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Developing a Regional Agricultural Nonpoint Salinity Pollution Management Framework: Application to the San Joaquin River, California

Ariel Dinar,¹ Laura Forni,² Marina Mautner,² Nigel Quinn³

¹School of Public Policy, University of California, Riverside, USA

²Stockholm Environment Institute, Davis, CA, USA

³HydroEcological Engineering Advanced Decision Support Group, Berkeley National Laboratory, Berkeley, CA, USA

Summary:

Climate change continuously imperils the sustainability of water resources and land worldwide by adding to the human-induced problems of water scarcity, quality, and misallocation. The environmental problems and production losses associated with irrigated agriculture such as the salinity pollution of river water and aquifers highlight the water-quality concern that requires a paradigm shift in resource-management policy and introduction of new tools to assist in reaching sustainable solutions to such problems. Giving the nonpoint source nature of salinity emission from irrigated agriculture makes the management of salinity pollution of a river by the adjacent agricultural region more complicated. This paper develops a ‘proof of concept’ framework that links two existing models, the WARMF and the APSIDE, to create a simulation of salinity and drainage production and farm optimization in response to external water and climate conditions and nonpoint source regulations. The model is applied to the San Joaquin River in California. Results indicate that surface water restrictions cause increases in salinity loads as more groundwater is used. The incorporation of fees for imported water is a potential policy option that can help farmers maintain lower levels of salinity loads values. The paper suggests for future work that in cases of more restricted surface water availability, a collaboration among farmers via developing trade in pollution permits may provide a sustainable regional management of the salinity pollution externality.

Acknowledgements: The work leading to this paper was funded by the Giannini Foundation for Agricultural Economics Mini-grant Program. Financial support for the development of the real-time salinity management concept has been provided by the US Bureau of Reclamation, Division of Planning, and the California Department of Water Resources, through Proposition 84- funded grants. Ariel Dinar would like to acknowledge support from the W4190 Multistate NIFA-USDA-funded project, “Management and Policy Challenges in a Water-Scarce World.”

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Abstract

Climate change continuously imperils the sustainability of water resources and land worldwide by adding to the human-induced problems of water scarcity, quality, and misallocation. The environmental problems and production losses associated with irrigated agriculture such as the salinity pollution of river water and aquifers highlight the water-quality concern that requires a paradigm shift in resource-management policy and introduction of new tools to assist in reaching sustainable solutions to such problems. Giving the nonpoint source nature of salinity emission from irrigated agriculture makes the management of salinity pollution of a river by the adjacent agricultural region more complicated. This paper develops a ‘proof of concept’ framework that links two existing models, the WARMF and the APSIDE, to create a simulation of salinity and drainage production and farm optimization in response to external water and climate conditions and nonpoint source regulations. The model is applied to the San Joaquin River in California. Results indicate that surface water restrictions cause increases in salinity loads as more groundwater is used. The incorporation of fees for imported water is a potential policy option that can help farmers maintain lower levels of salinity loads values. The paper suggests for future work that in cases of more restricted surface water availability, a collaboration among farmers via developing trade in pollution permits may provide a sustainable regional management of the salinity pollution externality.

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Keywords: San Joaquin River, Nonpoint source pollution, Decision support system, Salinity, Regional model, WARMF, APSIDE.

1. Introduction

Irrigated agriculture in semi-arid regions typically produces drainage return flows with high salinity content. These return flows are discharged to water bodies that are regulated to minimize negative externalities in the form of damage to crops and the environment. When these negative externalities exceed certain thresholds, the regulator can respond by assessing fines or other means of encouraging compliance with water quality objectives. Some numerical simulation models can be configured to act as decision support tools that provide alerts of potential violations of water quality objectives and can assist in the development of schemas for creating incentives or assessing fines to encourage compliance. These tools can have the added benefit of allowing for equitable imposition of proposed incentives or fines on those polluters who bear the primary responsibility for the load exceedances. This paper presents an approach using a regional model framework that links and updates existing modeling tools currently in use by practitioners to address such needs.

The nonpoint source nature of agricultural salinity pollution poses a dual challenge for regulators by making it difficult to identify primary polluters, and to quantify pollution loads on a continuous basis. Not all drainage outlets can be monitored; therefore, calibrated simulation models play an important role in predicting pollutant loads under various permutations of hydrological and water quality inputs. Models allow alternative regulatory approaches, including schemes such as voluntary agreements and cap-and-trade in pollution permits to be evaluated, provided they can be adequately calibrated.

