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# The Root of the Problem: Capturing the Impacts of Irrigation Water Salinity on Crop Choice

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We compile panel data on salinity and crop choice for over 13,000 parcels in California's Sacramento–San Joaquin Delta from 2009 to 2016. We use parcel fixed effects in a multinomial logit model to predict crop choice as a function of irrigation water salinity, allowing for unobserved parcel-level heterogeneity that causes spatial variability in needs for salinity management. This contrasts with previous work, where measures of salinity capture the impact of both variation in irrigation water salinity and underlying soil/parcel conditions. We find increased odds of planting both low-value, tolerant crops and certain high-value, salt-sensitive crops relative to orchards. Implications for Delta revenues are discussed.

*Key words*: California agriculture, Delta region, multinomial logit model with fixed effects, Sacramento–San Joaquin Valley, soil quality

## Introduction

Increasing water and soil salinity is a growing problem in many arid and semi-arid regions of the world (Mukherjee and Schwabe, 2014; Chen and Mueller, 2018). The natural ecosystem and water diversion infrastructure in California's San Joaquin–Sacramento Delta (henceforth simply the Delta), an estuary that yields roughly a billion dollars in annual revenues (Delta Protection Commission, 2020), mean that managing increasing salinity is an ever-present problem (Delta Stewardship Council, 2022). Soil salinity increases the amount of energy crops must use to extract water from the soil, potentially decreasing yields (Ayers and Westcot, 1994; Nicolas et al., 2023). If mitigating salinity is not possible, or if yield declines are large, farmers may transition to more salt-tolerant crops, which are generally lower in value. For this reason, understanding how salinity impacts crop choice is imperative, especially given projections for climate change to cause increasing irrigation water salinity in many regions of the world, including the Delta (Fleenor et al., 2008; Corwin, 2021).

One major limitation to understanding how salinity affects cropping decisions is that researchers generally observe crop choices and irrigation water salinity; however, salinity in a crop's root zone (especially during planting and shortly thereafter) has the most impact on plant growth (Hoffman, 2010). Unfortunately, regional-scale data on root-zone salinity is sparse or nonexistent in many

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regions (including the Delta), so researchers may use irrigation water salinity as a proxy for root-zone salinity (e.g., Uz, Buck, and Sunding, 2022). While the two may be highly correlated, the relationship is complicated by numerous factors. For instance, cumulative use of saline irrigation can eventually increase salinity in the root zone (Ayers and Westcot, 1994; Nicolas et al., 2023); alternatively, if irrigation water is less saline, root-zone salinity can be decreased via leaching, the process of applying excess water to flush salts from the soils (Hoffman, 2010; Letey et al., 2011). Effectiveness of leaching, in turn, may depend upon soil type and the depth of the root zone for a given crop (Machado and Serralheiro, 2017), and leaching may not be possible if the water table depth is too shallow, if irrigation water is too saline, or if soils do not drain well (Hoffman, 2010). Next, the amount of salt a crop can tolerate in the root zone will depend upon the crop's exposure and vulnerability to other stressors—like the salinity of applied irrigation water, drought, and the microbial community of the soil (Muhammad et al., 2024)—as well as the parcel-specific history of crop choice and management decisions. Thus, the volume and salinity level of water needed to maintain root-zone salinity at crop-tolerable levels via leaching (and other practices) depends upon the above-mentioned parcel-specific variables and their synergistic effects, which may make salinity management more or less problematic on any given parcel (Hoffman, 2010). These spatial differences in the need for salinity management are a function of natural conditions and the complex infrastructure that moves water through the Delta from northern California to the south, predisposing certain parcels to more saline soil conditions (and required salinity mitigation), regardless of the salinity of irrigation water in any given year. These location-specific effects may become even more relevant as increasing sea levels and seawater intrusion in coastal areas increase soil salinity (Corwin, 2021).

In this work, we use 19,270 observations from 13,284 parcels spanning 2009–2016 in a multinomial logit model to predict parcel-level crop choice in relation to observed changes in irrigation water salinity. We make two contributions to the empirical literature on salinity and crop choice. First, we compile and analyze more disaggregated data of parcel-level crop choice than has been accomplished in prior work. Previous research (e.g., Uz, Buck, and Sunding, 2022), has categorized crops into broad groups (e.g., salt-sensitive and salt-tolerant). Rather than forcing diverse crops into broad categories, we exploit economic and agronomic knowledge of each of the three dimensions of differences in crops—salt tolerance, prices, and crop type—to construct 13 crop group categories. This approach preserves the observed crop diversity of our study region, the California Delta, where rich soils and abundant surface water availability allow more than 70 different crops to be grown. Second, we exploit the panel nature of our data and estimate a parcel fixed-effects multinomial logit model to examine the impact of changes in irrigation water salinity on crop choices while allowing for parcel-level heterogeneity in growing conditions, including root-zone salinity. While fixed-effects multinomial logit models have been recently used in areas such as voters' choices (Arnorsson and Zoega, 2018), consumer choice (Ivanova et al., 2018), and residential mobility decisions after natural disasters (Hikichi et al., 2019), this is the first (to our knowledge) use of parcel-level fixed effects in the context of agriculture or crop choice. We compare the results of the fixed-effects model to a standard pooled multinomial logit model and develop novel insights into the relative importance of annual surface water salinity and unobserved farm-level factors in shaping farmers' crop choices.

Using these two models, we ask whether mixed findings from previous work on salinity in the Delta can be reconciled. We argue that our two models capture different phenomena. The pooled multinomial logit model predicts crop choices as a function of the combined effects of the salinity of irrigation water applied in any given year and parcel-level heterogeneity in observed variables, unobservable variables, and their synergies. For example, while we can observe variables like a parcel's soil type, elevation, and the depth of the water table, a parcel with both poorly draining soils and a shallow water table will be very problematic compared to a parcel with just one of these conditions. We then ask whether annual variability in irrigation water salinity will induce farmers to switch from salt-sensitive (often higher revenue) crops to crops that are more salt-tolerant (and often lower revenue) when we allow for unobserved parcel-level heterogeneity via a fixed-effects model.

Overall, we find different predictions for crop choices in the pooled versus fixed-effects multinomial logit models. The estimated impact of irrigation water salinity on crop choice is much larger when parcel-level heterogeneity is not accounted for via fixed effects. However, the fixed effects model still finds that irrigation water salinity impacts cropping decisions, increasing odds of planting both low-value field and grain crops and salt-sensitive, high-value truck and berry crops, relative to orchards. Our findings suggest that while irrigation water quality is moving some farmers toward salt-tolerant crops, existing irrigation water salinity levels may still be conducive to certain valuable, nonorchard crops. These results highlight the need for a better understanding of the long-term interactions between factors like irrigation water salinity, root-zone salinity and other soil conditions, given the complex spatial variability in Delta parcel-level growing conditions.

## Background and Previous Literature

### *The Sacramento–San Joaquin Delta*

The Sacramento–San Joaquin Delta is one of the largest estuaries in the United States, formed where water from California's San Francisco Bay converges with the San Joaquin and Sacramento Rivers. The Delta provides water for roughly two-thirds of Californians and includes a vast levee system that channels water around various islands and farmland as part of California's State Water Project. Salinity has long been a problem in the California Delta, due to both natural and anthropogenic influences (Delta Stewardship Council, 2022). Farmers in the Delta use surface water for irrigation, and surface water salinity exhibits high variation across locations in the Delta and is generally higher in dry years. In the Delta's western region, seawater mixes with freshwater flows, increasing salinity of irrigation water. This is also true in the south Delta, where water diversions and pumping for irrigation, in conjunction with irrigation return flows from the north, increase the salinity of surface water used by farmers (California Department of Water Resources, 2023). Soils also inherently vary across the Delta, including silt, clay, loam, and mucky soils associated with the geological formation of the region (Durand et al., 2020). Together, the complex interactions between geography and institutions of the Delta predispose different regions to have varying soil salinity levels, which means geographic differences in leaching requirements—the amount of extra water that must be applied to the soil to keep root zone soil salinity at levels tolerable for a farmer's chosen crop (Hoffman, 2010). Delta farmers are well acquainted with these salinity challenges and may tailor their irrigation methods and timing to seasonal and even daily changes in salinity that result from tidal conditions (Delta Stewardship Council, 2021). Last, weather changes (e.g., decreased freshwater flows released from reservoirs during droughts) and policy makers' drought management decisions also have significant effects on location-specific irrigation water salinity in any given year (Durand et al., 2020). Acknowledging the various factors that predispose regions of the Delta to higher salinity levels, state regulations require pumping operations in the south Delta region to maintain irrigation water salinity below the level of 700–1,000 microsiemens/centimeter ($\mu$s/cm), a controversial standard often viewed as too high by growers (Delta Stewardship Council, 2022).

### *Previous Literature: Salinity and Crop Choice*

Despite the importance of the Delta region to the California economy, relatively little research exists on the threat posed by increasing salinity of irrigation water. Within previous work there are two very different projections for future impacts of irrigation water salinity on Delta crops. In one view, areas with continually high irrigation water salinity levels have accumulated salt in soils to the point where they cannot grow salt-sensitive crops, so they have already transitioned to more salt-tolerant options. This was the finding proposed by Medellín–Azuara et al. (2014), who studied the effect of different salinity scenarios on cropping patterns and crop revenues relative to the baseline of 2007. The researchers combined an agricultural production model (projecting yield changes as a function of salinity levels) with hydrologic models (predicting salinity changes) in a linear programming model that estimated salinity-related changes in agricultural output. Farmers were assumed to choose crops to maximize profits under various simulations of varying salinity conditions. The authors found that even large climate-change related increases in salinity over baseline conditions would have minor impacts (decreasing Delta revenues by less than 1%). This finding is consistent with the idea that annual changes in irrigation water salinity have little impact on short-run cropping decisions because irrigation water (in areas that have not transitioned away from sensitive crops) is not saline enough to damage the crop or prevent its use for leaching, ensuring soil conditions are unchanged in the short run. Notably, this assumption that management actions can be used to keep root zone salinities at thresholds tolerable to the crop is often controversial with farmers facing costs and challenges of salinity management. Other examples of a linear-programming approach include Knapp, Schwabe, and Baerenklau (2014), who developed a regional-scale programming model to show how economic and hydrologic conditions impact optimal drainage of soils to manage salinity in the Delta. Welle and Mauter (2017) projected changes in yields for crops observed via satellite data as a function of soil salinity levels. The authors found California's total salinity-related agricultural revenue losses were $3.7 billion in 2014. The authors found that areas with high existing soil salinity levels do grow more salt-tolerant, low-revenue crops; however, the authors were unable to account for crop switching and interpolated soil salinity levels for all Delta parcels from a limited number of soil monitoring stations.

