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Behavioral Salinity Response: Estimating Salinity Policies from Remote Sensed Micro-Data

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Abstract

In arid regions, including Australia's Murray-Darling basin and California's Central Valley, increasing salinity is a problem affecting agriculture, regional economies, urban areas, and the environment. The direct costs of salinity to agriculture in the Murray-Darling basin and California’s Central Valley are on the order of $500 million per year. Policymakers want to design policies to effectively manage salinity and, as such, need to understand how farmers respond to changing salinity levels. Reduced crop yields account for the largest direct cost of salinity to agriculture however farmers are able to mitigate effects through field management. Consequently, there is a difference between experimentally estimated yield-salinity functions and those which result from farmer behavioral response to salinity. The latter are relevant for salinity policy analysis and, to our knowledge, have not previously been estimated in the literature. We model farmers as profit-maximizing crop portfolio managers and estimate the behavioral yield-salinity functions for 6 crop groups using geo-referenced field data. We find behavioral yield-salinity functions are close to those generated in experimental settings but costs using experimental functions understate the costs of salinity.

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Introduction

In arid regions, including Australia's Murray-Darling basin and California's Central Valley, increasing salinity is a problem affecting agriculture, regional economies, urban areas, and the environment. Some estimates place the direct costs of salinity to agriculture in the Murray-Darling basin at $340 million per year (Council 1999). [1] Howitt et al. (2009) estimated that the direct agricultural salinity costs in the Central Valley of California range between $450 and $750 million per year. In both regions, including damages to urban users, the environment, and industry increase estimates of the total cost to over $1 billion per year. California has recently responded with the Central Valley Salinity Coalition and CV-SALTS program to fund salinity research. Australia funded the $1.4 billion (AU) National Action Plan for Salinity beginning in 2000, which was replaced by the Caring for our Country program in 2008. Research under these programs has advanced understanding of the salinity problem, however policy recommendations under the programs have been largely ineffective. This is, in part, because much of the analysis neglects social and economic information about the possible response of farmers to proposed policies (Pannell and Roberts 2010). In order to better inform policy decisions and accurately quantify agricultural salinity impacts we need to understand the behavioral response of farmers to salinity. In this paper we address one aspect of farmer response and estimate crop-specific yield-salinity functions using geo-referenced data on observed land use. We refer to them as behavioral yield-salinity functions.

Reduced crop yields account for the largest direct cost of salinity to agriculture. The relationship between root-zone salinity and crop yield varies by crop and field-specific conditions. Soil scientists have established the yield-salinity relationship in experimental settings however, in practice, farmers faced with high salinity have a number of management options which may change the nature of this relationship. For example, with sufficient depth to groundwater, applying water in excess of crop consumption will allow leaching of salts below the root-zone. With saline groundwater intrusion into the root-zone, switching to micro-irrigation or facilitating drainage may mitigate the impacts of salinity. In addition to adjusting irrigation techniques,

[1] All dollars in $US 2008 unless otherwise noted. Salinity refers to all sources including dryland, surface, and groundwater.

irrigation technology, or both, other salinity management strategies include crop rotation, field flushing, adjusting fertilizer application, field drainage, establishing native salt-tolerant vegetation, and land fallowing. The extent to which farmers use these different options depends on the type of salinity and field-specific factors including micro-climate, soil characteristics, and the quality of the available irrigation water. Furthermore, management alternatives have different effects on crop yields depending on the crop cultivated and the rotation history of the field. We expect that the farmer considers the relative costs of the management alternatives, the marginal crop-specific yield effects of management strategies, and relative crop prices when making management decisions. As such, the yield-salinity relationships estimated in controlled experimental settings and those implied by observed farmer behavior may differ. The latter have significance in salinity policy analysis and, to our knowledge, the existing literature has not estimated these relationships.

We estimate the behavioral yield-salinity functions for six crop groups using geo-referenced field data on agricultural land in Kern County, California between 1997 and 2009. We model farmers as profit maximizing “crop portfolio” managers using a two-step estimation procedure under the Mean Variance (MV) portfolio management model (Markowitz 1952 , Markowitz 1959). First, we estimate an aggregate and scalable measure of the risk-aversion coefficient of farmers in Kern County. The risk-aversion coefficient captures farmers’ attitudes toward additional variance in returns. We substitute the estimated risk aversion coefficient into a second-stage model which estimates the expected yield reduction, due to increasing salinity, that coincides with their tolerance for variation on returns. Over a given range of salinity we observe land use decisions and estimate the variance-covariance matrix between returns of relevant crops. All else constant, yield must change over salinity zones such that the resulting land use patterns represent the optimums in the MV framework.

Our analysis is also relevant for evaluating the use of physical relationships in economic models. It is common to impose physical relationships in economic models. For example, biological growth functions for fish, climate-induced yield change, and other agronomic relationships. These implicitly assume that behavior does not affect the relationship. To test this hypothesis we compare salinity cost estimates using a calibrated agricultural production model with experimental and behavioral functions. We show the difference in cost estimates and discuss areas for future research.

The paper is structured as follows. First, we motivate the problem by estimating a Multinomial Logit model (MNL) of crop choice in Kern County to demonstrate the importance of salinity in planting decisions. Next, we review relevant soil science literature and determine an appropriate functional form for the relationship between salinity and crop yield. In the following section we detail the two-step MV model used to estimate the parameters of the hypothesized functions. Finally, we show the relevance of behavioral salinity response estimates and compare the experimental and behavioral functions for the costs of increasing salinity in California's Central Valley using the Statewide Agricultural Production Model (SWAP). We show that experimental yield-salinity functions understate the costs of salinity to farmers and discuss implications for imposing physical relationships in economic models.

A Multinomial Logit Model of Land Use Decisions

If farmers do not respond to changes in field-level salinity then we have no reason to expect a divergence between experimental and behavioral yield-salinity relationships. To investigate whether farmers respond to salinity by altering their land use decisions we estimate a Multinomial Logit (MNL) model of crop choice. Researchers often use discrete choice models to model agricultural land use decisions (Wu and Babcock 2004, Landis 1998). These models have seen broad use in economic literature, initially in transportation choice models and then spreading to agriculture and resource research. Researchers have applied discrete choice models to watering technology adoption and choice (Lichtenberg 1989, Caswell and Zilberman 1985), crop rotation and tillage choice (Wu and Babcock 1998), and land use choices (Hardie and Parks 1997, Wu and Segerson 1995).

Our data are from geo-referenced land use surveys and remote sensing equipment that tracked each individual field in Kern County, California (located in the southern part of the San Joaquin Valley) between 1997 and 2009. The gross value of agricultural production in Kern reaches over $4 billion per year, with grapes, almonds, and pistachios representing the three most valuable crops.[2] Kern County produces a wide range of crops, which we have aggregated into 12 groups: lucerne, dry beans, corn, cotton, cucurbits, grain or field, potatoes, processing tomatoes, vegetables, fruit and nuts, vines, and fallow land. We base our crop groups on the California Department of Water Resources (DWR) definitions used for planning and analysis in California.