Published literature on economic and regulatory aspects of nonpoint source pollution in irrigated agriculture highlights a variety of socio-political issues. These include the role of asymmetric information, value of information, effectiveness of policy interventions, and adoption of pollution-reduction production practices. An early work by Griffin and Bromley (1982) established a conceptual model for analyzing agricultural nonpoint pollution. An important aspect of pollution quantification is the representation of the biophysical processes linking production decisions to emission loads. Production decisions are reflected in the type and quantity of inputs in management practices and in local biophysical conditions.

An extension of the analysis in Griffin and Bromley (1982) was proposed by Shortle and Dunn (1986) who included stochastic components in the pollution functions that arose from

random natural processes as a means of addressing the lack of information about key biophysical processes. Shortle et al. (1998) reviewed various nonpoint source pollution control regulations (either incentives, taxes, or quotas) on inputs. These are second-best interventions in the absence of direct measurements of polluter discharges. The authors identify a reduction in the cost-effectiveness of these pollution control measures when applied uniformly across diverse agriculturally dominated subareas that are heterogeneous in terms of water management practices and landscape characteristics that can lead to different receiving water impact functions. Larson et al. (1996) developed a cost-effective approach that was used to determine the best single-input tax policy for nonpoint source pollution in agriculture. They examined the question of reducing nitrate leaching from lettuce fields in California. Under the right circumstances irrigation applied water can be the easiest single input to regulate since nitrate loading to groundwater is directly related to soil leaching rates. However for other contaminants such as salinity – salt loads in subsurface drainage return flows may not be well correlated with surface water applications since the majority of the salt captured by the drain may originate from deeper in the aquifer rather than from infiltrating water. Ribaud et al. (1999) considers transaction costs and other political, legal, or informational constraints for dealing with nonpoint source pollution regulation that could be applied to achieve specific environmental goals in a cost-effective manner. The authors discussed the economic characteristics of five instruments that could be used to reduce agricultural nonpoint source pollution (economic incentives, standards, education, liability, and research).

Several authors, including Kolstad (1987), Wu and Babcock (1996), Doole (2010), and Doole and Pannell (2011) considered regulation that had a spatial component in the presence of heterogeneity instead of regionally uniform instruments. In these works, authors demonstrated that spatially uniform policies resulted in economic efficiency losses and reduction in welfare. Esteban and Albiac (2016) demonstrated and quantified the welfare loss from a spatially uniform regulatory policy to reduce salinity pollution and the efficiency gains from different policy measures based on the same spatial characteristics.

Very few studies consider joint management of the nonpoint source pollution in a regional setting, using cooperative arrangements and trade, including trade in water rights/quotas and use of pollution permission permits in a regional setting. Several examples from actual cases exist. The Murray Darling Basin Authority (Murray-Darling Basin Authority, 2001) initiated a basin-

wide agreement, a joint work program designed for setting salt disposal permits based on historical loads, including a revised cost-sharing formula and salinity credit allocation shares for Victoria, New South Wales, South Australia states, and the Commonwealth (Quinn, 2011). In the Hunter Basin of New South Wales, Australia (Department of Environment and Conservation, New South Wales, 2003; NSW Minerals Council, 2014), a scheme of salt permit discharges has been put into place. The main idea of this scheme was to permit discharge of salt loads only when there was available salt load assimilative capacity in the Hunter River that drains the Hunter Basin. Salt load discharges to the River were scheduled by quantity, time, and location based on stakeholder need and calculations of salt load assimilative capacity using a simple spreadsheet mass-balance model (Quinn, 2011).

Yaron and Ratner (1990) examined the problem of increasing use of high-salinity water as an irrigation source. They analyzed the economic potential of cooperative settlements in Israel and calculated income distribution schemes for three farms, using cooperative game theory (GT) algorithms. Dinar et al. (1992) also applied cooperative GT to a regional use of irrigation water under scarcity and salinity. Their model addressed inter-farm cooperation in water use for irrigation and determined of the optimal water quantity and quality mix for each water user in the region.

