. Non-agricultural land cover classes, for example, fallow[9], forest, shrubland, barren, water, wetlands, and open space, were

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

[9] 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).

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.

We 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 3.2 because we focus on field-level decisions instead of pixel-level[10]. These Common Land Unit (CLU) field points are defined as the centroid of the field. Next, the CDL data are assigned to give the CLU field points using a spatial join tool in ArcGIS (ArcGIS Resource Center 2018) to capture field-level crop choice decisions. Based on the spatially joined crop data, we make two types of crop categories for econometric estimation: (i) five categories (i.e., Field Crops, Forage Crops, Fruit Crops, Vegetable Crops, and Other Crops[11]) and soil salinity tolerance level of each crop type followed by the weighted average in each crop type; as well as (ii) seven categories of the selected major crops among 72 crops in the study region according to their share (i.e., Alfalfa, Cotton, Winter Wheat, Tomato, Corn, Almond, Others[12]) and soil salinity tolerance level by each selected major crop followed crop tolerance index.

3.2. Soil Salinity

Our key variable of interest that impacts crop choices, soil salinity, is defined as the occurring when the water containing the dissolved salts is transpired by crops and evaporated into the air, leading to the appearance of salts on the soil surface. we use 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 the soil. This remote-sensing

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[10] 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.

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

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

approach with high resolution, as Scudiero et al. (2017)[13] mentioned, provides a more precise assessment of soil salinity than traditional sampling methods with coarse resolution, allowing the capture of abrupt changes between neighboring fields. Specifically, we focus on the soil salinity in the root zone (i.e., soil volume down to a depth of about 0 to 4 feet) rather than on the soil surface (i.e., sometimes visible as salt crusts), because the former is a prevalent salinity indicator used for agricultural evaluation.

The remote-sensed root zone soil salinity in the WSJV covering the five counties, as shown in Figure 2, is obtained from Scudiero et al. (2017) via personal communication. Figure 2 shows five levels of root zone salinity quantified as the EC_e classification by Richards (1954). The percentage of soil salinity level in the total area is shown 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 extremely saline (145,070 acres, 8%). This salinity data is assigned to the given CLU field points by using spatial join in ArcGIS after the CDLs joining (see Figure 3).

3.3. Irrigation Classification

To identify the irrigated agricultural lands in WSJV, we use the MIrAD-US land cover, which is from the U.S. Geological Survey. The MIrAD-US reveals the detailed spatial patterns of irrigation change across the nation. These data center on 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 is 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.

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[13] 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).

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 into the field by the map unit associated with the point at each field. These soil properties are 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 conditions, unlike altered drainage, which is mainly caused by artificial drainage or irrigation; in summary, it is the rate at which water is removed from the soil. This natural soil drainage in the WSJV is categorized into four discrete classes as follows: well-drained, moderately well-drained, somewhat poorly drained, and poorly drained. Clay soil mainly distributed in the WSJVusually has poor drainage levels because of less permeability compared to sand soil with a faster water infiltration rate. This implies that the higher the clay ratio, the more serious the drainage problems due to the remaining salinity.

In terms of other soil properties, bulk density indicates the soil compaction and reflects the movement of air and water through the soil. If the bulk density is higher than the thresholds, the soil function will be impaired, because high bulk density has low soil compaction and porosity, which can restrict root growth and impact the movement of air and water through the soil. Root zone available water storage[14] is the plant-available water volume that the soil can hold within the root zone. The water-holding in the root zone can be stored and used for crop

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

uptake, and thereby it is a critical variable affecting crop yield potential and stability. Soil organic carbon[15] can enhance soil structure and fertility by providing energy sources for soil microorganisms to affect plant growth. Soil pH (H_2O)[16] is an important variable to impacts various chemical or biological activities in the soil. Therefore its levels that are too high or too low can induce soil deterioration resulting in the reduction of crop yields. . The average National Commodity Crop Productivity Index (NCCPI)[17] provides condensed information about average crop productivity based on the inherent soil properties. The NCCPI incorporates several factors related to crop production, such as landscape and climate characteristics, and imposes a rating (score) on the production.

Elevation indicates the height from the fixed reference point and the slope is the degree to which a surface is tilted and is a measure of elevation change. Although the 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, the steeper slopes generally have lower soil moisture than the 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 when the steep slope increases (Liu et al. 2000; Kapolka and Dollhopf 2001). Here, we take the log of slope to use a more normally distributed variable across the fields.