Geo-referenced parcels in the data set contain information on the crop cultivated, parcel area, farm management company, soil type, shallow groundwater salinity, and field slope. The unit of measurement is an individual field and the Kern County Geographic Information Systems Office compiled the land use data. We measure salinity as shallow groundwater salinity at an average depth of 3 meters. Shallow groundwater salinity information is geo-referenced and obtained from a 2002 analysis by the California Department of Water Resources.[3] Using a Krigging technique in GIS, we represent the level of shallow groundwater salinity as a continuous variable ranging from 0 to 24, measured in dS/m (Schoups 2004). We obtained soil quality data from the USDA Soil Survey Geographic Database (SSURGO) for 2002 and ordered by the USDA into 7 categories, 1 through 7, in decreasing quality.[4] We represent field size with a continuous measure of area, as reported in pesticide use reports and cross-checked using area calculation tools in ArcGIS. Figure 1 shows an overlay of land use and salinity in 2002 and Tables 1 and 2 summarize the data.

[2]See: http://www.kernag.com/caap/crop-reports/crop10_19/crop2010.pdf.
[3] http://www.sjd.water.ca.gov/publications/drainage/dmr/01dmr/01DMReport.pdf
[4] http://soils.usda.gov/survey/geography/ssurgo/

Figure 1. Kern County 2002 Agricultural Land Use and Salinity

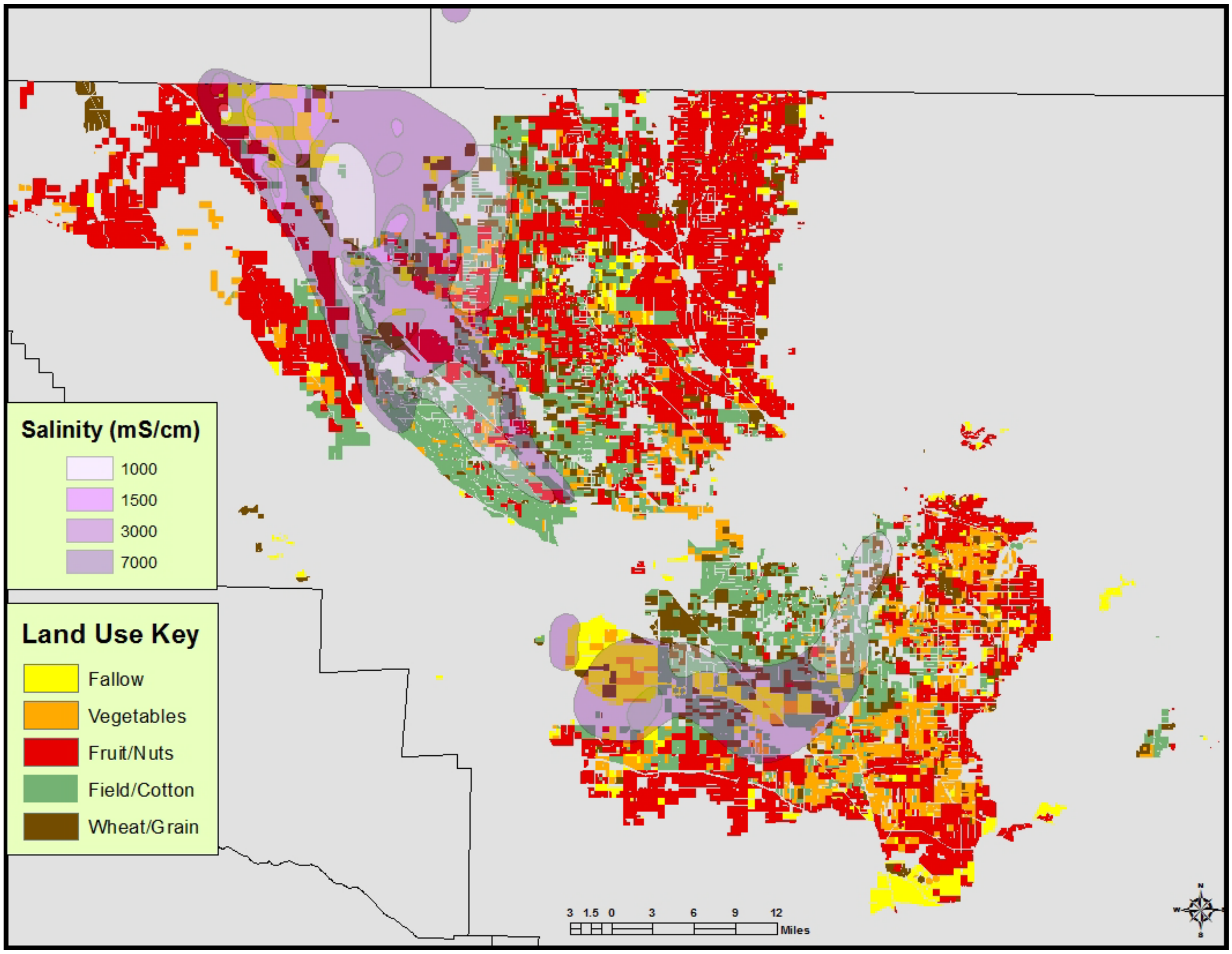


Table 1. Kern County 2002 Field-Level Data Summary

Variable	Observations	Units	Mean	Std. Dev.	Min	Max
Slope	13,989	Degrees	0.20	0.31	0.00	2.83
Salinity	13,989	dS/m	0.69	2.04	0.00	23.00
Hectares	13,989	ha	37.43	40.14	0.50	259.00
Soil	13,989	SSURGO Definition	2.16	0.83	0.00	8.00

Table 2. Kern County Land Use 2002

Crop Group	Number of Fields	Hectares (total)	Average Field Size (ha)	Percent of Total Area
Lucerne	1,902	62,687	32.9	11.91
Dry Beans	135	4,490	33.3	0.85
Corn	512	17,780	34.7	3.38
Cotton	2,111	90,063	42.7	17.12
Cucurbits	125	2,227	17.8	0.42
Grain and Field	1,744	66,563	38.2	12.65
Potatoes	411	13,339	32.5	2.54
Processing Tomatoes	256	8,638	33.8	1.64
Vegetables	1,208	33,175	27.5	6.31
Fruit and Nuts	2,982	111,352	37.4	21.16
Vine	1,313	51,855	39.5	9.86
Fallow	1,290	63,998	49.6	12.16
Total	13,989	526,167		-

We use geo-referenced data to estimate the determinants of land use decisions in Kern County. As salinity increases, crop yields decline and the rate of this decline varies by crop. All else constant, we hypothesize that a profit maximizing farmer facing high field salinity will shift toward more salt-tolerant crop rotations. For example, orchards have relatively lower salt tolerance than cotton thus, we hypothesize that cotton area will increase as salinity increases. Other field characteristics, including soil quality, field size, field slope, and well as micro-climate, will also influence land use decisions. All else constant, we hypothesize that farmers will allocate higher value rotations to land within the farm that has premium soil quality. Additionally, within a farm, fields have a specific size and shape to accommodate machinery and realize economies of scale. We rarely observe farmers sub-dividing fields within a short sequence of years, thus we include parcel (field) size in the model. Finally, fields with steeper slope there have a higher capital investment required to ensure sufficient irrigation and management of capital.