Several additional works that represent various efforts and methods include the following: Nicholson et al. (2020) made a comprehensive assessment of decision support tools used by farmers, advisors, water managers and policy makers across the European Union as an aid to meeting the EU Common Agricultural Policy objectives and targets. Chowdary et al, (2005) developed and used a GIS-based decision support framework that integrated field scale models of nonpoint source pollution processes for assessment of nonpoint source pollution measures of groundwater use irrigated areas in India. A GIS was used to represent the spatial variation in input data over the project area and to produce a map that displayed output from the recharge and nitrogen balance models. Different strategies for water and fertilizer were evaluated using this framework to foster long-term sustainability of productive agriculture in large irrigation projects.

Quinn (2011) compared the use of monitoring, modeling and information dissemination for salt management in the Hunter River Basin in Australia to a more model-intensive approach deployed in the San Joaquin River Basin in California. Decision support systems for these river

basins were developed to achieve environmental compliance and sustain irrigated agriculture in an equitable and socially and politically acceptable manner. In both Basins web-based stakeholder information dissemination was a key for the achievement of a high level of stakeholder involvement and the formulation of effective decision support salinity management tools. The paper also compared the opportunities and constraints governing salinity management in the two basins as well as the integrated use of monitoring, modeling, and information technology to achieve project objectives.

In the present study we provide a scalable decision support model for a regional water quality (salinity) management problem that incorporates water/irrigation regions, each serving a number of individual farmers. The model operates at the subarea level where each subarea has distinct features that include political and hydrologic boundaries and that recognize different access to water supply and drainage resources. These subareas have been recognized by the State of California water regulatory agency with jurisdiction over the project area. We highlight the role of top-down regulations as well as market-based arrangements that might form a basis for cap and trade in pollution permits. We compare and discuss the physical as well as the net benefit consequences of various policy interventions. This paper develops as follows: First, we present the analytical model aimed to evaluate the various options for pollution control at the subarea (regional) levels. Next, we introduce a proposed empirical framework to be applied to the San Joaquin River in California, given existing model resources in use by regulatory agencies. Then, we define a subset of seven subareas within the region as the basis for the empirical application aimed to test the analytical model. Finally, we evaluate the results to expand the method to incorporate future cooperative strategies.

2. Analytical model

We refer to a region that is composed of N subareas ($n=1, 2, \dots, N$). Each subarea n could comprise water/irrigation districts that incorporate several agricultural producers regulated by individual water district mandates. Each subarea n includes K_n ($k_n=1, 2, \dots, K_n$) agricultural producers that are considered nonpoint source polluters of a given pollutant, or of a set of several pollutants (for simplicity we will refer to salinity as the pollutant in question). Each agricultural producer applies water on agricultural crops to produce market products. A byproduct in the form of agricultural

pollution is the irrigation return flow that may contain a regulated water quality pollutant, which we will specify to be salinity.

Each of the k producers in the n -th subarea may have different factors affecting agricultural production conditions (natural, technical) that can lead to different cropping patterns, crop yields, net revenue, and the salt concentration and salt load of the return flow. We define a production function of agricultural yield and return flow for producer k as (for simplicity we drop the indexes k and n):

$$(1) \begin{cases} Y = f(W, C, T | \underline{X}) \\ Q = g(W, C, T | \underline{X}) \\ S = h(W, C, T | \underline{X}) \end{cases}$$

where Y is yield per acre of a given crop, W is water applied per acre, C is salinity level of applied water, T is irrigation technology used (expressed in integer values to indicate various irrigation technologies available to each agricultural grower within a designated subarea), Q is volume of return flow produced on that farm, S is the salt concentration of the return flows, and \underline{X} is a vector of all fixed effects related to the location of that producer. We will discuss later the first and second order conditions of the production function derivatives, namely the shape of these three components of the production function.

Given equation (1), agricultural producers within a designated subarea maximize their net revenue under constraints imposed by both natural and regulatory conditions:

$$(2) \pi_{k_n} = \sum_{Crops} p \cdot Y \cdot L - w \cdot W - t \cdot T$$

s. t.:

$$(3) \sum_{Crops} L \leq \bar{L}$$

$$(4) \sum_{Crops} L \cdot W \leq \bar{W}$$

(5) Additional constrains imposed on each agricultural producer within a designated subarea by subarea management, which we will discuss below.

where, for each agricultural producer, within a designated subarea p is the price per unit of crop, L is the area grown with that crop, w is the price of water, t is the per-acre cost of the technology, \bar{L} is the total cultivable land of the agricultural producer, and \bar{W} is the water quota imposed by

the subarea on the agricultural producer. Net revenue is defined as the revenue from crop sales minus variable costs of production and payments of fees for exceedance of pollution load.