3.5. Climate Conditions

We determine 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 by PRISM Climate Group. We construct long-run average weather variables (i.e.,

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[15] Further information on this variable beyond the Soil Quality Indicator Sheets, see Thiele-Bruhn (2016).
[16] Further information on this variable beyond the Soil Quality Indicator Sheets, see Batjes (1995).
[17] 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.

Regarding the impact of temperature, we follow the piecewise linear approach, which is applied to predict the 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 that are 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 from March 1 to September 30. Next, we average these DDs and precipitation variables for 36 years of data and then finally merge them with field-level CDL data.

4. Model

In this section, we specify the conceptual model and empirical model to underly 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).

4.1. Conceptual Model

Each farmer cultivating a field i in year t is assumed to make a crop choice decision to maximize the 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 in 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} to indicate different levels of soil salinity, soil properties, and climate conditions. Typically, the deterministic portion V_j can be assumed in a 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 representative 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):

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

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

4.2. Econometric Model

We estimate how farmers change crop choices in response to different soil salinity levels with a field-level dataset covering 9 years. Concerning five salinity levels, soil properties, and climate conditions, as well as year 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* refers time period of 2007–2016. *j* represents different crop choices and two alternative classifications are used in model estimation: (i) five categories *J*={Other Crops, Field Crops, Forage Crops, Fruit Crops, Vegetable Crops} and (ii) seven categories *J*={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. β_j is the coefficient vector including the intercept β_{0j}, while β_{kj} is the slope coefficient. Because the probabilities must sum to one, we restrict $\beta_j = 0$ for one of the alternatives as the base category. Consequently, only 4 (*J-1*) for and 6 (*J-1*) are estimations for five categories and seven categories, respectively. In this study, we 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 the 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 the differences across counties. Robust standard errors are clustered at the county level to allow error correlation for a given field over time and spatial correlation within a county. We 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:

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

Here, X_{it} is the explanatory variable 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 because they depend on the probabilities that vary across all explanatory variables in the model. This implies that the MEs are not constant and may be positive for some values of explanatory variables and be negative for others. Here, the MEs are calculated at the means (MEM) of the explanatory variables as follows:

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

where $\bar{P}_{jt}$ is computed by holding X_{it} at their mean values. In this study, we evaluated the MEM. Another way, average marginal effects (AME)[18] based on actual values of the explanatory variables can be used. While MEM and AME yield different evaluations, there is no consensus as to which of the two is the most representative (Greene, William 2012; Wulff 2015), so both can be utilized to get MEs.

Equation (6) represents MEM for continuous variables. Yet, we have categorical variables, such as five soil salinity levels and four soil drainage classes. In this case, taking the difference in estimated probabilities between the different levels of the categorical variable is suitable to analyze MEM. If, say, x denotes the dummy explanatory variable to capture the categorical effect and X^*denotes other explanatory variables at their means. Due to the discrete change for the categorical variable, the effect of x on the predicted probabilities of $C_{it} = j$ is:

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

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

5. Results

The results in Table 3 and Table 4 present the marginal effects of all variables from the MNL regression models in five categories and seven categories among selected major crops, respectively. The interpretation of the marginal effects on continuous variables indicates 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) suggests the difference in predicted probabilities of choosing a particular alternative due to a variable taking that particular level compared to the base category. The marginal effects of different soil salinity levels on crop choices are of great interest. This finding demonstrates how the change in soil salinity encourages or discourages the probability of a particular crop being grown in a given field.

Table 3 indicates the marginal effects of soil salinity levels in five categories. Overall, at all levels of soil salinity except for slightly saline soil levels, 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 probabilities of culturing field crops and vegetable crops in a slightly saline soil (i.e., EC_e 2-4 dS/m) field are 3.16% -and 5.31%is lower than those in a nonsaline soil (i.e., EC_e 2-4 dS/m) field. These results are statistically significant at the 1% level of significance. Meanwhile, the probability of planting forage crops in a field having slightly saline soil is 5.98% higher than that in a field having nonsaline soil, and the variance is statistically significant at the 1% level. These results are in contradiction with our expectations, based on the relative salt tolerance index for those crops. Perhaps this level is close to the natural saline level and does not substantially render yield loss.