Given that regressors (field slope, field size, soil quality, and micro-climate) do not vary across alternatives, we use the Multinomial Logit (MNL) (Greene 2003). Formally, as in Green (2003 pg. 720), let $p_{ij} = \Pr[y_i = j]$ represent the probability of observing crop *j* on field *i*, for *j* = 1,2,…,12 and *i* = 1, 2,…, 13,898. Model M1 defines the MNL model.

(M1) $$p_{ij} = \frac{e^{\mathbf{x}_i^{'}\beta_j}}{\sum_{l=1}^{12} e^{\mathbf{x}_i^{'}\beta_l}}, \text{ where } j = 1, 2, \ldots, 12$$

Define $\mathbf{x}$ as a vector of the alternative invariant regressors: field size, soil quality, salinity level, and slope. Since the probabilities sum to one, we impose a restriction to ensure identification. We restrict $\beta_1 = 0$. Consequently, all estimates have lucerne (crop 1) as the base outcome. We interpret all the coefficient estimates as: compared to lucerne the likelihood of observing a crop *j* changes by β_j. In order to calculate percentage changes we calculate the marginal effects as nonlinear combinations of the predictor variables. The marginal effects take the form $\frac{\partial \Pr[crop = i]}{\partial x_i} = p_{ij}\left(\beta_j - \sum_{l=1}^{12} p_{il}\beta_l\right)$, where x_i is the variable of interest. We hold all other variables constant at their mean during the computation.

MNL Model Results

We estimate the MNL model using maximum likelihood in Stata 10. We reject the null hypothesis that all coefficients equal zero, indicating that the model has good overall fit, with an estimated pseudo-R^2 of 0.085. To rule out heteroskedasticity, we estimated the model with robust standard errors and found no change in the standard error or coefficient estimates, indicating we have robust estimates. Additionally, we considered a series of F-tests to determine if individual coefficients should be included in the model, we find that all regressors should be included in the model. We confirmed this by a series of likelihood ratio tests comparing the full model to a restricted model (with one regressor dropped). The full model additionally has the lowest AIC and BIC, indicating it is the best model by that criteria.

The majority of the coefficient estimates have statistical significant at the 1–5% level, with nearly all significant at the 10% level. Statistically insignificant coefficient estimates largely result from a small number of observations of a specific crop. However, we have no theoretical basis to justify dropping these crops from the regression models thus, we include all crops in the final model. We omit the coefficient estimates in this paper, but we will provide them upon request. Instead, we report the estimated marginal effects along with the respective statistics. Table 3 summarizes the estimated marginal effects from the MNL model.

Table 3. Estimated Marginal Effects

Marginal Effect	Lucerne	Bean/Berry	Corn	Cotton	Cucurbit	Grain/Field
Salinity	**0.0379*** **	**0.00352*** **	**0.000601**	**0.0526*** **	**-0.000447**	**0.0302*** **
	(0.00204)	(0.000360)	(0.00167)	(0.00194)	(0.000524)	(0.00198)
Soil	**-0.00110**	**-0.00377*** **	**0.00699*** **	**-0.00791* **	**-0.000173**	**0.0328*** **
	(0.00414)	(0.00115)	(0.00206)	(0.00433)	(0.000518)	(0.00365)
Slope	**0.0461*** **	**-0.000244**	**-0.000878**	**0.00768**	**0.00560*** **	**0.0243** **
	(0.0104)	(0.00319)	(0.00626)	(0.0119)	(0.00109)	(0.0105)
Hectare	**-0.000226*** **	**-2.27e-05** **	**-6.37e-06**	**0.000139*** **	**-8.86e-05*** **	**5.64e-05* **
	(4.21e-05)	(1.16e-05)	(2.08e-05)	(3.37e-05)	(9.50e-06)	(3.35e-05)
Observations	13,989	13,989	13,989	13,989	13,989	13,989

Marginal Effect	Potato	Tomato	Vegetable	Fruit/Nuts	Vine	Fallow
Salinity	**-0.0202*** **	**0.00315*** **	**-0.0184*** **	**-0.0482*** **	**-0.0655*** **	**0.0248*** **
	(0.00105)	(0.000856)	(0.00298)	(0.00427)	(0.00204)	(0.00136)
Soil	**0.00312*** **	**-0.00995*** **	**-0.0141*** **	**-0.0353*** **	**-0.0104*** **	**0.0397*** **
	(0.000897)	(0.00162)	(0.00305)	(0.00464)	(0.00180)	(0.00275)
Slope	**0.0116*** **	**-0.00815**	**0.0576*** **	**-0.121*** **	**-0.0105** **	**-0.0121**
	(0.00245)	(0.00507)	(0.00603)	(0.0148)	(0.00418)	(0.00973)
Hectare	**-7.49e-06**	**-1.49e-05**	**-0.000298*** **	**0.000186*** **	**5.50e-05*** **	**0.000227*** **
	(8.64e-06)	(1.48e-05)	(3.81e-05)	(3.87e-05)	(1.21e-05)	(2.17e-05)
Observations	13,989	13,989	13,989	13,989	13,989	13,989

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

The results of the MNL model show strong support for the underlying hypothesis that farmers respond to changes in salinity, soil, and slope by changing planting decisions. For example, when salinity increases by one dS/m we can expect to have a 5.2 percentage point increase in cotton and a 4.82 percentage point decrease in orchards. All else constant at the average, farmers plant more salt tolerant crops as salinity increases. We consider the marginal effects of salinity and soil quality in more detail below.

Table 4 reproduces the estimated marginal effects of salinity and the approximate (experimental) salt threshold tolerance of the crops in the model. Threshold salinity tolerance equals the level of salinity (in dS/m) at which yield declines by 10 percent. This represents an approximate measure of crop salt tolerance; the rate of decline differs by crop group. The data show that as salinity increases, all else constant and at the mean, farmers have a greater probability of planting more salt tolerant crops. In other words, farmers respond to changes in salinity. A striking feature of Table 4 is that marginal salinity effects are ordered by salt tolerance suggesting that, not only do farmers respond to salinity, farmers respond as if they understand the specific responses of individual crops. For example, vegetables and fruit and nut crops have a greater sensitivity to salt and a lower likelihood of being observed, 1.8 percentage points and 4.8 percentage points respectively, for a one dS/m increase in salinity. Grain and other field crops have the greatest salt tolerance, as salinity increases by one dS/m they increase by 3 percentage points. For crops that have moderate salt tolerance, such as cucurbits and grain corn, the marginal effects have much smaller magnitude (or no significance), generally under 1 percentage point.