The solution to (2) – (5) provides for each agricultural grower within a designated subarea the area under production with each crop selected, the total amount of water applied, the technology selected for each crop, the total profit, the total volume of return flow from the designated subarea, and the salt concentration of the return flow that can be used to compute drainage salt (mass) loads. While we may predict the volume Q and salt loading with associated S for each subarea, that information is not available to either the subarea management or to the federal regulator.

The subarea managers have access to monitoring data that provides the total volume of Q from all agricultural producers and its quality S that can be used to estimate salt loading. Salt loading is the factor each subarea manager is obligated not to exceed on a monthly and annual basis by the regulator, as defined within the Total Maximum Daily Load (TMDL) allocation for each subarea. TMDLs are the policy vehicle that is used by the US Environmental Protection Agency to limit non-point source pollution to level that do not exceed the assimilative capacity of the receiving water body. TMDL's are keyed to water quality standards or objectives at a compliance monitoring station for the pollutant in the receiving water designed to be protective. The agricultural non-point source pollutant management problem is a typical principal-agent problem under circumstances of asymmetry of information. Hence, we need to introduce several simplifying assumptions. We start by drawing (Figure 1) a schematic regional setting, using four agriculturally dominated subareas located on the Valley floor and a water body in the form of a river (describing the actual situation in the region that we will empirically analyze). (The remaining three subareas are tributary river watersheds where water flow is controlled by upstream dams and reservoirs and whose operation is largely independent of agricultural drainage decision making.

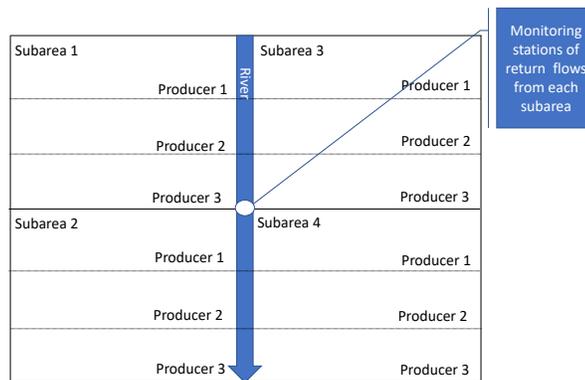


Figure 1. A schematic representation of the region with subareas, agricultural producers, and a regulated receiving water body (river).

Water supply for the westside of the San Joaquin River Basin (SJR) is provided by a water agency (e.g., United States Bureau of Reclamation) to the two westside subareas (Grasslands and the North-West Side subareas), according to water contracts negotiated between the water agency and individual water districts within each subarea. The individual water districts, in turn, allocate and distribute water supply according to agreements made with agricultural producers within each subarea. Water supply to subareas on the eastside of the SJRB derives largely from snowpack runoff from the Sierra-Nevada Mountain range, stored in downstream reservoirs along each major San Joaquin River (SJR) tributary. A state government water quality regulator (such as the California State Water Board with the regional Water Quality Control Boards as enforcer) sets salt load objectives for the Basin in accordance with a Total Maximum Daily Load (TMDL) allocation developed by the Environmental Protection Agency for the Basin. The load-based TMDL was further refined to develop subarea-level salt load allocations that took account of different water year hydrologies. The conservative nature of the TMDL computation that utilizes the lowest 10% average low flow condition resulted in allocations that were unattainable without major impact to the agricultural economy in each subarea. Hence the initial TMDL allocations were replaced by concentration objectives based on a 30-day running average EC for the most downstream monitoring location on the SJR – Vernalis. A concentration objective allows agricultural producers and other salinity dischargers to utilize more of the

available salt load assimilative capacity in the SJR. This initial compliance monitoring objective has been supplemented with two additional upstream salinity objectives ostensibly to protect the water quality of agricultural diversions made by westside agricultural producers. These additional salinity objectives are set at 1,550 uS/cm year-round as opposed to the 1,000 uS/cm non-irrigation season and 700 uS/cm objective set at Vernalis. The regulator suggested a number of approaches by which the original salinity load allocations under the TMDL might form the basis for salt load reduction strategies or cost allocation in situations where these various salt load objectives were violated.