In contrast to the linear programming models, an alternative approach is to use observed salinity and crop choice data to infer how changes in salinity impact the probability of growing various crops. Uz, Buck, and Sunding (2022) estimated an econometric model predicting crop choices in relation to irrigation water salinity for the Sacramento–San Joaquin Delta from 2003 to 2010. The researchers used a logit model that predicted the odds of growing a salt-sensitive versus a salt-tolerant crop. They found that increasing surface water salinity decreased the odds of growing salt-sensitive crops; a mixed (random coefficients) logit model was then estimated and used to predict farmer-specific responses to changes in salinity across the Delta. The authors found heterogeneity in responsiveness to irrigation water salinity and projected potentially large decreases in acreage for salt-sensitive (generally high-value) crops under simulated scenarios of increasing irrigation water salinity. Outside the Delta, MacEwan, Howitt, and Medellín-Azuara (2016) compiled data on crops planted on approximately 1 million acres in Kern County, California, and estimated a cross-sectional multinomial logit model of crop choice. The authors found strong support for the hypothesis that growers respond to changes in salinity, soil, and slope by switching crops. These researchers found that a 1 dS/m (equivalent to 1,000 $\mu$s/cm) increase in salinity leads to a 5.2% increase in the odds of a farmer planting relatively salt-tolerant cotton while decreasing the odds of growing salt-sensitive orchards by 4.8%. More recently, Lee and Hendricks (2022) used field-level crop and soil salinity data to estimate the effects of soil salinity on crop choice; they found that higher soil salinity induces a shift toward salt-tolerant crops. While the use of soil salinity data is novel, it may lead to biased estimates because soil salinity is endogenous: Soil salinities affect crop choice, but crop choices and associated management practices may also impact soil salinity levels.

Our work differs from the prior econometric models in two ways. First, previous researchers have been unable to account for parcel-level unobservable conditions, which include synergies between observed variables that create challenges for salinity management, as described in the previous section. These unobservable parcel-level variables may make annual variation in irrigation water salinity a more severe and/or costly problem in any given year. For example, if root-zone salinity is high, less saline irrigation water is needed to sufficiently leach the soils, but ability to leach will also depend upon soil type and the slope of the land. For this reason, pooled econometric models may quantify the impact of salinity on crop choice (for individual parcels across time) as well as cross-parcel variation in existing soil/location conditions. This may be problematic given that the areas with the worst salinity in irrigation water also tend to be those with poor soils (i.e., the regions of the Delta that have already transitioned away from sensitive crops). Second, prior work in the Delta has grouped crops based on their salt sensitivity (Uz, Buck, and Sunding, 2022), but sensitive/moderately sensitive crops include numerous crop types (ranging from alfalfa to orchards) with very different growing operations and per acre returns. To add nuance to our measurement of crop choices, we use detailed crop groupings that account for both crop prices and the fact that crops are inherently different to grow. Putting these two objectives together, we contrast a pooled multinomial logit model—like prior work, this model captures changes in Delta crop choices both across and within parcels—with a fixed-effects model that isolates the impact of irrigation water salinity changes on crop choice for individual parcels. Holding unobserved parcel-level conditions constant, we evaluate whether increased irrigation water salinity levels cause Delta farmers to favor crops that are more salt tolerant (and tend to have lower values).

## Model

We focus on the farmer's seasonal crop production function,wherein the farmer will choose a crop that maximizes profits, given the salinity of the irrigation water received in a given season. We assume a season $t$ crop $j$ yield for farmer $i$ is denoted by $y_{ijt}$ and expressed as follows:

$$y_{ijt} = f\left(\boldsymbol{x}_{ijt}; s_{it}, \boldsymbol{w}_t, \boldsymbol{l}_i\right). \tag{1}$$

In equation (1), crop yield depends on a vector, $\boldsymbol{x}_{ijt}$, of production inputs (e.g., seed, labor, fuel, equipment, and chemicals). Higher salinity in irrigation water, $s_{it}$, tends to directly reduce crop yields. Given the hydrology of the Delta, we can assume that the quality of irrigation water received at a parcel $i$ is exogenous to the farmer's profit maximization problem. A farmer may, however, undertake salinity management actions (e.g., leaching, salinity monitoring, modifying intake times). Thus, included in vector $\boldsymbol{x}_{ijt}$ are inputs for salinity management actions such as labor, equipment for salinity measurements, soil amendments, and other practices used to maintain crop yields (Muhammad et al., 2024). Crop yield is also affected by a vector of seasonal factors, $\boldsymbol{w}_t$, which include rainfall or drought conditions and the state's freshwater flow management actions that may affect general salinity conditions in the Delta. Location-specific factors, $\boldsymbol{l}_i$, that also affect yields include soil salinity, soil type, elevation, and slope of parcel $i$. Per Hoffman (2010), we assume that while soil salinity varies for each parcel $i$, it can be managed such that it remains constant in the short term. We assume that the farmer is a price taker in product and input markets and maximizes profits for each crop, given as

$$\pi_{ijt} = p_{jt} y_{ijt} - \boldsymbol{c}'_{jt} \boldsymbol{x}_t, \tag{2}$$

where $p_{jt}$ is the price for crop $j$ in year $t$ and $\boldsymbol{c}'_{jt}$ is a vector of input costs. For each crop $j$, the farmer optimizes the use of inputs, $x^*_{ijt}$, and the normalized profit function is expressed as $\pi^*_{ijt} = \pi(x^*_{ijt}; p_{jt}, \boldsymbol{c}_{jt}, s_{it}, \boldsymbol{w}_t \boldsymbol{l}_i)$. Assuming that farmer $i$ has a choice of $J$ crops, the crop-choice problem is given as

$$\pi_{it} = \max_J \left\{\pi^*_{1t}(\cdot), \pi^*_{2t}(\cdot), \ldots, \pi^*{}_{Jt}(\cdot)\right\} \quad \text{where } j \in [1,2,\ldots,J]. \tag{3}$$

As equation (3) shows, the crop that yields the highest per acre profit for given levels of irrigation water salinity, seasonal, and location-specific variables is chosen.

We cannot observe farmers' yields or input costs; however, we can observe their final crop choices. As such, we use a multinomial logit model (Chamberlain, 1980) to show how changing salinity levels impact the decision to grow various crops. However, we must also allow for the fact that there are unobserved parcel-specific conditions. If they are correlated with irrigation water salinity, these conditions may bias estimates of the effect of irrigation water salinity on crop choice.

We have a sample of $N$ parcels with observations across $T$ years. For each parcel in each year, the observed crop choice, $o_j$, is one of 13 crop groups (described in the data section). Following convention in formulating dichotomous choice models, we define $y^*_{itj}$ as the latent propensity for each farmer $i$ at year $t$ to choose crop group $j$ as

$$y^*_{itj} = \alpha_{ij} + s_{it}\beta_j + z_{it}\boldsymbol{\gamma} + \varepsilon_{itj}, \tag{4}$$

where $\beta_j$ is the coefficient for irrigation water salinity, $s_{it}$; and $z_{it}$ gathers the seasonal ($\boldsymbol{w}_t$) and location-specific ($\boldsymbol{l}_i$) variables. Seasonal factors include annual indicator variables that control for weather, and location-specific variables include size, soil type, elevation, and slope of parcel $i$. The intercept, $\alpha_{ij}$, is a random variable that captures the panel-level heterogeneity, and the error term, $\varepsilon_{itj}$, is a type I (Gumbel-type) extreme-value random variable, *i.i.d.* across all outcomes $j$. The link to the chosen crop group, $o_j$ is defined by

$$\forall\, j \in (1,\ldots,J) : \Pr\left(y_{it} = o_j \mid \alpha_i, \beta, s_{it}, z_{it}, \boldsymbol{\gamma}\right) = \Pr\left(\max_{k\in(1,\ldots,J)} y^*_{itk} = y^*_{itj} \mid \alpha_i, \beta, s_{it}, z_{it}, \boldsymbol{\gamma}\right). \tag{5}$$

We define the salt-sensitive orchard crop group as the base outcome, $B$, and obtain the probability of choosing each crop group as

$$\begin{aligned} \Pr\left(y_{it} = o_j \mid \alpha_i, \beta, s_{it}, z_{it}, \boldsymbol{\gamma}\right) &= \frac{\exp\left(\alpha_{ij} + s_{it}\beta_j + z_{it}\boldsymbol{\gamma}\right)}{1 + \sum_{k\neq B}\exp\left(\alpha_{ij} + s_{it}\beta_j + z_{it}\boldsymbol{\gamma}\right)} \quad j \neq B \\ &= \frac{1}{1 + \sum_{k\neq B}\exp\left(\alpha_{ij} + s_{it}\beta_j + z_{it}\boldsymbol{\gamma}\right)} \quad j = B. \end{aligned} \tag{6}$$

The parameters in equation (6) can be estimated by maximum likelihood. This is the multinomial logit model with fixed effects as described by Chamberlain (1980). If location-specific factors (e.g., size, soil type, elevation, and slope of the parcel) adequately capture parcel-level soil salinity conditions, then pooled multinomial logit model will give consistent estimates of $\beta_j$, and $\alpha_{ij} = \alpha_i$. However, location and seasonal factors interact to create location-specific salinity environments, which may not ve fully captured by the observable variables in $\boldsymbol{l}_i$. In particular, parcel-level soil or root-zone salinity, for which regional-scale data do not exist, may not be fully captured by size, soil type, elevation, and slope of parcel. The advantage of the multinomial logit model with fixed effects is that it allows for individual unobserved heterogeneity with respect to the intercepts, $\alpha_{ij}$.

## Data

### *Crop, Parcel, and Salinity Data*

We gather spatial data on annual field-level crop plantings for 2009–2017 from pesticide use reports (PUR) filed by farmers with the county agricultural commissioner. Using 2013 county tax parcel information, each cropped field is placed in a tax parcel to assign farmer/parcel-level fixed effects in the empirical model. A tax parcel ("parcel" from here onwards) is a contiguous agricultural area owned by one landowner. PUR data contain information for crops planted in each field; in this analysis, we restrict our analysis to the crop grown in the largest field in each parcel.[1]

[1] This is not a restrictive assumption for our data because we found that the majority of the parcels in the data (57%) contained a single cropped field, 16% of the parcels report two fields, 7.5% report three fields, and the remaining 20% report four or more fields. Moreover, a majority of the time, a parcel with more than one field grew the same crop on the second field or grew a crop from the same crop group (crop groups are discussed in the data section) or left the field uncultivated. The online supplement (see www.jareonline.org) includes more detail on the data collection and verification procedures.