Table 4. Marginal Effects of Salinity by Threshold Salt Tolerance

Crop Group	Threshold dS/m	Marginal Effect
Vegetable	1.4	-0.0184***
Fruit/Nuts	1.4	-0.0482***
Potato	1.7	-0.0202***
Vine	1.7	-0.0655***
Tomato	1.9	0.00315***
Lucerne	2.2	0.0379***
Cucurbit	2.4	-0.000447
Corn	3.7	0.000601
Dry Beans	4.9	0.00352***
Cotton	5.1	0.0526***
Grain/Field	6.7	0.0302***
Fallow	n/a	0.0248***

In addition to salinity, soil quality represents an important determinant of land use decisions. All else constant we hypothesize that farmers will grow the more valuable crops on higher quality land. The MNL estimation results confirm this hypothesis, as shown in Table 5. We show the average, gross profits per hectare, for each crop group ordered against the marginal effect of soil quality. Recall that a one "class" (SSURGO classification index) increase in the soil variable represents a decrease in the quality of the soil. Thus, the marginal effects of soil show that the change in the probability of observing a given crop due to a one unit decrease in soil quality, all else constant at the mean. For example, when soil class decreases by one unit (by SSURGO definition) we realize a 3.28 percentage point increase in grain and other field crops and a 1.41 percentage point decrease in vegetable crops. Table 5 shows that, in general, farmers plant higher value crops to higher soil quality land, all else constant at the mean.

Table 5. Marginal Effects of Soil Quality by Gross Returns (Gross Revenue per hectare)

Crop Group	Gross Returns	Marginal Effect
Fallow	n/a	0.0397***
Grain/Field	141	0.0328***
Corn	205	0.00699***
Lucerne	306	-0.00110
Dry Bean	383	-0.00377***
Cotton	474	-0.00791*
Tomato	700	-0.00995***
Fruit/Nuts	1,793	-0.0353***
Potato	2,089	0.00312***
Vegetable	2,833	-0.0141***
Cucurbit	3,144	-0.000173
Vine	4,350	-0.0104***

The MNL model shows that farmers respond as hypothesized to changes in salinity, soil quality, and slope. This indicates that farmers are aware of, and alter their behavior in response to, salinity, however this is not accounted for in salinity models. For example, using experimental yield-salinity relationships in simulation models may incorrectly specify the true (behavioral) yield-salinity relationship. To the extent that farmers can rotate crops, install drainage, or invest in other capital to mitigate the effects of salt, the experimental and behavioral yield-salinity functions may differ.

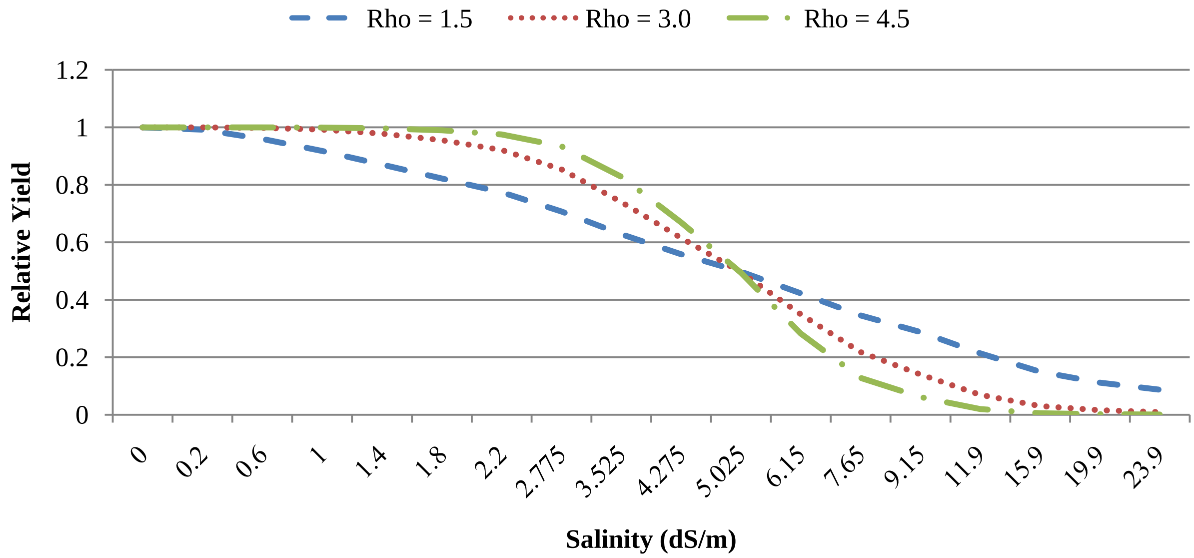
Experimental Yield-Salinity Functions

There is a well documented relationship between root zone salinity and crop yields in the soil science literature. In general, as salinity in the root zone increases crop yield decreases and this relationship varies by crop. Initial models specified a linear threshold relationship, where yield did not change at low levels of salinity and then declined linearly over some range until salinity reached a threshold level where yields declined to zero (Feinerman, Yaron and Bielorai 1982). Subsequent research using similar data sets found that a smooth, s-shaped, curve fit the data better (VanGenuchten 1984, VanGenuchten and Hoffman 1984, VanGenuchten and Gupta 1993). Equation E1 defines the yield-salinity relationship for any given crop.

$$\text{(E1)} \qquad Y = \frac{Y_{\max}}{1 + \left(\frac{c}{c_{50}}\right)^{\rho}}$$

In Equation E1, Y represents the actual yield, $Y_{\max}$ represents the maximum yield under no salinity, and c measures the root zone salinity in dS/m. The parameters c_{50} represents the level of salinity where crop yield declines by 50 percent. We estimate the parameter ρ based on experimental data. Using experimental plot data, VanGenuchten and Gupta (1993) found that ρ equals approximately 3 for most crops and c_{50} varies depending on the crop. Figure 2 shows some sample experimental salinity functions for varying values of ρ, holding c_{50} fixed at 5.0. As ρ increases, the relative yield declines more rapidly as salinity reaches the threshold values, lower values indicate a smoother, approaching linear, decrease in yields. We estimate the key parameter of the yield-salinity relationship (E1), ρ, using observed data.

Figure 2. Experimental Yield-Salinity Functions for Varying Values of Rho



Typically, studies that estimate the costs of salinity to agriculture substitute this relationship into a standard profit maximization problem, where the parameters correspond to those estimated using experimental plot data (Howitt et al. 2008). This assumes that Equation E1 represents the true yield-salinity relationship farmers face. There are several potential problems with this approach. First, researchers can often only observe approximate salinity data (e.g. groundwater salinity), not salinity at the root zone. For example, in our Kern County dataset, we measure salinity in shallow groundwater at an average depth of 3m. Salinity in the shallow groundwater can only proxy for field-level or root-zone salinity. Additionally, as discussed in the introduction, and supported by the MNL results, farmers face a number of management options to mitigate the effects of salinity. Even with high salinity farmers may realize higher yields than suggested by the experimental functions. The difference between experimental and behavioral yield-salinity parameters is an empirical question.