The salinity load (mass of salt from all producers calculated by summing the product of drainage volume and salt concentration from each producer) produced on subarea n is the result of the return flows (drainage) from the agricultural activity of all producers, such that $\sum_{k_n} S_n Q_n \leq \bar{S}_n$. There is no practical way that the regulator could equitably assign salt pollution levels to the individual agricultural producers or enforce this regulation at reasonable cost on individual agricultural producers. Therefore, the regulator has chosen to allow stakeholders to internally govern the strategies to attain and abide by river EC objectives while encouraging stakeholders to consider the subarea as the organizing entity for stakeholder action. Stakeholder compliance is monitored by the Regional Board using data supplied by State and Federal water agencies.

To maintain compliance the agricultural producers can dynamically allocate salt loads to each subarea given that available salt load assimilative capacity at each compliance station is the product of the total assimilative capacity (defined by the current flow multiplied by the EC objective) and the current salt load in the river.

The monthly salt load cap can be calculated for each subarea individually based on the calculated TMDL allocations and the current salt loading to the river from each subarea (measured in terms of tons of salt: $S_L = d$ [salt concentration, S ; volume, Q]), where S_L is salt load.¹ Using this stakeholder maintained salinity load cap approach subareas would pay a fine F to the regulator that could be a price per unit of salt load above the cap or some other equitable formula for dividing the fine amongst stakeholders. F can be specific to each subarea or similar for all subareas

¹ In the San Joaquin River the current TMDL criterion is a 30-day running average salt concentration that is multiplied by a monthly design flow to determine allowable salt loading.

(see Esteban and Albiac (2016) for critique on uniform tax). F is then equitably distributed according to some formula (by land area, drainage volume, incremental salt load etc.) among all K_n agricultural producers in the different subareas (or by water user associations/districts in each subarea). We assume for simplicity that since we have here a non-point source salinity management problem where the exact source of salt is not known, the most straightforward and cost-effective initial approach would be to distribute F is to divide it equally per acre of land in production, or per acre-foot of irrigation water supply delivered. These initial approaches ignore the fact that some crops are associated with higher drainage return flow volumes and that subsurface drainage return flow salt loads may be poorly correlated with irrigation applications. Alternative allocation formulas may be relevant and will be considered in the empirical model. We assume that the (hypothetical) subarea manager² has the authority or power to impose these allocations of River salt load assimilative capacity. We also do not want to set an optimal level for F , but rather take F as given in the empirical analysis. We will use several levels of F in a sensitivity analysis to evaluate the effect of F on the behavior of the agricultural decisionmakers at the subarea level.

An additional consideration is in the temporal administration of fines and fee schedules which has bearing on the design of a decision support system to aid the subarea manager orchestrate stakeholder response to potential violations of River salinity objectives. An approach that attempts to respond to potential exceedance of salt load assimilative capacity at each compliance site in real-time would require model simulation tools that ran on a monthly timestep at a minimum. An optimization model would choose between available salt load reduction strategies, purchase of available water supply for dilution purposes or payment of fines each month. Alternatively, accounting could be postponed to the end of each year and fines imposed retroactively. The latter strategy would rely on uncertainty and the fear of a potential exceedance to motivate compliance. However, the decision tool needed to support this strategy could be simplified to operate on an annual timestep.

² While there is no actual subarea manager, it is assumed that the model allocations are respected by the individual farmers and other decision makers at the water district level.

3. Individual polluter responses to water quality regulations

We expect that each stakeholder within each subarea will respond to F , depending on the level of F and the conditions (cropping patterns, physical conditions such as soil properties, etc...) in that subarea. In the empirical application, we will look at the effects of surface water and irrigation land and water limits and fees, as these are the main forms of regulation that can affect salinity load in the case of a nonpoint source pollution. In future empirical applications, we propose limits on the output of the model, specifically the salinity loading. Here we outline the full analytical model.

Given F , each subarea faces the following two options:

- (a) Maintain the current (status quo) level of salt loading if $F \leq$ the cost of abatement. The cost of abatement could include changing the crop mix and/or land use changes (e.g., fallowing land)³, surface and/or subsurface drainage reuse, investing in more efficient irrigation technology, changing irrigation scheduling, and other options.
- (b) Abate to a level of allowable salt loading \leq than the cap. Each subarea will require abatement activities (detailed below) to the point where the marginal abatement cost equals F .