Irrigation water salinity data are obtained from the network of salinity monitoring stations in the Delta (Burau, Ruhl, and Work, 2016). Monthly averages of salinity for the growing season (April–August) and spring season (April–June) are calculated and spline interpolation (Mitáš and Mitášová, 1988) is used to assign a growing season and spring season salinity value to each parcel in the sample. In all years, salinity is highest in the western and southern regions of the Delta. Increasing infiltration of sea water increases salinity in the west, while pumping operations for California's State Water Project, which transfers water from regions north of the Delta to south-of-Delta users, increases salinity in the southern Delta (Calfed Water Quality Program, 2007). During our period of analysis, salinity spiked dramatically in 2015, the peak of a severe drought that began in 2012.

We compile additional parcel-level data for parcel/soil characteristics that could potentially affect soil salinization using the USDA Soil Survey Geographic Database (SSURGO). These include variables such as soil quality, land slope, and shallow groundwater depth. Parcel-level elevation data, used as a proxy control for flood risk, are also included, as this variable is important for cropping decisions on areas of the Delta that are levee-protected islands below sea level.

### *Crop Groups*

The approximately 70 Delta crops—ranging from grains and field crops to orchards and berries—vary dramatically in terms of production practices, salinity tolerance, and average per acre prices. We group crops based on the similarity of salinity tolerance developed by Hoffman (2010)—tolerant (T), moderately tolerant (MT), moderately sensitive (MS), and sensitive (S)—as well as on production and economic characteristics. Table 1 lists the crops grown in the Delta and their assignment to the crop groups used for this analysis. In some cases, a single crop is deemed distinct enough from others crops to warrant designation to a single crop group. For example, pasture (T), corn (MS), tomatoes (MS), and vineyards (MS) are each a distinct crop group, while other groups contain several crops (e.g., orchards (S) includes almonds, pears, walnuts, and cherries). Overall, the allocation of Delta agricultural acreage by crop salinity tolerance shows some general patterns: For all years 2009–2016, a majority of the agricultural acreage in the Delta is in moderately sensitive crops (60% or greater). The next largest acreage is in moderately tolerant crops (between 15% and 20% depending on the year). While tolerant crops are a very small percentage of Delta acreage (less than 5%), sensitive crops, which include orchards and vineyards, have increased over time from 6% to 12%.

Table 2 shows average per acre prices (USD) for each of the Delta crop groups for 2009–2016. Comparing Tables 1 and 2, we see that the most sensitive crops tend to have the highest prices, with orchard (S) and truck and berry crops (S) yielding the highest per acre prices (about $9,000 per acre in 2016). Within the categories of moderately sensitive crops, the largest acreage in the Delta, there is a large difference in per acre prices, justifying our decision to keep them as separate crop groups. Alfalfa (MS), rice (MS), and corn (MS) have prices that are lower (about $1,100/acre in 2016) than the truck (MS) group, and vineyards (MS) prices are much higher (about $5,000/acre in 2016). Finally, we excluded crops from our analysis if potential crop groups (e.g., turf crops, moderately tolerant orchards) comprised less than 1% of total parcel crop choices.

## Estimation Strategy and Model Parameterization

Building on the multinomial logit model in equation (6), we estimate two models: a standard multinomial logit model using our detailed crop groups (Model 1) and our preferred fixed-effects multinomial logit model (Model 2). The fixed-effects, multinomial logit model is estimated in using the xtmlogit command in STATA.[2] In our primary specification, we follow Uz, Buck, and Sunding (2022) in using lagged growing season (April–August) salinity as the explanatory variable for crop

[2] Pforr (2014) created Stata programming for the multinomial logit model with fixed effects as described by Chamberlain (1980). This work became the xtmlogit command in Stata and has been used in a wide variety of contexts since. See Nguyen and Canh (2021) and DesJardins et al. (2019) as recent examples using fixed effects in panels of repeated choices.

**Table 1. Delta Crop Groups**

| Number | Crop Group Abbreviation | Group Description | Relative Salinity Tolerance | Acreage (%) | Individual Crop Shares (% of Group Acreage) |
|---|---|---|---|---|---|
| 1 | Pasture (T) | Pasture | T | 9,270.63 (5.60%) | Pasture[a] |
| 2 | Alfalfa (MS) | Field crops | MS | 30,415.58 (18.37%) | Alfalfa (99.9%), clover (0.15%)2, orchard grass (0.02%) |
| 3 | Field (MT) | Field crops | MT | 12,500.41 (7.55%) | Safflower (38%), rye (22%), forage hay/silage (18%)3, Sudan grass (12%), sorghum (9%) |
| 4 | Beans (S) | Beans | S | 5,421.29 (7.55%) | Dried beans (100%) |
| 5 | Rice (MS) | Grains, some beans and oilseeds | MS | 3,860.29 (3.27%) | Rice (49%), lima beans (24%), sunflowers (24%), wild rice (5%) |
| 6 | Corn (MS) | Grains | MS | 25,206.29 (15.22%) | Corn (100%) |
| 7 | Grains (MT&T) | Grains | MT, T | 15,636.44 (9.44%) | Wheat (78%), oats (20%), soybean, triticale, barley |
| 8 | Truck and berry (S) | Vegetables and berries | S | 1,643.19 (0.99%) | All berries (including blackberry, blueberry, boysenberry, strawberry) (36%), carrots (20%), green beans (21%), broccoli, cantaloupe, garlic |
| 9 | Truck (MS) | Vegetables and fruits | MS | 7,530.27 (4.55%) | Cucumber (32%), pumpkin (17%), pepper (14%), watermelon (8%), lettuce, melon, potato, cactus pear, cantaloupe, cilantro, parsley, sweet basil, vegetables, cabbage, brussels sprouts |
| 10 | Truck (MT&T) | Vegetables | MT | 1,242.073 (0.75%) | Asparagus (75%), squash (23%), artichoke |
| 11 | Tomatoes (MS) | Vegetables | MS | 12,627.22 (7.63%) | Tomato (100%) |
| 12 | Orchards (S) | Fruit and nut orchards | S | 18,378.76 (11.10%) | Almonds (26%), pear (23%), cherry (20%), walnut (20%), chestnut, citrus, kiwi, nectarine, lime, orange, peach, pecan, persimmon, pumelo, apple, apricot |
| 13 | Vineyards (MS) | Vineyards | MS | 21,858.77 (12.21%) | Grapes/vineyards (100%) |

*Notes:* Salinity tolerances are defined as tolerant (T), moderately tolerant (MT), moderately sensitive (MS), and sensitive (S).

[a] Pasture is a combination of various grasses in the MT or MS group.

[b] Pesticide Use Report data did not specify the variety of clover planted. Since most varieties of clover are MS and fewer are MT, we placed clover in the MS group.

[c] Forage hay/silage contains a variety of crops, but most are in the MT category so we placed this category in the Field (MT) group.

**Table 2. Per Acre Prices for Delta Crop Groups**

| Crop Group | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|---|---|
| Alfalfa (MS) | 818.40 | 864.50 | 1,616.70 | 1,489.40 | 1,591.74 | 1,854.20 | 1,260.63 | 1,173.92 |
| Field crops (MT) | 700.60 | 671.42 | 1,420.66 | 1,404.00 | 1,482.91 | 1,731.45 | 1,161.80 | 838.17 |
| Beans (S) | 877.83 | 486.78 | 1,157.68 | 1,392.30 | 858.00 | 1,279.87 | 1,783.50 | 1,272.00 |
| Grains (MS, Rice) | 1,301.52 | 1,183.05 | 1,360.25 | 1,516.94 | 1,265.83 | 2,111.28 | 2,040.70 | 1,221.24 |
| Grains (MS, Corn) | 918.63 | 941.50 | 1,071.20 | 1,151.98 | 1,069.32 | 934.00 | 731.46 | 809.64 |
| Grains (MT&T) | 653.39 | 557.78 | 597.40 | 689.30 | 727.90 | 770.80 | 707.61 | 366.25 |
| Truck and berry (S) | 23,374.50 | 17,538.00 | 20,318.90 | 14,842.80 | 14,284.50 | 21,000.00 | 17,016.80 | 21,250.00 |
| Truck (MS) | 6,394.97 | 4,910.26 | 6,615.91 | 5,975.80 | 6,860.70 | 6,962.43 | 7,433.13 | 6,689.44 |
| Truck (MT&T) | 7,008.10 | 4,197.60 | 4,922.40 | 5,693.30 | 3,930.80 | 5,541.24 | 11,606.40 | 8,753.80 |
| Tomatoes (MS) | 4,427.50 | 3,327.60 | 3,335.00 | 3,382.72 | 3,596.40 | 4,017.60 | 3,996.01 | 3,952.59 |
| Orchards (S) | 5,777.48 | 5,573.06 | 5,718.38 | 7,144.76 | 6,643.85 | 7,672.31 | 6,801.95 | 5,019.50 |
| Vineyards (MS) | 3,101.56 | 2,594.64 | 3,074.28 | 4,983.44 | 6,045.61 | 4,720.00 | 3,818.88 | 4,342.14 |

*Notes:* Salinity tolerances are defined as tolerant (T), moderately tolerant (MT), moderately sensitive (MS), and sensitive (S). Prices are per acre (USD), based on yields (ton/acre) for a given year. For crop groups with multiple crops, prices are weighted in proportion to their share of acreage in each year. Per acre price calculations were made using only those crops included in county crop reports, which exclude minority crops (e.g., squash, artichoke).

choice.[3] The previous season's irrigation water salinity is exogenous to current season's crop choice, and farmers use the prior year's irrigation water salinity to make decisions about crop choice and salinity management. We also estimate both models using spring salinity (April–June), as farmers may decide which annual crops to plant based on the salinity of irrigation water available around the time of planting, when crops may be most sensitive to salinity levels (Hoffman, 2010).

For the pooled multinomial logit models (Model 1), control variables included in $\boldsymbol{Z}_{it}$ (equation 6) are elevation, soil-characteristic control variables, annual indicator variables (using 2009 as the base year), spring precipitation (January–April), and parcel acreage.[4] Summary statistics for control variables appear in Appendix Table S1. Standard errors are clustered at the parcel level. In the fixed-effects model, all time-invariant variables are eliminated, leaving just lagged growing season salinity, annual indicator variables, and spring precipitation.

Last, all multinomial logit models use orchards (S) as the base crop group. This crop group has the second-highest price per acre (as shown in Table 2), and crops in this category are perennials that may take many years to mature and yield profits. The annual dummy variables used in all specifications account for temporal variations in crop prices, weather, and statewide water management.