Compared to a field having moderately saline soil (i.e., EC_e -8 dS/m), the probabilities of planting fruit crops and vegetable crops in a field having slightly saline soil or higher are 2.24% higher and 9.38% lower, respectively. These results are both statistically significant at the 1% level. The probability of culturing forage crops in a field having slightly saline soil is 5.98% higher than that in a field having nonsaline soil, and this result is statistically significant at the 1% level. The probabilities of planting field crops and fruit crops in a field having strongly saline soils (i.e., EC_e 8-16 dS/m) are 17.26% higher and 8.32% lower than those in a field having nonsaline soil. The results show statistical significance at the 5% and 1% levels for field and fruit crops, respectively. However, the probability of planting vegetable crops in a field having strongly saline soil is 16.33% lower than that in a field having nonsaline soil, and this is statistically significant at the 1% level. Compared to a field having nonsaline soil, a field having extremely saline soil (i.e., ECe >16 dS/m) shows 25.84% and 11.62% higher possibility of culture field crops and fruit crops, respectively. It exhibits statistical significance at the 5% and 1% levels for field and fruit crops, respectively. However, the probabilities of culturing forage crops and vegetable crops in a field having extremely saline soils (i.e., ECe >16 dS/m) are 16.48% lower and 15.72% higher than those in a field having nonsaline soil. The results show statistical significance at the 10% and 1% levels for field and fruit crops, respectively. As the level of soil salinity increases, the probability that salt-tolerant crops will be selected by farmers for cultivation increases gradually. In contrast, salt-sensitive crops are incrementally less likely to be selected by farmers as cultivated crops. This suggests that the extent of farmers' adaptations to salinity change is highly associated with the degree of soil salinity.

It is observed that soil salinity shows all positive and statistically significant marginal effects on fruit crops w at the slightly saline soil or higher. In the light of the relative salinity tolerance index, we anticipate that the probability of culturing salt-sensitive fruit crops in a given field would decrease. This is possibly ascribed to the fact that most crops including 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. Also, crop rotation[19] will not apply to perennial crops like almonds. For example, almond trees generally live for 25 to 30 years depending on the growing conditions, their yield tends to decline gradually after reaching the maximum yields of about 15 years. Given the roughly seven years for the almond tree to reach the point where it can launch for commercial production, the peak production only last for seven years (Almond Board of California 2016; Ternus-Bellamy 2019). Because of the long time and other input costs of perennial 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 other annual crops.

Our estimations may have some endogeneity bias. For example, if the selected crop consumes water containing high salinity, then the irrigation process will potentially increase soil salinity. Moreover, the farmer might intentionally grow a crop that consumes more water to flush the salts out of the soil. Therefore, the crop choice of farmers in response to soil salinity also depends on the salinity and amount of water applied and the water used by the crop for irrigation. Unfortunately, we can not determine the direction of the endogeneity bias in this work.

Table 4 shows the marginal effects of soil salinity on seven categories of the selected major crops in the WSJV according to their shares. Overall, except for cotton and almond, the marginal effects of soil salinity on alfalfa, winter wheat, tomato, and corn show signs that match

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[19] 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).

expectations in the light of the relative salinity tolerance index for those crops at almost all soil salinity levels apart from slightly saline soil level, and they are also statistically significant. Specifically, the probability of planting alfalfa in a field having slightly saline soils (i.e., EC_e 2-4 dS/m) is 5.39% higher than that in a field having nonsaline soil (i.e., EC_e 2-4 dS/m). This result is statistically significant at the 1% level. Meanwhile, the probability that a field having slightly saline soil is planted with cotton and tomato is 5.65% and 2.20% lower than that of a field having nonsaline soil, respectively. Both results are statistically significant at the 1% level. Likewise, the result of the five categories above is in contradiction with our expectations, based on the relative salt tolerance index for those crops.