Estimating Behavioral Salinity-Yield Parameters

We hypothesize that Equation E1 represents the shape of the behavioral yield-salinity relationship, but that the parameters implied by farmer behavior may differ from those estimated using experimental data. The extent to which experimental and behavioral parameters deviate tests of the validity of Equation E1 in bio-economic models. We define the behavioral yield-salinity function in Equation E2.

$$\text{(E2)} \qquad \hat{Y}_i = \frac{Y_{i,\max}}{1+\left(\dfrac{c}{\hat{\delta}\, c_{i,50}}\right)^{\hat{\rho}_i}}$$

We aggregate crops into 6 groups $i \in \{lucerne,\ cotton,\ corn,\ grain,\ vegetables,\ fruit/nuts\}$ where $\hat{Y}_i$ represents the actual yield and $Y_{i,\max}$ represents the maximum yield (in U.S. tons per hectare). We report yield in U.S. tons[5] because this is consistent with the data in the model we use to estimate the cost of salinity under behavioral and experimental parameters (discussed in a later section). As in Equation E1, c represents the root-zone salinity and $c_{i,50}$ represents the crop-specific parameter at which yields decline by 50 percent. We hypothesize that $c_{i,50}$ will equal the parameter as estimated using the experimental data. However, since we observe shallow groundwater salinity, a proxy for root-zone salinity, we introduce a scale parameter, δ, which does not vary across all crops and captures the difference between root-zone and groundwater salinity. The parameter $\hat{\rho}_i$ represents the crop-specific smoothness parameter, which may vary from the experimental parameter estimates due to farmer behavior.

We estimate behavioral salinity parameters using a two-step procedure in the MV portfolio framework. The MV framework provides a simple representation of risk and portfolio management. However, for our purposes adding additional complexity to the risk framework unnecessarily takes away from the fundamentals of the model. Additionally, the literature still accepts Markowitz's seminal work as a reasonable characterization and as one consistent with utility maximization (Levy and Levy 1999, Kroll, Levy and Markowitz 1984, Tew, Reid and Rafsnider 1992). In this framework we model farmers as profit maximizing crop-portfolio managers. Given an allocation of land and variance-covariance of gross returns for crops, the farmer acts to minimize the variance on returns subject to a minimum return constraint. By solving the model over a range of minimum returns, we can form the efficient frontier which represents the risk-return tradeoff the farmer faces.

[5] Recall that 1 U.S. ton = 907.18 kg.

We observe land use decisions and salinity levels, and thus can disaggregate the 13,989 fields into 30 (or more/less) salinity level ranges (bands). Thus we observe the proportion of the portfolio allocated to a given crop for every salinity range. Given a measure of farmers' risk-aversion, which is scalable and independent of salinity, we can infer the implied yield-reduction (behavioral yield-salinity relationship) which must hold in order for the observed crop mix to represent an optimal solution. MNL model results show that, all else constant, as salinity increases we observe a greater proportion of salt-tolerant crops. The changing crop proportions, modeled in the MV framework, allow us to estimate the behavioral yield-salinity parameters.

In the first step we estimate an aggregate measure of farmer risk aversion. Farmers have Arrow-Pratt Risk Aversion Coefficient, γ, (Pratt 1964) determined by historic revenue variation in each crop, independent of salinity. We hypothesize that farmers are risk averse with respect to variations in revenue based on stochastic prices and microclimates, not salinity, thus risk aversion is independent of salinity. This is a reasonable assumption since farmers can observe soil salinity and take abatement actions accordingly. Consequently, in the MV model we only need to know the average returns for each crop and the corresponding variance-covariance matrix of revenues. As defined above, $i \in \{lucerne,\ cotton,\ corn,\ grain,\ vegetables,\ fruit/nuts\}$. We use Kern County Agricultural Commissioner Data to estimate the gross revenues for each of the six crops in the model. We use a time series of 1980 to 2009, in real 2008 dollars, to estimate the average returns and variance-covariance matrix.[6] In the MV model the risk aversion coefficient simply equals the reciprocal of the shadow value on the return constraint. Problem P1 defines the optimization problem.

[6] The data are available at: http://www.nass.usda.gov/Statistics_by_State/California/Publications/AgComm/Detail/index.asp.

$$
\text{(P1)} \qquad \begin{aligned}
&Min \sum_i \sum_j \alpha_i \sigma_{i,j} \\
&\quad s.t. \\
&\quad \mu_i \cdot \alpha_i \geq \gamma \\
&\quad \sum_i \alpha_i = 1 \\
&\quad \alpha_i \geq 0
\end{aligned}
$$

The farmer's (Problem P1) chooses the proportional allocation, α_i, of each crop *i* in the portfolio, which must be positive and sum to one. The minimum return, γ, measures the average return in Kern County, based on average crop proportions, between 1980 and 2009. The parameters $\sigma_{i,j}$ and μ_i represent the elements contained in the variance-covariance matrix and average returns for crop *i (*and *j)*, respectively.

We estimate the model using the General Algebraic Modeling System (GAMS). The Arrow-Pratt Risk Aversion Coefficient is the reciprocal of the shadow value on the return constraint (Pratt 1964, Markowitz 1952). We estimate the farmer risk aversion coefficient for Kern County as 12.58. This coefficient indicates that farmers are averse to risk, an empirically accepted fact, consistent with the presence of insurance in agriculture. This is a simple representation of risk compared with more recent specifications. However, the point of this exercise is not to revisit risk aversion but, rather, to construct a transparent model that can infer behavioral yield-salinity parameters from observed data.

In the second step we formulate a model which explains the variation in yield as a function of salinity, given the farmers' preferences for risk estimated in the first step. Over each salinity range we observe the proportional crop allocation, farmers' risk aversion coefficient, and the variance-covariance matrix of gross revenues. As the proportional allocation of crops changes across different salinity ranges we estimate the corresponding reduction in yield.[7] We retain the s-shaped relationship from the experimental literature and the estimated 50 percent yield ($c_{i,50}$) reduction parameters. Table 6 summarizes the base parameters used in the model, which we

[7] We could equivalently specify the variation in gross revenues, but variation in yield is a simpler specification.

derive from Steppuhn, VanGenuchten, and Grieve (2005). Problem P2 describes the estimating equation for the scale parameter, δ, and the behavioral curve smoothness parameters, ρ_i.

$$\text{(P2)} \qquad \frac{Y_{i,\max}}{1+\left(c_k \big/ \delta c_{i,50} \right)^{\rho_i}} = 2 \cdot \hat{\gamma} \sum_i \sigma_{i,j} p_{k,i,j} + \varepsilon_{i,k} = 0.$$

The subscript k denotes the salinity region, where $k = 1, 2, \ldots, 17$; *i* and *j* denote crops, where $i \neq j$; $\hat{\gamma}$ represents the previously estimated risk aversion coefficient; and $p_{i,j,k}$ is the proportion of crops *i* and *j* in salinity region *k*. We use the highest observed yield per hectare between 1980 and 2009 from the Agricultural Commissioner's time series database as the maximum yield. The scale factor δ estimates the relationship between shallow groundwater salinity and root-zone salinity. We specify the errors as $\varepsilon_{i,k}$, for each crop in every salinity region.