We propose two hypotheses: First, *ceteris paribus*, an increase in surface water salinity should increase the probability of growing all crops relative to the orchards (S) group in the pooled model. Because the pooled model salinity coefficient may capture both differences in soil conditions across parcels and within-parcel changes in irrigation water salinity over time, parcels with high combined soil and irrigation water salinity levels should be less likely to be growing orchard crops. Second, we expect differences between the results of the fixed-effects (Model 2) and pooled models (Model 1), with the fixed-effects model estimating how individual parcels respond to changing irrigation water salinity levels over time, holding location-specific factors constant. Thus, we expect to find that increases in irrigation water salinity impact crop choice for fewer crop groups in the fixed-effects model.

[3] As described previously, Delta farmers rely on surface water that flows through the region from the Sacramento and San Joaquin Rivers. Given the hydrology of the Delta, it is reasonable to assume that the quality of irrigation water for a given parcel is exogenous to the farmer's profit maximization problem and cannot be a function of the crop chosen by the farmer (as might be the case in other areas if farmers were using groundwater with accumulated salts).

[4] We estimated specifications that controlled for average (per acre) prices for each crop group; unfortunately, these were highly collinear with annual dummy variables, even when we only included revenue values for key crops of interest (e.g., orchards). Because we cannot observe farmers' costs (only their crop prices) throughout the panel, we chose to include the annual fixed effects in place of crop returns to control for both trends in prices and unobservable trends in costs and other factors unique to each year.

**Table 3. Pooled Multinomial and Fixed-Effects Multinomial Logit Model Results (relative risk ratio estimates)**

| | **Model 1: Pooled Multinomial Logit Results ($N$ = 19,270)** | | **Model 2: Fixed-Effects Multinomial Logit Model ($N$ = 13,284)** | |
|---|---|---|---|---|
| | ***lag_salinity_growing*** | ***spring_salinity*** | ***lag_salinity_growing*** | ***spring_salinity*** |
| **Crop Group** | **1** | **2** | **3** | **4** |
| Pasture (T) | 1.002*** | 1.002*** | 1.002 | 1.004** |
| Alfalfa (MS) | 1.002*** | 1.002*** | 1.001 | 1.000 |
| Field crops (MT) | 1.002*** | 1.002*** | 1.002* | 1.001 |
| Beans (S) | 1.002*** | 1.002*** | 1.002 | 1.000 |
| Grains (MS, Rice) | 1.000 | 1.000 | 1.006*** | 1.004*** |
| Grains (MS, Corn) | 1.002*** | 1.002*** | 1.002** | 1.001 |
| Grains (MT&T) | 1.002*** | 1.002*** | 1.002* | 1.001 |
| Truck and berry (S) | 1.002*** | 1.002*** | 1.004*** | 1.000 |
| Truck and berry (MS) | 1.002*** | 1.002*** | 1.002 | 1.000 |
| Truck and berry (MT&T) | 1.002*** | 1.003*** | 1.003* | 1.002 |
| Tomatoes (MS) | 1.002*** | 1.002*** | 1.002 | 1.000 |
| Vineyards (MS) | 1.000 | 1.000 | 1.002** | 1.000 |
| | | | | |
| Parcel controls | Yes | Yes | Yes | Yes |
| Parcel fixed effects | No | No | Yes | Yes |
| Annual fixed effects | Yes | Yes | Yes | Yes |
| | | | | |
| Akaike information criterion | 79,478.5 | 79,451.2 | 14,749.5 | 14,767.0 |
| Bayesian information criterion | 80,988.8 | 80,961.5 | 15,558.8 | 15,576.3 |

*Notes:* Salinity tolerances are defined as tolerant (T), moderately tolerant (MT), moderately sensitive (MS), and sensitive (S). Orchards (S) is the reference crop. Parcel controls include elevation, soil type, slope gradient, available water storage capacity, annual precipitation, parcel acreage, spring water table depth. Full definitions and summary statistics for control variables appear in Appendix B. A Hausman test rejects the null hypothesis that the pooled model for *lag_salinity_growing* provides consistent estimates (chi-squared tes*t*-statistic of 60.130, *p*-value 0.000). Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level, respectively.

## Results

Table 3 presents estimated coefficients for our salinity variables (*lag_salinity_growing* and *spring_salinity*) for the multinomial logit and fixed-effects multinomial logit models. For ease of interpretation, estimated coefficients are presented as relative risk ratios: A coefficient greater (less) than 1 for a croup group means that a 1-$\mu$s/cm increase in irrigation water salinity at the parcel increases (decreases) the probability of growing a crop from that group, relative to orchards. We suppress standard errors in Table 3 and present unexponentiated coefficients and their standard errors in Table S2 in the online supplement.

Pooled model (Model 1) results for the coefficients for *lag_salinity_growing* are presented in column 1 of Table 3. Estimated coefficients are greater than one and statistically significant (99% confidence) for all crop categories, except for Rice (MS) and Vineyards (MS). *Ceteris paribus*, higher levels of irrigation water salinity from the prior year increase the relative risk of growing crops from each of these groups, compared to the orchards (S) group. Notably, these crops that are preferred to orchards (S) include the full spectrum of tolerant, moderately tolerant, moderately sensitive, and sensitive nonorchard crops.

Model 1 results using *spring_salinity* are presented in column 2 of Table 3. These results are identical to those using lagged growing salinity.[5] All relative risk ratios (except rice (MS) and vineyards (MS)) are again greater than one and statistically significant, indicating higher levels of irrigation water salinity in spring months increase the probability of planting crops from all crop groups (with the exception of rice), relative to orchards.

Table 3 presents results for the fixed-effects multinomial logits (Model 2) for *lag_salinity_growing* (column 3) and for *spring_salinity* in (column 4). Compared to the pooled model, the number of observations in the sample falls from 19,270 to 13,284 because 999 parcels did not switch crops during the study period. In Model 2, column 3 (*lag_salinity_growing* as the variable of interest), relative risk ratios are greater than 1 and significant at 99% confidence for just two crops: truck and berry crops (S) and rice (MS). This stands in sharp contrast to 10 crop groups with coefficients significant with 99% confidence in the pooled model. Thus, holding all unobservable parcel-level variables fixed, these two crop groups, though also salt-sensitive, are more likely to be planted (relative to the orchards (S) group) as irrigation water salinity increases. Relative risk ratios are also greater than 1 and significant (95% confidence) for two other moderately sensitive crops: corn (MS) and vineyards (MS). Next, we also find certain tolerant/moderately tolerant crops with relative risk ratios greater than 1, though with lower significance levels (90%) than the pooled model; these include field crops (MT), grains (MT and T), and truck crops (MT and T). Unlike the pooled model, the fixed-effects model finds that changes in irrigation water quality in any given year have no impact on growing pasture (T), alfalfa (MS), truck crops (MS), beans (S), and tomatoes (MS) relative to orchard crops. Next, in column 4, the fixed-effects model with *spring_salinity* as the coefficient of interest, we find that irrigation water salinity has no impact on cropping decisions, with the exception of increasing probability of growing rice (MS) (99% confidence) and pasture (T) (95% confidence) crops relative to orchards (S). This contrasts with the pooled multinomial logit using *spring_salinity* (column 2), where we find that all crop groups (with the exception of Rice (MS)) are more likely to be planted than the orchards (S) group.

Key findings from these results are as follows: The pooled model increasing irrigation water salinity leads nearly all crops to be preferred, relative to sensitive, long-term orchard crops. However, when we implement parcel fixed effects—such that the salinity coefficient captures only the impact of temporal variation in irrigation water salinity—irrigation water salinity has less of an impact on crop choices than pooled models suggest.[6] Unlike the pooled model, the fixed-effects model finds that increasing irrigation water salinity has no impact on the decision to grow pasture (T), alfalfa (MS), truck crops (MS), beans (S), and tomatoes (MS), relative to orchard crops. In comparing the pooled and fixed-effects models, failure to control for parcel-level heterogeneity may misstate the impact of irrigation water salinity alone on crop choice. The two models are capturing different phenomena; consequently, care must be taken in interpreting estimates and making projections with a pooled model, where coefficient estimates capture the impact of variation in irrigation water salinity levels as well as cross-parcel heterogeneity in soil conditions. For example, if not interpreted in this context, the pooled model coefficient for spring irrigation water salinity implies that farmers would use short-term, planting season irrigation-water salinity values when deciding whether to grow lower-value annual crops. A more detailed discussion of these results is presented in the discussion section.

Last, Table 4 shows average marginal effects for the pooled multinomial logit model using *lag_salinity_growing*.[7] Per Hypothesis 1, these marginal effects represent the combined effect of annual changes in irrigation water salinity and underlying parcel-level conditions that vary geographically across the Delta. Results are presented as the percentage point change in probability a crop category is chosen for a 1-ds/m (1,000-$\mu$s/cm) increase in irrigation water salinity. For reference,

[5] We tested specifications using multiple lags and multiyear averages of growing season salinity; however, these results were either not significant for the salinity variable or very similar to our chosen salinity variable, the (1-year) lagged growing season salinity.

[6] Hausman tests reject the null hypothesis that the pooled models provide consistent parameter estimates, and information criteria show our fixed-effects specification as the preferred model. The Hausman test statistic and $p$-value appear in Table 3.

[7] Marginal effects cannot be calculated for the fixed effects model because we cannot calculate the value of the intercept, given that we do not have values for the unobserved parcel-level conditions.

**Table 4. Average Marginal Effects for Pooled Multinomial Logit Model**

| Crop Group | Percentage Point Change in Probability for a 1 dS/m (1,000 $\mu$s/cm) Increase in *lag_salinity_growing* |
|---|---|
| Pasture (T) | 1.730 |
| Alfalfa (MS) | 7.040*** |
| Field crops (MT) | 3.080*** |
| Beans (S) | 0.874*** |
| Grains (MS, Rice) | −2.000*** |
| Grains (MS, Corn) | 2.030 |
| Grains (MT&T) | 2.870*** |
| Truck and berry (S) | 0.781*** |
| Truck (MS) | 2.190*** |
| Tomatoes (MS) | 4.640*** |
| Truck (MT&T) | 1.060*** |
| Orchards (S) | −12.66*** |
| Vineyards (MS) | −11.64*** |

*Notes:* Salinity tolerances are defined as tolerant (T), moderately tolerant (MT), moderately sensitive (MS), and sensitive (S). Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level, respectively.

average irrigation water salinity in our sample is 374.78 $\mu$s/cm,[8] with a large standard deviation of 349.8 $\mu$s/cm and a maximum of 9,986.49 $\mu$s/cm, or nearly 10 ds/m. Interpreting these estimates, we see that a 1-ds/m increase in irrigation water salinity is associated with a 12.66-percentage point decrease in the probability of growing an orchard (S) crop, *ceteris paribus*. Average marginal effects are also negative for vineyards (MS) (11.64%) and rice (MS) (2.0%) but positive for all other crop categories.