Compared to a field having moderately saline soils (i.e., ECe -8 dS/m), the field having slightly saline soil or higher show 6.77% and 1.05% higher probability of culture winter wheat and almond, respectively. It shows statistical significance at the 5% and 1% levels for winter wheat and almond, respectively. The probability that a field having moderately saline soil is planted with cotton and tomato is 8.76% and 4.35% lower than that of a field having nonsaline soil, respectively. It shows statistical significance at the 10% and 1% levels for cotton and tomato, respectively. Meanwhile, the probabilities of planting alfalfa and corn in a field having strongly saline soil are 10.97% and 3.02% lower than those in a field having nonsaline soil, respectively. It shows statistical significance at the 5% and 1% levels for alfalfa and corn crops, respectively. The probabilities that a field having extremely saline soil (i.e., ECe >16 dS/m) is planted with winter wheat and almond are 17.80% and 4.60% higher than those of a field having nonsaline soil. These results show statistical significance at the 1% level. However, the probability of culturing alfalfa, cotton, tomato, and corn in a field having extremely saline soil is

17.50%, 24.10%, 11.67%, and 2.94% lower than those of crops in a field having nonsaline soil, respectively. Such results are all statistically significant at either the 5% or 1% level.

In the seven categories, cotton (a field crop) and almonds (a fruit crop) show notably opposite trends to expectations. Cotton was expected to be highly selected for farmers facing more salinity because it was a salt-tolerant crop. Its sign was expected to be positive and consistent with the results of field crops in the five categories shown earlier. However, the result was statistically significant and opposite to expectations. This may stem from cotton's water use intensity (see Table 2). Even though cotton is a salt-tolerant crop, farmers are 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 soil salinity on the likelihood of choosing a salt-tolerant crop.

Almond, like cotton, has different statistical signs to expectation. 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 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 soil salinity on farmers' almond selection also has the potential to increase.

Conversely, winter wheat and corn as field crops showed signs that matched their relative salinity tolerance indices with statistically significant. Moderately salt-tolerant winter wheat is also the best choice for farmers facing soil 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, as the soil drainage classes are poor, it decreases the likelihood of selecting moderately salinity-sensitive fruit crops. The effect of soil drainage class could partly be responsible for soil salinity impacts because poor drainage can increase soil salinity. This can be seen in field crops and fruit crops. The probability that a field is planted with salt-tolerant field crops is higher if it has a more poorly drained soil class relative to a well-drained soil class. Conversely, the probability that a field is planted with salt-sensitive fruit crops is lower if it has a more poorly drained soil class relative to a well-drained soil class. Likewise, seven categories of selected major crops in Table 4 Table 4can be interpreted in the same way for the soil drainage classes. In summary, as the soil drainage classes are poor, it encourages the likelihood of choosing salt-tolerant cotton and discourages the likelihood of selecting salt-sensitive almonds. The results for cotton and almond are consistent with the results for field crops and fruit crops, respectively. However, it is 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 as well. However, precipitation has significant effects on all crop categories. In the case of DDs between 10°C and 20°C, it has the most significant impact on crop choice.

6. Conclusions

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

A robust literature examines the effect of soil salinity on productivity and crop yields, however, studies are available to investigate the changes in cropping patterns as an adaptation strategy to soil salinity. We quantify the adaptation to soil salinity by farmers in the WSJV by econometrically estimating how farmers change crop choices in response to different soil salinity levels. We 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. To investigate farmers' crop choices, we estimate a multinomial logit model with fixed effects for two types of crop categories: five categories and seven categories by selected major crops in the study region.

Our estimated total marginal effect shows that as the salinity level increases, increases the probability of choosing a salt-tolerant crop. Our 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, our 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.

Tables and Figures

Table 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 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 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. 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)

Table 3. Continued

	Tolerant	Moderately Sensitive	Moderately Sensitive	Moderately Sensitive	Moderately Sensitive
Variables	Field crops	Forage crops	Fruit crops	Vegetable crops	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 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 4. Continued