Table 6. Parameter Summary

Crop Group	Max Yield (U.S. tons per hectare)	C-50
Lucerne	3.64	18.20
Vegetables	2.63	8.90
Grain	1.82	24.30
Corn	3.04	10.90
Cotton	0.23	28.50
Fruit and Nuts	0.57	5.09

Given the limited number of salinity ranges (30 in our specification), and the presence of strong priors from the experimental literature, we use Generalized Cross Entropy (GCE) to estimate the parameters (Mittelhammer, Judge and Miller 2003). Entropy refers to the measure of disorder, or lack of information, in a system. GCE is a two-step estimation procedure where, in the first step, a Generalized Maximum Entropy model solves for the optimal prior probability weights over the parameter distribution. In the second step, GCE uses these weights to estimate the full model and corresponding error probability weights. Intuitively, maximum entropy corresponds to the maximally uninformative weight distribution, thus GCE imposes as little additional structure on the model while satisfying data and adding up constraints. We use a constant prior of 3.0 for the behavioral smoothness parameters, ρ_i, and a uniform support space between 1.5

and 12. The scale parameter has no prior and a support between 0 and 1. We estimate the model in GAMS.

The estimate of the scale parameter is 0.904, indicating that the salinity at which yield declines by 50 percent is scaled by 0.904 when using shallow groundwater salinity as a proxy for root-zone salinity. Table 7 summarizes the smoothness parameter estimates from the behavioral yield-salinity model compared to the experimental results from VanGenuchten and Gupta (1993). Behavioral parameter estimates differ from experimental parameter estimates by up to 28 percent because they capture the farmer behavioral response to changing salinity levels.

Table 7. Behavioral Parameter Estimates

Crop Group	Behavioral Rho	Experimental Rho	Percent Difference
Lucerne	2.42	2.51	-3.75
Vegetables	2.67	2.86	-6.71
Grain	2.32	3.25	-28.71
Corn	2.61	2.58	1.09
Cotton	2.27	3.00	-24.50
Fruit and Nuts	2.91	3.02	-3.77

Figures 3 and 4 help to clarify and interpret the differences in parameter estimates. Figure 3 shows the yield-salinity relationship from experimental data and Figure 4 shows the behavioral relationship estimate from our behavioral model. The most striking result is that the order of effects is preserved under our behavioral model. In other words, farmers behave as if they understand the relative yield effects of salinity across crops. Cotton and grain have the highest salt tolerance whereas vegetables and fruit and nut crops have little salt tolerance. Under both the experimental and behavioral models fruit and nuts realize the most significant yield losses and cotton has the greatest tolerance. In general, the behavioral model shows that yields drop off faster than predicted by the experimental model, over some ranges, and have a slower rate of decline over other ranges. This result is consistent with farmers taking action to mitigate the effects of salinity.

Figure 3. Experimental Yield-Salinity Relationship

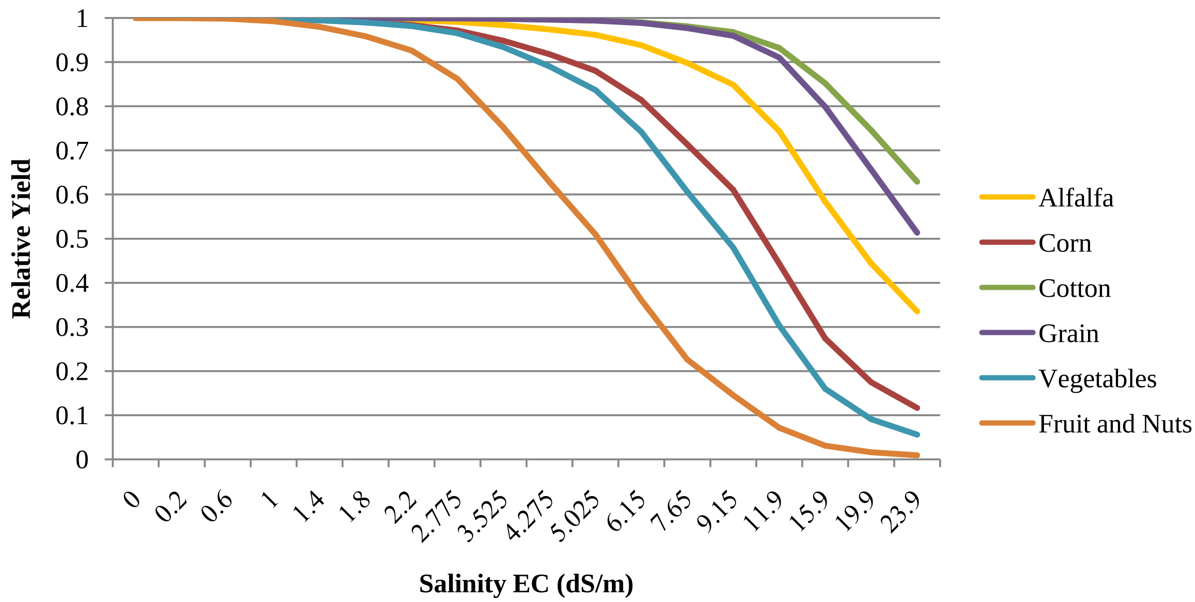
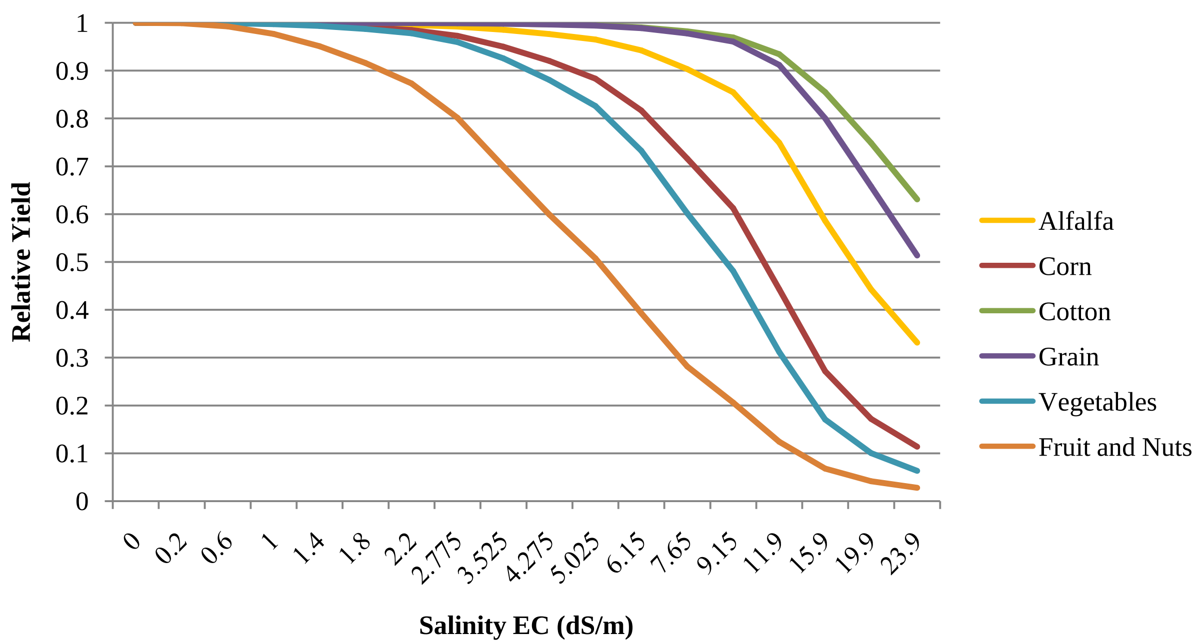


Figure 4. Behavioral Yield-Salinity Relationship



For further clarity, we show the yield-salinity relationship for select crops to demonstrate how these differ between experimental parameters and estimated behavioral parameters. We show the fruit and nuts crop group and the cotton crop group, representing crops at two ends of the salt tolerance spectrum. Differences between experimental and behavioral curves will translate into differences in salinity cost estimates.