We consider the abatement in (a) and (b) to be “individual responses” to the salinity management regulation. That is, each subarea acts on its own, given its resources and local conditions.⁴

Each subarea is characterized by an aggregate revenue function (of all agricultural producers within each water district), minus fines on excess salt loading and minus abatement cost, such that

$$(6) \quad \Pi_n = \sum_{k_n=1}^{K_n} \pi_{k_n} - F_n - A_n$$

$$(7) \quad F_n = d(Q, S) \cdot \vartheta$$

$$(8) \quad A_n = \sum_{k_n=1}^{K_n} m_{k_n}(\Gamma_{k_n}\{1, 2, 3 \dots N\})$$

³ Changes in land use (crop mix or fallowing land) is an important component to maximize revenue and obtain maximum resource use efficiency. In the empirical model, changes in land use is incorporated at a later stage in the model development process.

⁴ In the empirical application section, we also consider some of the individual responses, such as restrictions on water quotas, restrictions on cropping patterns, land fallowing, and investment in water-conserving irrigation technologies, as regulatory-imposed policies.

where F_n is a fine on excess salt loads, ϑ is pollution fine per unit of excess salt load, d is salt load, A_n is abatement cost, and $\Gamma_{k_n}\{1, 2, 3 \dots N\}$ is set of abatement options, such as changing cropping patterns, fallowing land, adopting more efficient irrigation technologies, investing in monitoring drainage quantity and quality. Each subarea can select one of these abatement options or a subset of the abatement options.

4. Allocation of joint costs and benefits in the case of individual responses

We estimate the subarea net benefits as revenues minus variable operational costs and incremental costs. The incremental costs include costs associated with activities that polluters introduce in the agricultural production process in response to the regulatory interventions, or constraints on input use imposed by the regulator for each subarea. In the case of a fine imposed on the entire region for exceeding the pollution EC objective, the subarea level of fine is allocated, based on several allocation principles, and the subarea amount of fine, Θ_j , is added to the incremental costs.

We consider a couple of schemes for the allocation of the costs of pollution control, or regulatory fines, among resource management regions: namely, the subareas. For example, allocation of fines could be based on measurable inputs to the production process that are known to lead to pollution, such as fertilizers, land (especially, poor soil), or surface water (Helfand and House, 1995; Gardner and Young, 1990; Larson et al., 1996).

4.1 Allocation of regulatory fines based on surface water applied

This allocation scheme simply suggests that each polluter (subarea) will be charged in proportion to the volume of surface water applied on that subarea. Therefore, the cost to subarea j is

$$(9) \quad \Theta_j = F \frac{SW_j}{\sum_{j \in N} SW_i}$$

where Θ_j is the regulatory fine allocated to subarea j ; F is total regional regulatory fine. This scheme allocates all the regulatory fine among all N subareas. SW_j is the volume of surface water applied for irrigation in subarea j (a summation over all irrigated area). The disadvantage of this regulatory method is that it doesn't target those stakeholders who physically discharge to the SJR not take account of the significant reuse that occurs in some areas that helps to curtail salt loading to the River. It is a blunt policy instrument that is nonetheless relatively easy to administer.

4.2 Allocation of regulatory fines based on total irrigation water applied

This allocation scheme simply suggests that each polluter (subarea) will be charged in proportion to the total volume of water applied (surface water + groundwater + recycled wastewater) on that subarea. Therefore, the cost to subarea j is

$$(10) \quad \Theta_j = F \frac{W_j}{\sum_{j \in N} W_i}$$

The drawbacks to this policy are the same as the prior policy although it does account for groundwater use that can add significant salt to the total salt discharged from each region since the EC of groundwater is typically more than double that of applied surface water on the westside of the Valley and more than four times the average EC of eastside water applications.

4.3 Allocation of regulatory fines based on salt load generation

This allocation scheme simply suggests that each polluter (subarea) will be charged in proportion to the amount of salt load it generates. Therefore, the cost to subarea j is

$$(11) \quad \Theta_j = F \frac{S_j}{\sum_{j \in N} S_i}$$

Where S_j is the quantity of salt load generated by subarea j. This policy is the most equitable but also the most difficult to administer since current monitoring and modeling is insufficient to accurately measure or estimate salt load export from each subarea. Current models are not capable of recognizing the amount off drainage reuse within each subarea.