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

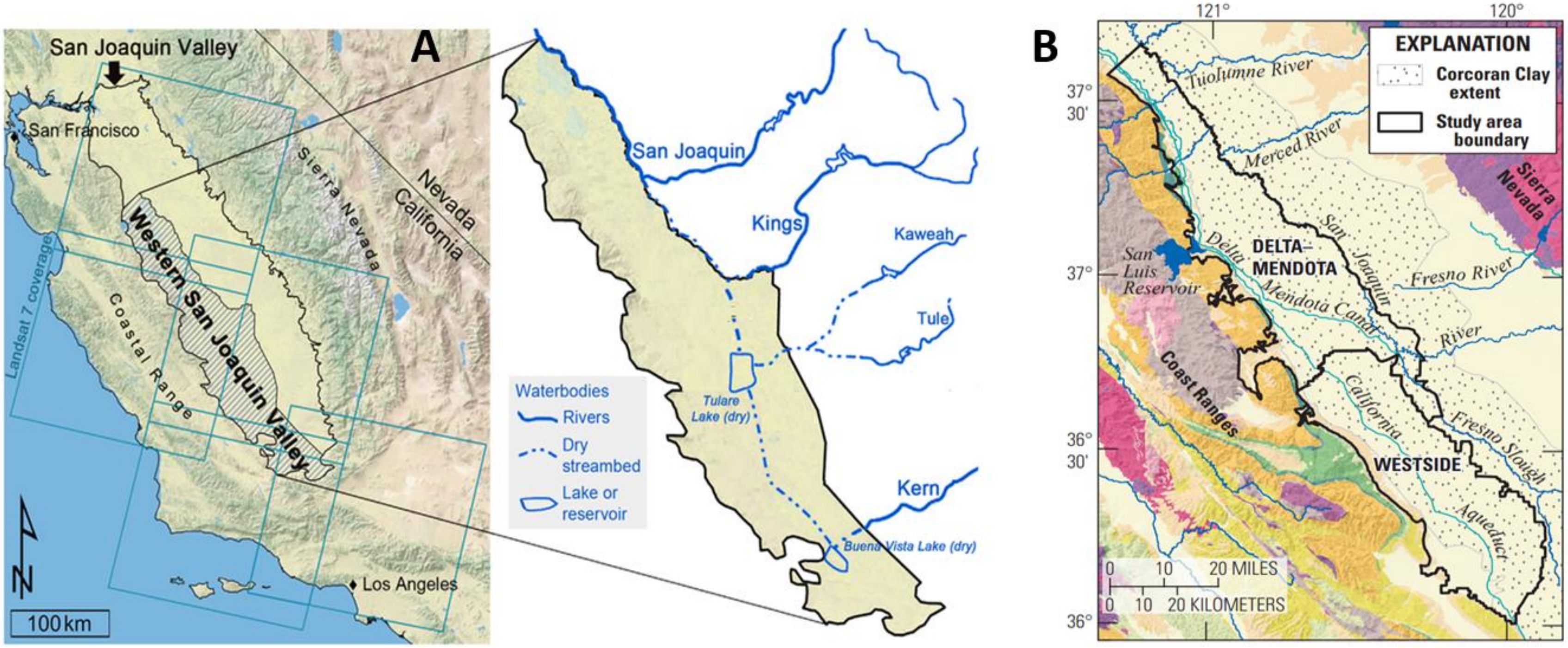

Figure 1. Overview of the study region: Western San Joaquin Valle California, USA**.**

Note: Adapted and modified from Scudiero et al. (2016).