## Robustness Checks

### *Individual Crop Logit Models*

As a robustness check for the fixed-effects multinomial logit models, we estimate standard logit models that show the impact of controlling for/failing to allow for unobserved heterogeneity in parcel conditions when quantifying the impact of irrigation water salinity on crop choice. To accomplish this, we estimate 13 logit models, one for each crop category: In each model, the dependent variable is equal to 1 if the crop grown is from the category in question and 0 otherwise. This is analogous to our pooled multinomial logit model but without the need for a reference crop. For example, we estimate a logit model for the odds of growing a crop from the orchard (S) group relative to all others. Then, we estimate the same 13 separate logit models, quantifying the odds of growing a given crop in relation to changes in *lag_salinity_growing*; however, we also control for the initial crop grown on a parcel. Thus, we estimate the odds of growing an orchard crop, but only for crops that grew orchard crops in the initial year that parcel appeared in the dataset. This mirrors the fixed effects model in that we assume that parcels that start in each crop must have baseline soil salinities and other unobservable conditions suitable for that crop. Estimated coefficients capture the odds a parcel continues to grow/transitions out of each respective crop category, as a function of irrigation water salinity levels. We expect to find that irrigation water salinity has more of an impact on crop choice if the initial crop is not accounted for, as in our pooled and fixed-effects multinomial logit model comparison. Further, we assume that parcels that start in a moderately tolerant or tolerant crop must have baseline soil conditions that make them unable to transition to a more sensitive ones, whereas salinity levels may have an impact on the more sensitive, higher-revenue crops. If this is the case, we expect to find that the *lag_salinity_growing* odds

[8] Variable summary statistics appear in Table S1 in the online supplement.

**Table 5. Coefficient Estimates (log-odds ratios) for *lag_salinity_growing* from Individual Logit Models**

| Crop Group | Odds of Growing Crop Relative to All Others | Odds of Growing the Same Crop First Grown on Parcel |
|---|---|---|
| Pasture (T) | 1.000 | 1.001* |
| Alfalfa (MS) | 1.000** | 0.999** |
| Field crops (MT) | 1.000* | 1.000 |
| Beans (S) | 1.000*** | 1.003 |
| Grains (MS, Rice) | 0.998*** | 0.992*** |
| Grains (MS, Corn) | 1.000 | 0.999*** |
| Grains (MT&T) | 1.000** | 1.000 |
| Truck and berry (S) | 1.001*** | 1.001 |
| Truck (MS) | 1.000*** | 1.000 |
| Tomatoes (MS) | 1.0004*** | 0.999* |
| Truck (MT&T) | 1.001*** | 1.003* |
| Orchards (S) | 0.996*** | 0.998** |
| Vineyards (MS) | 0.999*** | 1.000 |

*Notes:* Salinity tolerances are defined as tolerant (T), moderately tolerant (MT), moderately sensitive (MS), and sensitive (S). Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level, respectively.

ratio coefficient is less than 1 and more significant for the moderately sensitive and sensitive crops, meaning that increasing salinity makes parcels that start in these crops more likely to transition out of them.

Results are presented in Table 5. All models were estimated with the same control variables as the baseline pooled multinomial logit models (Models 1). We suppress all control variables and show only the odds ratio coefficient estimates for *lag_salinity_growing* from each of the 13 logit models. Column 1 of Table 5 shows the exponentiated coefficients (odds ratios) for the models that do not control for initial crop grown. In the models not controlling for initial crop choice, we see odds ratios greater than 1 and significant with at least 90% confidence for numerous crops: alfalfa (MS), field crops (MT), beans (S), grains (MT and T), truck crops (MS), truck and berry crops (S), tomatoes (MS), and truck crops (MT and T). This means that increases in *lag_salinity_growing* increased the odds of growing these crops, *ceteris paribus*. Odds ratios are less than 1 and significant for rice (MS), orchards (S) and vineyards (MS). Column 2 of Table 5 shows results for the coefficient for *lag_salinity_growing* for the 13 separate logit models estimated only for parcels that initially grew the crop in question. These coefficient estimates are the odds of continuing to grow the given crop that was first grown when a parcel appeared in the dataset. Odds ratios are positive and significant in the logit models (90% confidence) for pasture (T) and truck crops (MT and T) only; increases in irrigation water salinity increased the likelihood that parcels that were initially growing these crops continued to do so. Odds ratios are less than 1 and significant for rice (MS) and corn (MS) (99% confidence), alfalfa (MS) and orchards (S) (95% confidence), and tomatoes (MS) (90% confidence). Parcels that started in these sensitive crops were less likely to continue growing them as a function of increasing salinity in irrigation water. All other crop categories have insignificant coefficients. As was the case for our pooled and fixed-effects multinomial logit models, when we partially control for unobserved parcel effects by controlling for initial crop choice, annual variation in irrigation water salinity impacts fewer crops relative to the pooled model. Unlike the logit models that do not account for the crop initially grown on a parcel, the estimated odds ratios (when we account for the crop initially grown) have expected values: More sensitive crops have decreased odds of being grown, relative to all others; more tolerant crops have increased odds of continuing to be grown.

**Table 6. Robustness Check, Alternative Reference Crop Categories**

| Pairwise Crop Category Comparisons | Relative Risk Ratios | Pairwise Crop Category Comparisons | Relative Risk Ratios |
|---|---|---|---|
| Pasture (T)-Rice (MS) | 1.002 | Truck and berry (S) -Corn (MS) | 1.001 |
| Pasture (T)-Vineyards (MS) | 1.002 | Truck and berry (S)-Grains (MT&T) | 1.001 |
| Pasture (T)-Orchards (S) | 1.002 | Truck and berry (S)-Vineyards (MS) | 1.002 |
| Alfalfa (MS)-Rice (MS) | 1.002 | Truck and berry (S)-Orchards (S) | 1.002 |
| Alfalfa (MS)-Truck and berry (S) | 1.000 | Truck (MS)-Rice (MS) | 1.002 |
| Alfalfa (MS)-Truck (MT&T) | 0.999 | Truck (MS)-Vineyards (MS) | 1.002 |
| Alfalfa (MS)-Vineyards (MS) | 1.001 | Truck (MS)-Orchards (S) | 1.002 |
| Alfalfa (MS)-Orchards (S) | 1.002 | Tomatoes (MS)-Rice (MS) | 1.002 |
| Field (MT)-Rice (MS) | 1.002 | Tomatoes (MS)-Vineyards (MS) | 1.002 |
| Field (MT)-Vineyards (MS) | 1.002 | Tomatoes (MS)-Orchards (S) | 1.002 |
| Field (MT)-Orchards (S) | 1.002 | Truck (MT&T)-Alfalfa (MS) | 1.001 |
| Beans (S)-Rice (MS) | 1.002 | Truck (MT&T)-Beans (S) | 1.001 |
| Beans (S)-Truck (MT&T) | 0.999 | Truck (MT&T)-Rice (MS) | 1.002 |
| Beans (S)-Vineyards (MS) | 1.001 | Truck (MT&T)-Corn (MS) | 1.001 |
| Beans (S)-Orchards (S) | 1.002 | Truck (MT&T)-Grains (MT&T) | 1.001 |
| Rice (MS)- Pasture (T) | 0.998 | Truck (MT&T)-Vineyards (MS) | 1.002 |
| Rice (MS)-Alfalfa (MS) | 0.998 | Truck (MT&T)-Orchards (S) | 1.002 |
| Rice (MS)-Field (MT) | 0.998 | Vineyards (MS)- Pasture (T) | 0.998 |
| Rice (MS)-Beans (S) | 0.998 | Vineyards (MS)-Alfalfa (MS) | 0.999 |
| Rice (MS) -Corn (MS) | 0.998 | Vineyards (MS)-Field (MT) | 0.999 |
| Rice (MS) -Grains (MT&T) | 0.998 | Vineyards (MS)-Beans (S) | 0.999 |
| Rice (MS) -Truck and berry (S) | 0.998 | Vineyards (MS)-Corn (MS) | 0.999 |
| Rice (MS)-Truck (MS) | 0.998 | Vineyards (MS)-Grains (MT&T) | 0.999 |
| Rice (MS)-Tomatoes (MS) | 0.998 | Vineyards (MS)-Truck and berry (S) | 0.998 |
| Rice (MS)-Truck (MT&T) | 0.998 | Vineyards (MS)-Truck (MS) | 0.998 |
| Corn (MS) -Rice (MS) | 1.002 | Vineyards (MS)-Tomatoes (MS) | 0.998 |
| Corn (MS)-Truck and berry (S) | 0.999 | Vineyards (MS)-Truck (MT&T) | 0.998 |
| Corn (MS)-Truck (MT&T) | 0.999 | Orchards (S)- Pasture (T) | 0.998 |
| Corn (MS)-Vineyards (MS) | 1.001 | Orchards (S)-Alfalfa (MS) | 0.998 |
| Corn (MS) -Orchards (S) | 1.002 | Orchards (S)-Field (MT) | 0.998 |
| Grains (MT&T)-Rice (MS) | 1.002 | Orchards (S)-Beans (S) | 0.998 |
| Grains (MT&T)-Truck and berry (S) | 1.000 | Orchards (S)-Corn (MS) | 0.998 |
| Grains (MT&T)-Truck (MT&T) | 0.999 | Orchards (S) -Grains (MT&T) | 0.998 |
| Grains (MT&T)-Vineyards (MS) | 1.001 | Orchards (S)-Truck and berry (S) | 0.998 |
| Grains (MT&T)-Orchards (S) | 1.002 | Orchards (S)-Truck (MS) | 0.998 |
| Truck and berry (S)-Alfalfa (MS) | 1.001 | Orchards (S)-Tomatoes (MS) | 0.998 |
| Truck and berry (S)-Rice (MS) | 1.002 | Orchards (S)-Truck (MT&T) | 0.998 |

*Notes:* Each crop group combination shows the relative risk ratio for planting the first crop group, relative to the second listed group. We present relative risk ratios for all crop group combinations with $p$-values significant at the <0.01 level.