Figure 5 shows the behavioral and experimental yield-salinity functions for the fruit and nuts crop group. Salinity at which yields decline by 50 percent is 5.09 dS/m for this crop group, which has almonds as a proxy crop. The scale parameter, as discussed above, equals 0.904. The experimental curve smoothness parameter equals 3.02 and our estimated behavioral parameter equals 2.91, indicating a smoother curve. As shown in Figure 5, the behavioral curve lies below the experimental curve over all levels of salinity. This indicates that policies based on experimental relationships, for this crop group and holding all else constant, may underestimate the effects of salinity.

Figure 5. Fruit and Nuts Yield-Salinity Functions

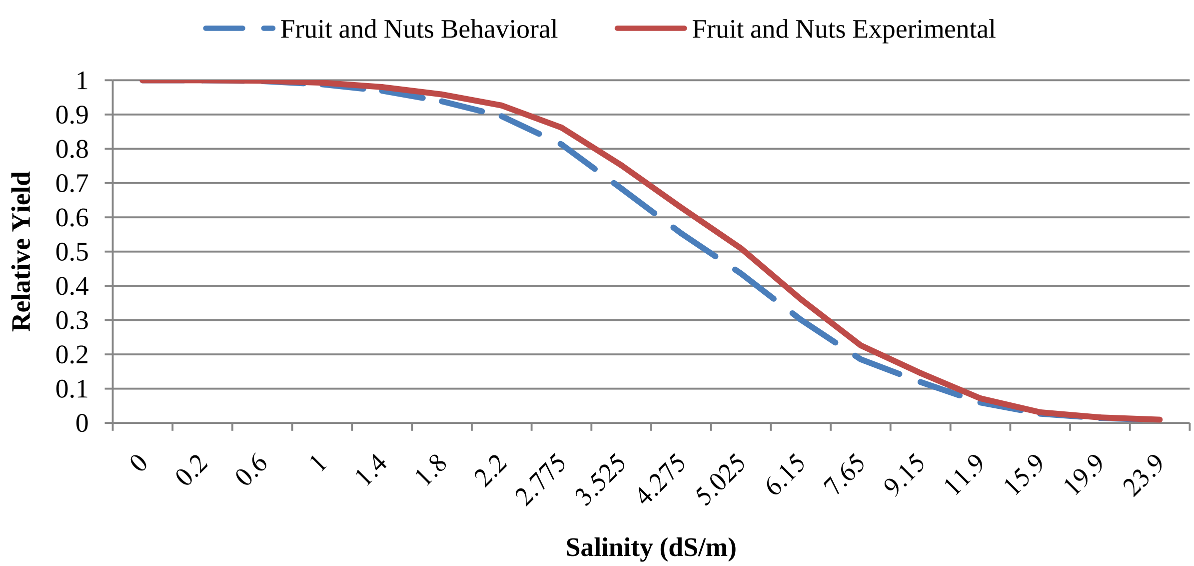
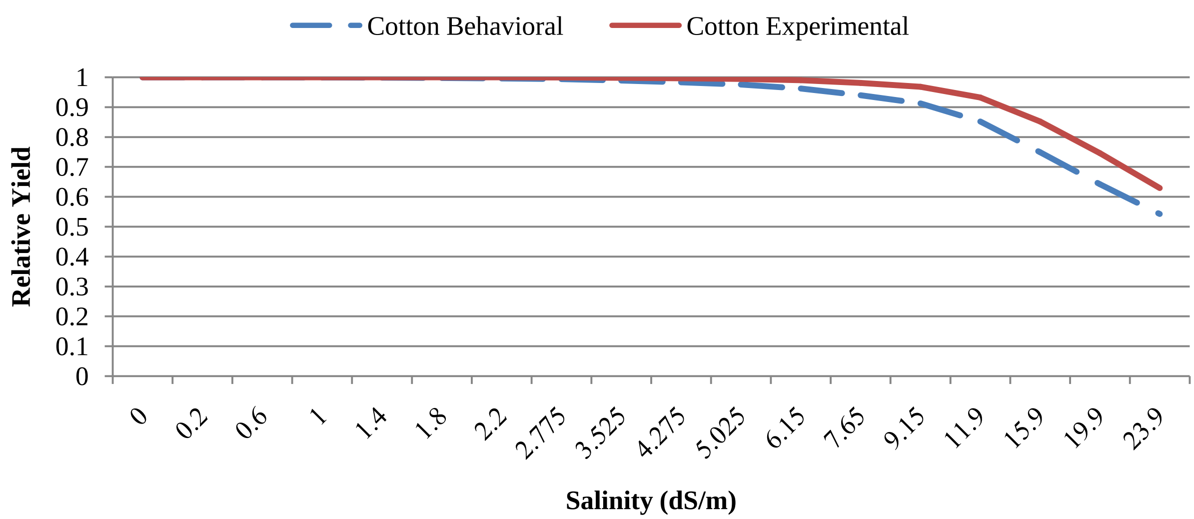


Figure 6 shows the behavioral and experimental yield-salinity functions for the cotton crop group. Cotton has relatively greater salt tolerance than other crop groups. The salinity at which yields decline by 50 percent equals 28.5 dS/m for this crop group. As shown, the salinity in Kern County in our dataset never reaches the 50 percent yield reduction threshold for cotton. The scale parameter does not vary, as discussed above, equaling 0.904 for all crops. The experimental curve smoothness parameter equals 3.00 and our estimated behavioral parameter equals 2.27, indicating a smoother curve. As shown, the behavioral curve is, over all salinity levels, lower than the experimental curve. This indicates that policies based on experimental relationships, for this crop group and holding all else constant, may underestimate the costs of salinity.

Figure 6. Cotton Yield-Salinity Functions



Comparing Behavioral and Experimental Cost Estimates

We compare estimates of the cost of salinity to agriculture using a calibrated optimization model with experimental and behavioral yield-salinity functions. The model we use is the Statewide Agricultural Production Model (SWAP) which is a Positive Mathematical Programming model of 93% of irrigated land in California (Howitt et al. 2011). We incorporate yield-response functions into the non-linear program to estimate the cost of salinity to agriculture. The SWAP model is specified with 20 crop groups, thus we apply estimates from the 6 crop groups in the behavioral model as representatives for the 20 crops. When representative crops aren't available (e.g. Rice), we leave the behavioral and experimental parameters the same.