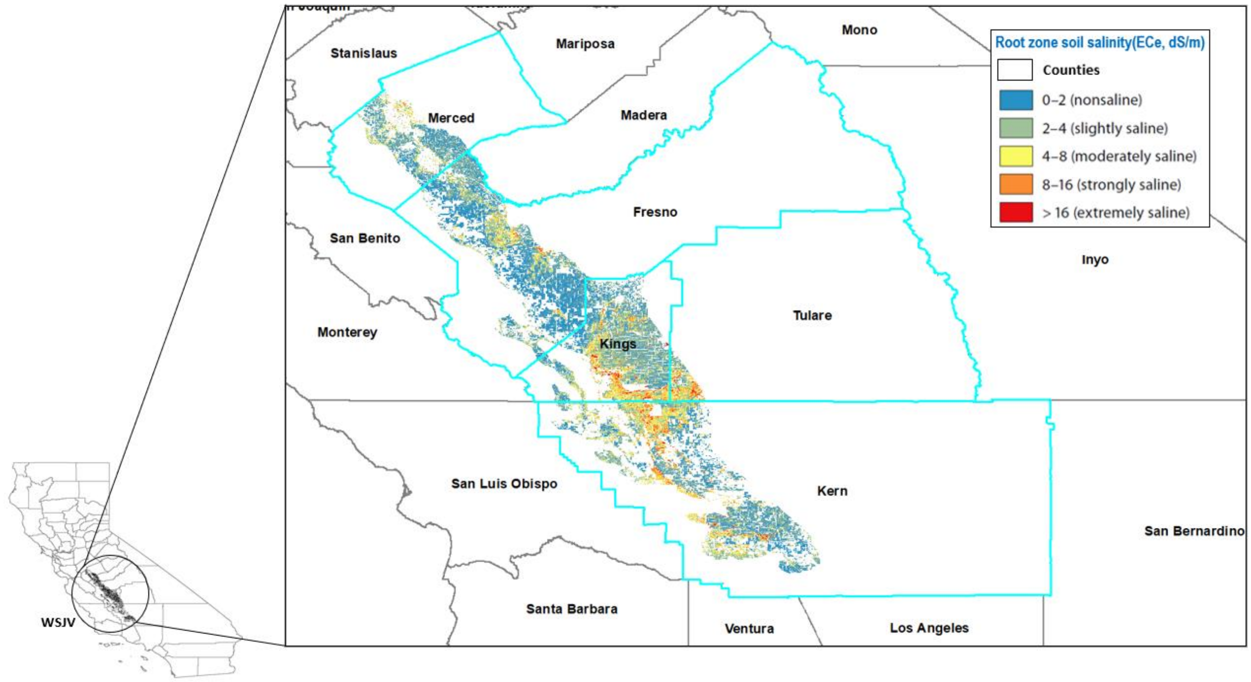

Figure 2. Map of remote-sensed root zone soil salinity in the WSJV covering the five counties

Note: The label in the box indicates the extent (in percentage) of soil salinity.

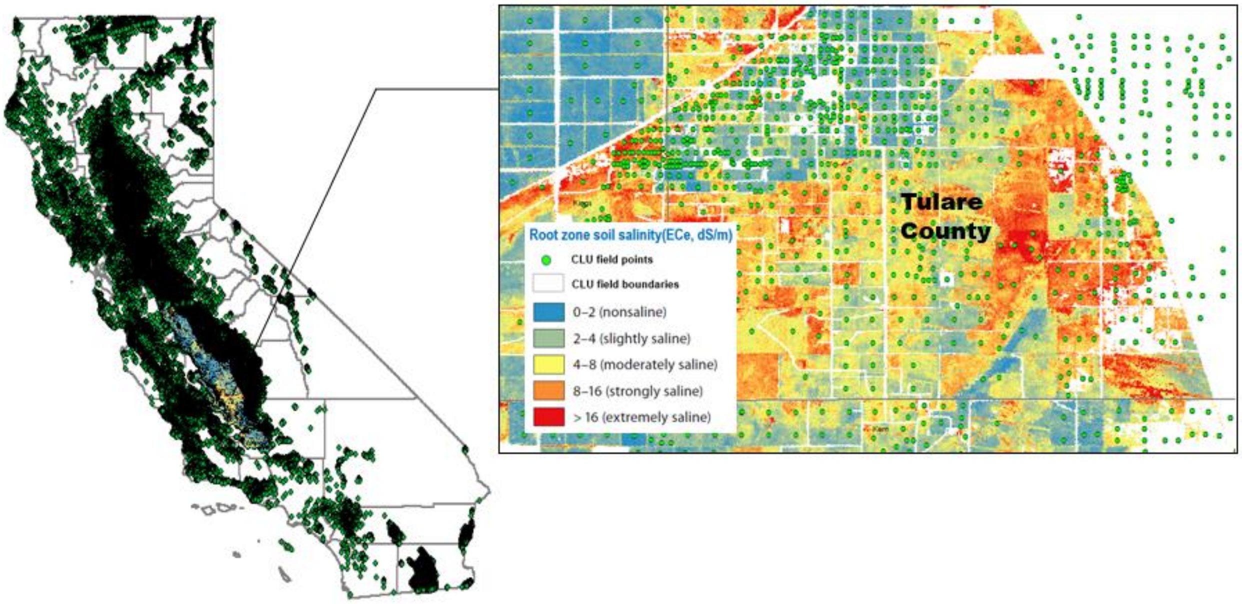

Figure 3. Example map of CDLs joined to remote-sensed root zone soil salinity with CLU field boundaries and points used as the unit of analysis for the econometric model

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

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