### *Use of Different Crop Groups as Reference Crop*

In our main results, we estimate the relative risk ratio coefficient for each crop category, with orchards (S) as the base crop. In this additional robustness check, with results in Table 6, we estimate the pooled multinomial logit 13 times, with each crop category used as the reference crop. Table 6 shows pairwise coefficient estimates (relative risk ratios) for every possible base and comparison crop combination; estimates show the relative risk ratio for growing the first-listed crop relative to the second. We show results only for relative risk ratios significant at a 99% level of confidence. Results are identical to those

**Table 7. Logit and Fixed-Effects Logit for Sensitive Versus Nonsensitive Crops**

| Variables | Logit ($N$ = 19,270) | Fixed-Effects Logit ($N$ = 8,143) |
|---|---|---|
| *lag_salinity_growing* | 0.99959*** | 0.99956** |
| | (0.000) | (0.000) |
| *2010* | 1.353*** | 0.637*** |
| | (0.121) | (0.097) |
| *2011* | 0.838*** | 0.466*** |
| | (0.055) | (0.057) |
| *2012* | 0.741*** | 0.527*** |
| | (0.048) | (0.064) |
| *2013* | 0.286*** | 0.542*** |
| | (0.043) | (0.128) |
| *2014* | 0.624*** | 0.566*** |
| | (0.044) | (0.070) |
| *2015* | 0.362*** | 0.848 |
| | (0.053) | (0.203) |
| *2016* | 1.547*** | 0.688** |
| | (0.155) | (0.113) |
| *wtdepth* | 1.002*** | |
| | (0.001) | |
| *soil_index* | 0.769*** | |
| | (0.044) | |
| *aws* | 1.046*** | |
| | (0.016) | |
| *slopegrade* | 1.150*** | |
| | (0.053) | |
| *parcel_acreage* | 1.000 | |
| | (0.000) | |
| *elevation* | 1.014** | |
| | (0.006) | |
| *precip* | 0.992*** | 1.000 |
| | (0.001) | (0.001) |
| Akaike information criterion | 19,944.60 | 6,262.30 |
| Bayesian information criterion | 20,070.40 | 6,325.30 |

*Notes:* Coefficients are expressed as odds ratios. We present five decimal places for our variable of interest, *lag_salinity_growing*. Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level, respectively.

in our main results (Table 3), with only the interpretations changing along with the chosen reference crop. As expected, we see a general pattern where more tolerant crops have higher relative risk of being planted compared to crops that are more sensitive. The exception to this pattern is truck and berry crops (of all categories), which have increased relative risk of being chosen compared to alternative sensitive and tolerant crops.

*Logit and Fixed-Effects Logit for Sensitive versus Nonsensitive Crops*

In this robustness check, we follow Uz, Buck, and Sunding (2022) in estimating a logit model where the dependent variable is whether the crop is a sensitive (MS and S) or tolerant (MT or T) crop. Table 7 shows results for the basic logit model where the dependent variables equal 1 if a salt-sensitive crop

**Table 8. Multinomial Logit Model, Different Crop Groupings**

| | Pooled Model *lag_salinity_growing* ($N$ = 19,270) | Fixed Effects *lag_salinity_growing* ($N$ = 12,006) |
|---|---|---|
| Truck and berry | 1.002*** | 1.001 |
| Grains | 1.001*** | 1.0009 |
| Field | 1.002*** | 1.0007 |
| | | |
| Akaike information criterion | 49,050.40 | 10,987.50 |
| Bayesian information criterion | 49,428.00 | 11,187.10 |

*Notes:* Orchards is the reference crop. Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level, respectively.

was planted on a given parcel and 0 otherwise. All other control variables are the same as in the pooled multinomial logit model (Model 1). We compare this to a fixed-effects (conditional logit) model. Results are again presented as odds ratios. In both models, increasing irrigation water salinity decreases the odds of growing sensitive crops. Consistent with our multinomial logit model results, estimates differ in the fixed-effects model. The coefficient estimate in the pooled logit model is more significant (99% confidence) than in the fixed effects model (95% confidence). This mirrors our main paper findings, where a pooled model may capture the impact of both irrigation water salinity and existing soil conditions on crop choice. A second key insight from this model is that in grouping all sensitive crops together, we miss out on our finding that irrigation-water salinity has varying impacts on salt-sensitive crops, as crop choices that are not affected by increases in irrigation water salinity may bias the overall impact of salinity on salt-sensitive crops (leading to an odds ratio closer to 1).

### *Multinomial Logit Model with Different Crop Groupings*

Table 8 shows results for pooled multinomial logit and fixed-effect multinomial logit models using broad croup groupings: orchards, grains, truck and berry crops, and field crops. Control variables are the same as those used in our original Models 1 and 2 using the detailed crop groupings. Coefficients are again presented as relative risk ratios, with standard errors suppressed. Column 1 shows the results for *lag_salinity_growing*: Coefficients are greater than 1 and significant for all crop groups, meaning that all crop groups are more likely to grown than the orchards (S) group. However, in the fixed effects model (column 2), coefficient estimates are all insignificant. Irrigation water salinity levels have no impact on crop choice when we control for unobserved parcel/farmer effects. This contrasts with our original models, where irrigation water salinity did impact crop choice for a handful of crops in the fixed-effects model. These results show the importance of our detailed crop groupings, as there are mixed findings for the impact of salinity on crop choice within the broader groupings.

## Discussion, Limitations, and Further Research

This paper uses multinomial logit models to estimate the impact of salinity in irrigation water on crop choice. We divide over 70 Delta crops into 13 crop groups that account both for the type of crop and the crop's salinity tolerance. We compare the results of a fixed-effects model to a pooled multinomial logit. While the pooled model captures the impacts of both annual changes in irrigation water salinity and cross-parcel unobserved parcel-level conditions, including soil salinity, the fixed-effects model isolates the impact of irrigation water salinity alone on farmers' parcel-level cropping decisions across time.

In results for the pooled multinomial logit model, we see increased relative risk of planting all crops, compared to orchards. Given that we expect these coefficients to capture the impact of both cross-sectional and temporal variation in irrigation water salinity and unobserved parcel conditions, these results should not be taken to mean that increasing irrigation water salinity in any given year makes farmers more likely to switch out of permanent orchards. Instead, as we expected, it may be that the nonorchard crops are grown in the areas that tend to have more saline irrigation water in any given year (and likely worse soil profiles) due to the complex interactions between soil salinity, surface water salinity, and water management institutions of the Delta. When we implement parcel fixed-effects to control for parcel-level unobserved heterogeneity, we find that variation in parcel-level irrigation water salinity has less of an impact on crop choices than pooled models suggest. Thus, in contexts such as the Delta, where variation in salinity across parcels is higher than variation for a given parcel over time, failure to control for parcel-level heterogeneity tends to misattribute the total impact of both irrigation water salinity and cross-parcel heterogeneity to irrigation water salinity alone.

While, as expected, we find irrigation water salinity has less of an impact on crop choice in the fixed-effects model, annual changes in irrigation water salinity do impact farmer decisions. Annual variation in irrigation water salinity increases odds of growing many crops relative to orchards, permanent crops often grown in intervals of 20 or more years. Surprisingly, the fixed-effects model finds increased relative risk of planting crops that are both more tolerant and sensitive/moderately sensitive, such as rice (MS) and truck and berry (S) crops that, like orchards, yield high prices per acre.

With regards to the increasing planting of more tolerant, low-value crops (relative to orchards) our fixed-effects results may mean that irrigation water salinity, in conjunction with parcel-level conditions, has degraded to an extent where it may be either not possible or too costly to keep soil conditions tolerable for the orchard crops in some areas of the Delta. Given the projections for sea-level intrusion into the Delta (Corwin, 2021), this could mean that Delta farmers' ability to maintain suitable soil conditions via leaching may further decrease, threatening areas of the Delta where salinity has historically been less of a concern.

In reference to the finding that increased salinity also increases relative probabilities of planting crops that are also sensitive/moderately sensitive, it is likely the case that salinity management is less of a concern for these crops than for the orchard (S) category, where many crops are investment-type crops (e.g., almonds, walnuts) expected to produce for up to 30 years (Almond Board of California, 2023). These results suggest irrigation water in some regions is not so saline that it precludes farmers from using that water to maintain parcel-level soil conditions at levels suitable for these sensitive and moderately sensitive crops, consistent with findings by Medellín–Azuara et al. (2014) that increases in salinity will have overall negligible impacts on Delta revenues. Intuitively, farmers are unlikely to choose low-value field crops so long as salinity management is possible for orchard alternatives that yield higher returns than the more tolerant crop groups. This may be why we find increased odds of planting truck and berry crops in all models, as these were the highest-revenue yielding crop group in the Delta in 2016 (Delta Protection Commission, 2020). Moreover, unobserved farmer preferences, institutions, and knowledge of salinity management could also be potential factors that make high-value crops less risky than we would otherwise think, despite increasing surface water salinity. Because so many Delta crops are salt-sensitive, farmers may choose the crops for which they have the best knowledge of salinity management. These factors may be the reason Uz, Buck, and Sunding (2022) finds large heterogeneity in responsiveness to irrigation water salinity in their mixed logit model.

In our logit model robustness check, where we estimate the odds parcels that initially grew a given crop continued to do so, our results are further reinforced: If we do not control for initial crop grown, we find that annual variation in salinity has a much larger impact on the odds of switching away from the initial crop, likely capturing the fact that many tolerant/moderately tolerant crops are already grown in the Delta regions with more saline soils. However, once we account for the initial crop, irrigation water salinity still increases the odds of switching out of a high-value orchard (S) crop. We also see that parcels that started in tomatoes (MS), rice (MS), corn (MS), and alfalfa (MS) have positive odds of switching out of these crops due to annual changes in irrigation water.[9] Thus, while some of these crops had increased likelihood of being planted *relative to orchards* in the fixed-effects, multinomial logit model, we still see that increasing irrigation water salinity is decreasing the overall likelihood that a farmer who was initially growing these crops can continue to do so. Notably, in this robustness check, irrigation water salinity has no impact on the odds that a farmer who initially grew truck and berry crops may continue to do so, a finding consistent with our fixed-effects model result that these high-value crops may be preferred to orchards.

One implication of this work is to warn that, for the crops that are less responsive to annual changes in water salinity, revenue projections in prior/future work that do not control for parcel-level fixed effects may be overstated. Similarly, we find that failure to use detailed crop groupings may lead the researcher to conclude that changes in irrigation water salinity has a homogenous impact on planting decisions for all crops within broadly defined groups (e.g., sensitive versus nonsensitive). It is important to note, however, that crop choice is one of many negative impacts of salinity on farmers; we focus on it because it is the most readily observable. However, farmers are still negatively impacted by lower yields, increased management costs, and long-term soil degradation, even if their crop choice is unaffected. Thus, this analysis should be interpreted as a lower-bound, partial assessment of salinity impacts in the Delta.