Changes in the salinity of the Sacramento-San Joaquin Delta, and the corresponding effect on agriculture, is currently at the forefront of policy debate. Thus we simulate a change in salinity and the corresponding effect on agriculture in the Delta regions (SWAP model regions 8-12). A comprehensive and detailed assessment of the effect of changing salinity on the Delta economy is beyond the scope of this paper and can be found in Medellin-Azuara et al. (2011). We specify a simple example to highlight the effects of behavioral and experimental yield-salinity relationships. We simulate a scenario where base salinity is set at zero for all land in all regions and we consider an increase to 3 dS/m across all land in all regions. This compared to a base case of no salinity to estimate the change in hectares and farm revenues across the Delta regions. No attempt is made to match base or policy model simulations to observed conditions, the model results presented here are simply a thought experiment to evaluate the importance of behavioral parameter estimates.

First, we summarize change in yield under the salinity increase considered, summarized in Table 8. Column 2 shows the base yield in U.S. tons per hectare. Columns 3 and 4 show the yield per hectare under salinity of 3.0 dS/m under the experimental and behavioral functions, respectively. These are averaged across all regions. In column 5 we report the percentage change between experimental and behavioral yield per hectare. As shown, the experimental functions overestimate yield per hectare for all crops. The largest is for grain (wheat as the proxy crop) where yields are overestimated by 2.4 percent based on the experimental functions. Consequently, we expect that salinity costs are underestimated based on the experimental yield functions. How this translates into cost (revenue loss) depends on the area changes by crop.

Table 8. Yield Change due to Salinity under Behavioral and Experimental Functions (U.S. tons per hectare)

Crop Group	Base Yield	Yield Under Experimental Functions	Yield Under Behavioral Functions	Pct Change (%) (Behavioral-Experimental)
Almonds/Pistachios	0.43	0.25	0.25	-0.56
Lucerne	2.83	2.52	2.50	-0.86
Corn	10.78	10.55	10.54	-0.10
Cotton	1.13	1.12	1.10	-1.32
Cucurbits	4.67	2.77	2.76	-0.56
Dry Beans	0.44	0.44	0.43	-2.39
Fresh Tomatoes	5.26	4.74	4.67	-1.54
Grain	1.05	1.04	1.02	-2.39
Onions/Garlic	7.28	6.56	6.46	-1.54
Other Deciduous	0.87	0.51	0.51	-0.56
Other Field	1.66	1.47	1.46	-0.86
Other Truck	2.33	2.10	2.06	-1.54
Pasture	0.81	0.76	0.75	-0.63
Potato	6.84	6.16	6.07	-1.54
Processing Tomatoes	14.78	13.32	13.12	-1.54
Rice	1.54	1.50	1.50	0.00
Safflower	0.60	0.53	0.53	-0.86
Sugar Beet	12.65	12.46	12.40	-0.47
Subtropical	5.21	3.09	3.07	-0.56
Vine	3.11	2.99	2.98	-0.46

Next, we summarize change in area by crop under base, experimental, and behavioral functions. This is shown in Table 9. We can see that the area effect (total across all regions) is less than the yield effect. This is what we expect since salinity of 3 dS/m is generally not high enough to result in significant fallowing. Looking at column 5 we see that the experimental yield response functions understate land out of production for most crops. The exception is corn, which realizes an increase in area under the behavioral functions. This is expected as corn is a relatively salt-tolerant crop.

Table 9. Land Use Change due to Salinity under Behavioral and Experimental Functions (hectares)

Crop Group	Base Hectares	Hectares Under Experimental Functions	Hectares Under Behavioral Functions	Pct Change (%) (Behavioral-Experimental)
Almonds/Pistachios	79,774	77,224	77,185	-0.05
Lucerne	74,017	73,710	73,675	-0.05
Corn	100,364	100,917	100,938	0.02
Cotton	33,862	33,945	33,885	-0.18
Cucurbits	10,834	10,003	9,992	-0.10
Dry Beans	8,229	8,271	8,244	-0.34
Fresh Tomatoes	8,132	8,089	8,082	-0.10
Grain	30,226	30,678	30,588	-0.29
Onions/Garlic	2,102	2,074	2,069	-0.25
Other Deciduous	54,130	51,962	51,962	0.00
Other Field	46,432	46,348	46,279	-0.15
Other Truck	26,130	25,879	25,836	-0.16
Pasture	61,057	62,482	62,482	0.00
Potato	792	779	776	-0.28
Processing Tomatoes	38,757	38,342	38,272	-0.18
Rice	4,925	4,928	4,928	0.00
Safflower	10,442	10,402	10,403	0.00
Sugar Beet	2,182	2,185	2,183	-0.07
Subtropical	619	588	587	-0.08
Vines	62,479	62,478	62,471	-0.01

Finally, we sumamrize the revenue loss under experimental and behavioral functions in Table 10. For the hypothetical policy considered, total farm revenue losses are just under $100 million due to the increase in salintiy. By inspecting column 4, we see that the experimental functions underestimate farm revenue losses due to salinity across all regions. In total, experimental functions lead to a 3.4 percent lower estimate of farm revenue losses across all affected regions. This translates into a difference of $3.1 million in cost estimate.

Table 10. Farm Revenue Losses due to Salinity under Behavioral and Experimental Functions (thousands of dollars)

SWAP Region	Revenue Loss Under Experimental Functions	Revenue Loss Under Behavioral Functions	Pct Change (Behavioral-Experimental)
8	24,841	25,544	2.83
9	10,408	10,928	5.00
10	24,685	25,999	5.32
11	16,640	16,951	1.86
12	17,735	18,056	1.81
Total	94,310	97,477	3.36

In general, we conclude that using experimental yield-salinity functions in optimization models results in a lower-bound estimate of salinity costs. The magnitude and extent of the effects illustrated here are only for a hypothetical example. In practice, the policy scenario should include observed base salinity levels and careful specification of the geographic areas that will be affected by the increase in salinity. However, our analysis shows that using experimental yield-salinity functions may underestimate salinity costs.

Conclusion

Pannell and Roberts raised an important point in their 2010 retrospective assessment of Australia's NAP for Salinity. Namely, we need to think about farmer behavior when designing policies and solutions to salinity problems. If we do not consider farmers responses then cost estimates and salinity policies may suffer from error and ineffectiveness. California faces similar issues and, as attention and research on agriculture and salinity increases, California can learn lessons from Australia's experience.

As salinity increases farmers shift away from salt-intolerant, higher value, rotations and into salt-tolerant low value rotations. In Kern County, California this results in a shift from almonds, pistachios, citrus, and grapes into cotton, grains, and other field crops. The extent of this shift depends, in part, on the relative yield effects of salinity and the actions that farmers take to dampen the effects of salinity. Our analysis shows that risk-averse farmers behave in a way consistent with the yield-salinity functions estimated in experimental settings. However, yields actually decline faster than implied by the experimental functions. This may occur because farmers shift into salt-tolerant rotations at lower levels of salinity than the optimal level implied by the experimental setting.

In this paper we addressed one aspect of the farmer response to salinity. Specifically, we asked: How do experimental yield-salinity functions differ from those implied by farmer behavior? We presented a framework for estimating behavioral parameters of yield reduction in response to salinity. The modeling approach depends on the relatively simple MV portfolio framework. We use this simple framework because it is transparent and represents the simplest framework for farmer land use decisions. Our results indicate that farmers in Kern County behave as if they respond to experimental yield-salinity functions. However, the differences between the experimental and behavioral curves translate into differences in estimates of salinity costs to agriculture.

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