While our work gives new insights on the impact of salinity on crop choice, one limitation is that we are unable to predict salinity-related changes in profits. The fixed-effect model does not allow for crop choice predictions because parcel-level heterogeneity is unobservable. Even if we could predict crop changes, salinity-mitigation actions and costs are unknown. Given this uncertainty, previous work (e.g., MacEwan, Howitt, and Medellín-Azuara, 2016) has projected changes in revenues, but not profits. Uz, Buck, and Sunding (2022) use a mixed logit model to simulate changes in acreage, but for the reasons stated here, do not estimate changes in profits. Given the contrast between our fixed-effects and pooled results, we caution against making predictions from a general multinomial or logit crop choice model.

Our results highlight the need for a better understanding of the long-term interaction between factors like irrigation water salinity, root-zone salinity, and other soil conditions in the context of the complex spatial variability in Delta parcel-level growing conditions. Because farm-level factors, both natural and human, may create unobserved heterogeneity in farmers' optimization problems, future research should develop insights into behavioral factors such as preferences, risk aversion, and information processing, all of which may impact how farmers respond to salinity concerns, regardless of actual measured levels of salinity in irrigation water and soils. In farmer contexts where so much is unobserved, developing panel data, although time and cost-intensive, pays dividends in our understanding of decision making. Finally, regional data collection efforts of soil conditions may contribute toward improving the understanding of farmers' decision making and help target state and regional efforts to mitigate salinity and increase the efficiency of adaptation efforts. Acquiring such data is imperative if the Delta is to maintain its role as the agricultural powerhouse of California in the face of climate change and projections for future increases in salinity in the Delta.

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[9] One limitation is that our model does not capture crop rotations. It may be possible that, for some of these crops, the multinomial logit model and the robustness check logit models may be capturing Delta farmers who rotate between crops like rice, corn, beans, safflower, and other grain crops. However, rotations are, of course, only possible for annual crops, not the (often perennial) high-value truck and berry and perennial orchard crops of key interest in our results. Second, when crops are rotated, many farmers keep their land in one crop (e.g., rice) for many years before switching; recent research finds that nearly 50% of rice growers do not rotate, and, when they do, it is not for salinity-related reasons (Rosenberg et al., 2022), meaning that there is little risk of causing bias in our coefficient estimates for lagged growing season salinity.

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# Online Supplement: The Root of the Problem: Capturing the Impacts of Irrigation Water Salinity on Crop Choice

**Janine Stone and Anita M. Chaudhry**

## Parcel-Data Processing

This appendix describes details on sources and methods used to compile parcel-level panel of crops and salinity. Summary statistics of these variables are contained in Table S1.

**Table A1: Variables and Definitions, and Summary Statistics of Salinity and Control Variables**

| Variable | Definition | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| *lag_salinity_growing* | April-August salinity levels (microsiemens/cm) | 363.18 | 335.67 | .0004 | 9,305.62 |
| *spring_salinity* | April-June salinity levels (microsiemens/cm) | 347.037 | 296.27 | 0.00 | 8,765.78 |
| *slopegrade* | Indicates the percentage gradient of the soil surface. | 0.77 | 0.90 | 0.00 | 22 |
| *elevation* | This variable captures the elevation of the midpoint of the parcel from the sea level (M). Especially important for cropping decisions on below-sea-level Delta islands. | 5.67 | 9.04 | -5.98 | 54.67 |
| *wtdepth_spring* | Minimum Spring (April_June) water table depth. | 82.74 | 61.02 | 0.00 | 200 |
| *aws* | Available water storage, the capacity of the soil to store water at a depth of 50 cm below ground surface. Measured in cm. | 8.18 | 2.30 | 0.00 | 18.00 |
| *soil_Index* | Irrigated Soil Capacity Class, a numerical index (1-8) indicating suitability for growing crops, accounting for soil texture, erosion potential, and other factors. Higher levels mean worse soils. | 2.31 | 0.61 | 1.00 | 8.00 |
| *precip* | Annual precipitation (cm) | 194.07 | 84.75 | 38.13 | 391.91 |
| *parcel_acerage* | Total acreage in a parcel | 129.19 | 260.34 | 0.0002 | 9,476.25 |

The material contained herein is supplementary to the article named in the title and published in the *Journal of Agricultural and Resource Economics* (*JARE*).

*Crop Field Polygons*

County crop data derived from the Pesticide Use Reports (PUR) were obtained from the California Agricultural Commissioners and Sealers Association (CACASA) for the years 2009 to 2016.[1] Data were acquired for all counties that intersect the legal Delta including Alameda, Contra Costa, Sacramento, San Joaquin, Solano, and Yolo. After merging the individual county datasets, we identified and resolved polygon overlap and duplication issues. These issues took one of two forms: bad polygon geometry resulting in slight overlaps with other field polygons, or duplication of fields wherein a single field polygon could have upwards of 30 records of matching geometry displayed as a single stacked polygon. The "slivers" that resulted from overlap issues were manually deleted from the datasets, while the resolution of the field duplication required cross referencing an existing dataset. By comparing our CACASA datasets with those available for public download from the County of San Joaquin's Agricultural Commissioner GIS data portal,[2] we identified two criteria that they were using to filter out duplicated polygons. The filtering revolved around two fields of attribution, the "is_active" and "status" fields. By retaining only polygons with both the value "issued" for "status" and a positive Boolean value for "is_active," the San Joaquin dataset significantly reduced the duplication issue. Applying these criteria to our delta wide dataset allowed us to similarly remove most of the duplication issues. Following that, a query that removed exact duplicates was applied to the dataset. Polygons meeting the above-mentioned criteria but also overlaying a polygon with the exact same crop list were deleted. Last, a query was used to remove polygons with crop lists that were either blank or not relevant to the project needs.

*Assigning Fields to Parcels*

A tax parcel ("parcel" from here onwards) is a contiguous agricultural area owned by one landowner. Pesticide use reports data contain information on crops planted in each field, but there may be several fields within a parcel. The delineation or the boundary of crop fields in pesticide use reports can shift spatially from year to year, especially if a crop switch occurs. Thus, crop field data were combined with 2013 parcel boundaries data to create a spatially stable framework on which to pin the often-shifting crop field data. We found that a majority of the parcels (57%) contained a single crop field, 16% of the parcels report two fields, 7.5% report three fields, and the remaining 20% of the sample reports 4 or more fields. When a parcel reported more than 2 fields, we restricted the analysis to the largest field within the parcel. This approach allowed us to examine cropping decisions from the landowners' perspectives, and our parcel-level fixed effects becomes equivalent to landowner level fixed effects. Dropping the smaller fields, when present, did not lose substantial crop choice variation data because, in a majority of the cases, the same crop was grown in the second field, or crops belonged to the same crop group as shown in Table 1.

An additional issue that potentially complicates analysis of pesticide use reports for econometric modeling purposes is the listing of multiple crops per field. The raw PUR data reported a far higher number of crops planted in each field, but careful data cleaning, which involved spelling checks, or putting together slightly different name variations (e.g., "SUGAR BEETS" and "SUGARBEETS"), we were able to reduce the number of crops markedly. A majority (80%) reported a single crop. In the remaining 20% of multi-cropped fields, data cleaning showed that the second land use was either the same crop, the same crop group as defined in Table 1, or uncultivated land. In a minority of the cases when two different crop groups were planted, we chose the first crop listed as the crop on that field. This allowed us to examine one crop per parcel in a parcel-year panel data.

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[1] http://cacasa.org/

[2] https://www.sjgov.org/department/agcomm/gis_crop_data

### *Salinity Data*

The salinity monitoring stations are spatially stratified throughout the Delta region to include the two main channels and branches consisting of the Sacramento and San Joaquin Rivers. Both the California Department of Water Resources and the US Geological Survey for the Bureau of Reclamation operate a total of 46 salinity monitoring stations as of 2016. Both the state and federal salinity datasets were obtained from the California Department of Water Resources California Data Exchange Center (2024). All monitoring stations were standardized to average monthly electrical conductivity, expressed in µs/cm. A GIS file consisting of point representations of the salinity monitoring stations was created, and then, for each month from January 2006 to December 2016, a raster field surface of predicted salinity across the Delta was created. This consisted of creating 120 raster surfaces for analysis. The spline interpolation method (Franke, 1982; Mitáš and Mitášová, 1988) was chosen to create each predictive surface. This interpolation method estimates raster cell values using a mathematical function that minimizes overall surface curvature, resulting in a smooth surface that passes exactly through the input points (salinity monitoring stations). Spline interpolation creates only a general trend of the area and acts as a sheet of rubber that passes through the available point but allows prediction of values in the areas between measurement points. This method is best for generating gently varying surfaces such as groundwater table heights, temperature, and salinity measurements. It ensures a smooth (continuous and differentiable) surface, together with continuous first-derivative surfaces. Rapid changes in gradient or slope can occur in the vicinity of the data points, hence an appropriate method for surface water salinity gradients. The parcels were overlaid on each salinity raster surface, and the average monthly salinity was calculated for each parcel and encoded as an attribute to the parcel.

### *Additional Data*

We added parcel level irrigation water salinity, land slope, land elevation, shallow groundwater depth, and water district boundaries, to each parcel. Elevation data were generated in GIS using the USGS 10-meter resolution digital elevation model, and soil indices were calculated using data from the Soil Survey Geographic Database (Natural Resources Conservation Service, 2024).

## Full Results for Pooled and Fixed-Effects Multinomial Logit Models and Robustness Checks

This appendix contains results (un-exponentiated coefficient estimates and standard errors for the pooled and fixed-effects multinomial logit models). We then present results for the three robustness checks described in the main paper.

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**Table B1 Full Results for Pooled Multinomial Logit Model**

| | Pasture | Alfalfa (MS) | Field (MT) | Beans (S) | Rice (MS) | Corn (MS) |
|---|---|---|---|---|---|---|
| *lag_salinity_growing* | 1.95E-03*** | 1.71E-03*** | 1.80E-03*** | 1.77E-03*** | -8.87E-06 | 1.63E-03*** |
| | (0.001) | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) |
| *2010* | -1.317*** | 0.0960 | -0.645*** | 1.835*** | -1.166*** | 1.090*** |
| | (0.297) | (0.120) | (0.194) | (0.229) | (0.310) | (0.137) |
| *2011* | -0.581*** | 0.0380 | 0.262* | 0.442** | -0.878*** | 0.548*** |
| | (0.159) | (0.081) | (0.141) | (0.214) | (0.223) | (0.094) |
| *2012* | -0.207 | -0.00204 | 0.629*** | -0.0790 | -0.456** | 0.180 |
| | (0.146) | (0.103) | (0.139) | (0.226) | (0.229) | (0.118) |
| *2013* | 1.873*** | -0.528** | 1.809*** | -2.781*** | 0.963* | -1.945*** |
| | (0.578) | (0.226) | (0.309) | (0.343) | (0.512) | (0.251) |
| *2014* | 0.193 | -0.403*** | 0.661*** | -1.285*** | 0.0598 | -0.931*** |
| | (0.186) | (0.103) | (0.138) | (0.248) | (0.249) | (0.119) |
| *2015* | 1.691*** | -0.840*** | 1.252*** | -2.733*** | 0.677 | -2.515*** |
| | (0.534) | (0.221) | (0.307) | (0.315) | (0.507) | (0.246) |
| *2016* | -2.134*** | -0.919*** | -1.164*** | 1.778*** | -1.713*** | 0.0191 |
| | (0.290) | (0.138) | (0.204) | (0.267) | (0.297) | (0.167) |
| *wtdepth_spring* | -0.013*** | -0.005*** | -0.005*** | 0.000 | -0.011*** | -0.006*** |
| | (0.003) | (0.001) | (0.001) | (0.002) | (0.003) | (0.001) |
| *soil_index* | 1.042*** | 0.585*** | 0.878*** | 0.177 | 1.827*** | 1.016*** |
| | (0.198) | (0.110) | (0.123) | (0.128) | (0.207) | (0.130) |
| *aws* | -0.140** | -0.061** | -0.052 | -0.024 | 0.216*** | 0.060* |
| | (0.070) | (0.031) | (0.037) | (0.045) | (0.042) | (0.033) |
| *slopegrade* | -0.343* | -0.111 | -0.209 | -0.0144 | -0.165 | -0.134 |
| | (0.195) | (0.139) | (0.144) | (0.143) | (0.208) | (0.140) |
| *field_acres* | 0.004*** | 0.003*** | 0.002 | 0.001 | 0.003*** | 0.004*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *elevation* | -0.059*** | -0.085*** | -0.063*** | -0.040*** | 0.031** | -0.097*** |
| | (0.022) | (0.008) | (0.010) | (0.009) | (0.013) | (0.009) |
| *precip* | 0.016*** | -0.002 | 0.011*** | -0.023*** | 0.013*** | -0.015*** |
| | (0.004) | (0.002) | (0.002) | (0.002) | (0.003) | (0.002) |
| *constant* | -5.226*** | 1.028* | -4.168*** | 2.098*** | -9.981*** | 1.073* |
| | (1.169) | (0.541) | (0.724) | (0.687) | (1.192) | (0.635) |

(Continued on next page…)

**Table B1. Continued from previous page**

| | Grains (MT &T) | T&B[1] (S) | Truck (MS) | Tomatoes (MS) | Truck (MT&T) | Vineyards (MS) |
|---|---|---|---|---|---|---|
| *lag_salinity_growing*[2] | 1.67E-03*** | 2.20E-03*** | 1.99E-03*** | 1.94E-03*** | 2.35E-03*** | 3.26E-04 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *2010* | 0.144 | -0.231 | -0.006 | -0.126 | 0.890*** | -1.165*** |
| | (0.149) | (0.395) | (0.200) | (0.151) | (0.287) | (0.147) |
| *2011* | 0.393*** | 0.489 | 0.0206 | -0.0948 | 0.396** | -0.453*** |
| | (0.112) | (0.305) | (0.163) | (0.108) | (0.169) | (0.092) |
| *2012* | 0.356*** | 0.956*** | 0.295* | -0.0817 | 0.221 | -0.00875 |
| | (0.125) | (0.311) | (0.164) | (0.126) | (0.213) | (0.112) |
| *2013* | 0.499* | 0.892* | 0.0307 | -0.902*** | -1.898*** | 2.183*** |
| | (0.265) | (0.514) | (0.334) | (0.256) | (0.561) | (0.292) |
| *2014* | 0.0445 | 0.616* | -0.0706 | -0.339*** | -0.771*** | 0.506*** |
| | (0.129) | (0.321) | (0.174) | (0.126) | (0.256) | (0.121) |
| *2015* | 0.0635 | 0.958* | -0.002 | -0.832*** | -2.743*** | 1.959*** |
| | (0.254) | (0.510) | (0.322) | (0.247) | (0.580) | (0.280) |
| *2016* | -0.791*** | -0.114 | -0.471** | -0.913*** | -0.246 | -1.384*** |
| | (0.170) | (0.432) | (0.210) | (0.165) | (0.394) | (0.154) |
| *wtdepth_spring* | -0.005*** | -0.008*** | -0.002 | -0.002 | -0.000 | -0.005*** |
| | (0.001) | (0.003) | (0.001) | (0.001) | (0.003) | (0.002) |
| *soil_index* | 0.939*** | 0.688*** | 0.755*** | 0.365** | 0.350 | 0.484*** |
| | (0.133) | (0.231) | (0.146) | (0.155) | (0.282) | (0.125) |
| *aws* | -0.004 | -0.046 | 0.077** | 0.083*** | 0.089 | -0.026 |
| | (0.033) | (0.073) | (0.037) | (0.032) | (0.075) | (0.035) |
| *slopegrade* | 0.007 | -0.480** | -0.350** | -0.0938 | -0.131 | 0.522*** |
| | (0.136) | (0.237) | (0.161) | (0.136) | (0.210) | (0.138) |
| *field_acres* | 0.002* | 0.000 | 0.002** | 0.003*** | 0.004*** | 0.002** |
| | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) |
| *elevation* | -0.072*** | -0.053*** | -0.053*** | -0.050*** | -0.124*** | -0.059*** |
| | (0.011) | (0.019) | (0.015) | (0.009) | (0.031) | (0.016) |
| *precip* | 0.003* | 0.002 | 0.002 | -0.004** | -0.016*** | 0.015*** |
| | (0.002) | (0.004) | (0.002) | (0.002) | (0.004) | (0.002) |
| *constant* | -2.437*** | -3.820*** | -3.631*** | -0.854 | -0.591 | -3.893*** |
| | (0.639) | (1.159) | (0.760) | (0.639) | (1.258) | (0.607) |

*Notes*: *N=19,270 AIC=79,478.5 BIC=80,988.8.* 1. T&B are Truck and berry crops.
2. We present additional decimal places in results for our variable of interest, *lag_salinity_growing.*
3. Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% level.

**Table B2. Full Results, Fixed-Effects Multinomial Logit Model**

| | **Pasture (T)** | **Alfalfa (MT)** | **Field (MT)** | **Beans (MS)** | **Rice (MS)** | **Corn (MS)** |
|---|---|---|---|---|---|---|
| *lag_salinity_growing* | 1.78E-03 | 1.37E-03 | 1.93E-03* | 1.65E-03 | 6.28E-03*** | 2.32E-03** |
| | (0.002) | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) |
| *2010* | 0.119 | -0.114 | 0.313 | 0.644 | 0.479 | 0.410 |
| | (0.908) | (0.438) | (0.484) | (0.553) | (0.626) | (0.473) |
| *2011* | -1.011 | -0.593 | 0.512 | -0.521 | -0.101 | 0.0173 |
| | (0.690) | (0.414) | (0.441) | (0.514) | (0.560) | (0.431) |
| *2012* | -1.324* | -1.566*** | -0.507 | -1.364** | -1.254** | -1.008** |
| | (0.724) | (0.454) | (0.471) | (0.555) | (0.576) | (0.469) |
| *2013* | -4.298*** | -2.692*** | -1.762** | -2.969*** | -3.932*** | -2.628*** |
| | (1.579) | (0.815) | (0.862) | (0.900) | (1.044) | (0.861) |
| *2014* | -3.051*** | -3.215*** | -2.115*** | -3.391*** | -2.818*** | -3.441*** |
| | (0.801) | (0.509) | (0.528) | (0.604) | (0.625) | (0.523) |
| *2015* | -4.806*** | -4.254*** | -3.705*** | -3.901*** | -5.305*** | -4.483*** |
| | (1.457) | (0.830) | (0.880) | (0.930) | (1.075) | (0.881) |
| *2016* | -4.058*** | -5.903*** | -4.943*** | -3.710*** | -5.200*** | -6.109*** |
| | (1.227) | (0.802) | (0.832) | (0.856) | (0.878) | (0.834) |
| *precip* | -0.010 | -0.000 | 0.000 | -0.005 | -0.008 | -0.002 |
| | (0.010) | (0.006) | (0.006) | (0.007) | (0.007) | (0.006) |

| | **Grains (MT &T)** | **T&B (S)** | **Truck (MS)** | **Tomatoes (MS)** | **Truck (MT &T)** | **Vineyards (MS)** |
|---|---|---|---|---|---|---|
| *lag_salinity_growing* | 1.90E-03* | 4.36E-03*** | 1.73E-03 | 1.74E-03 | 3.38E-03* | 2.39E-03** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) |
| *2010* | 0.414 | -0.836 | 0.226 | -0.810* | 0.952 | 1.829** |
| | (0.457) | (1.250) | (0.532) | (0.462) | (0.793) | (0.882) |
| *2011* | 0.239 | 0.0986 | -0.432 | -0.951** | -0.200 | 1.243** |
| | (0.429) | (0.963) | (0.461) | (0.428) | (0.624) | (0.629) |
| *2012* | -0.878* | -0.551 | -1.437*** | -1.777*** | -1.340* | 0.100 |
| | (0.465) | (1.029) | (0.488) | (0.468) | (0.799) | (0.526) |
| *2013* | -1.807** | -0.832 | -3.159*** | -2.662*** | -5.239*** | -3.803** |
| | (0.842) | (1.674) | (0.972) | (0.841) | (1.494) | (1.733) |
| *2014* | -2.532*** | -1.759* | -3.231*** | -3.107*** | -4.436*** | -1.079 |
| | (0.518) | (1.014) | (0.552) | (0.522) | (0.781) | (0.709) |
| *2015* | -3.545*** | -1.444 | -4.239*** | -3.543*** | -8.231*** | -4.413** |
| | (0.854) | (1.696) | (0.985) | (0.857) | (1.505) | (1.733) |
| *2016* | -5.217*** | -5.859*** | -4.841*** | -6.325*** | -5.848*** | -0.203 |
| | (0.820) | (1.559) | (0.875) | (0.826) | (1.154) | (1.033) |
| *precip* | 0.001 | 0.008 | -0.003 | 0.003 | -0.023** | -0.025** |
| | (0.006) | (0.012) | (0.007) | (0.006) | (0.010) | (0.011) |

*Notes*: N=13,284 AIC=14,749.5 BIC 15,558.8.
1. T&B are Truck and berry crops
2. We present five decimal places in results for our variable of interest, *lag_salinity_growing.*
3. Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% level.