4.4 Allocation of regulatory fines based on cultivated area

The allocation based on cultivated area uses a similar rule as in equation (11), except that Q_j is cultivated land and not disposed drainage.

$$(12) \quad \Theta_j = F \frac{L_j}{\sum_{j \in N} L_i}$$

where L_j is the cultivated land area in subregion j. This allocation policy was the one used in an analysis by Regional Board staff to demonstrate the potential fines that would have occurred under the published TMDL, using a suggested daily fine of \$5,000 per day for each overage of the EC objectives. The cultivated area in each subarea was the means by which the total fine was distributed among subareas and the stakeholders within each subarea.

The next sections apply the analytical framework to a specific region of the San Joaquin River that faces high salt load discharges to the river and is under strict regulation by state authorities. We first describe the empirical case and highlight the various aspects of the subarea water quality characteristics. Then we describe the empirical specifications of the model we employ in order to empirically estimate the effectiveness of policy interventions under varying external conditions, and under several behavioral scenarios of the different subareas in the region.

Two existing decision support tools—the Watershed Analysis Risk Management Framework (WARMF) and the Agricultural Production Salinity Irrigation Drainage Economics (APSIDE) numerical simulation models—are used to provide policy guidance in the current study. The WARMF model (Systech Water Resources Inc., 2017) model is a data-driven water quality simulation model that is currently jointly operated by the San Joaquin Valley Drainage Authority (the agricultural stakeholder coalition representing the Grasslands and North-west side subareas) and the US Bureau of Reclamation (entity deemed responsible for 47% of the salt load delivered as agricultural water supply to the westside of the San Joaquin River Basin). The WARMF model contains an historic database that is kept up to date with inflow and diversion data to and from the San Joaquin River taking into account meteorological data used to estimate crop evapotranspiration. An important note on the structure of the WARMF model is that the model is made up of approximately 309 catchments and 456 river and drainage segments. The model allows for the output of the salinity levels of each catchment and river segment over a selected period.

The APSIDE⁵ model (Quinn, 2018) is an agricultural production optimization model that is linked to a hydrology and salinity mass balance model that operates on a monthly timestep that aligns with the 30-day running average salinity objectives at three compliance stations on the River (Vernalis, Maze Road Bridge and Crows Landing Bridge). The lumped APSIDE hydrology and salinity model for each subarea needs to be calibrated against the WARMF model to reproduce flow and salt load drainage inflow to the San Joaquin River for the combined drain outlets. Most subareas have multiple drainage outlets that have been monitored for more than a decade. Once fully calibrated the APSIDE model serves as the decision support system that

⁵ APSIDE was developed for a prior EPA-sponsored project that focused on model integration to forecast future San Joaquin River water quality resulting from future projected climate change scenarios.

allows stakeholders to choose between various options (both short-term and long-term) for consistently meeting water quality objectives by maximizing use of available salt load assimilative capacity.

Thereas WARMF model is a data-driven, watershed-based water quality simulation model of the river basin whereas the APSIDE model is a scalable agricultural production optimization model that is capable to simulating salt fluxes between the surface, rootzone and shallow and deep groundwater aquifers. The models are necessarily linked since the drainage output produced by the APSIDE model under various management scenarios needs to overwrite the drainage estimates produced by the WARMF model simulation.

Simplifying assumptions made by the WARMF model include time invariant land use and cropping practices and static irrigation and drainage technology deployment. Since the WARMF model's major use in California is as a comprehensive water quality model – the added complexity and additional data requirements by treating land use and irrigation technology as time series was not considered of paramount importance to the model developer and user community. Likewise, the APSIDE hydrology and salinity sub models were calibrated against an average year hydrology in the WARMF model. The APSIDE model, with its annual or monthly average timestep will not be sensitive to inter-annual hydrologic variability and will not simulate extreme events which occur at a time scale of days rather than weeks or months.

5. Linking the APSIDE and the WARMF models

The analytical model is implemented by using a linked empirical model of the Updated and modified Agricultural Production Salinity Irrigation Drainage Economics (APSIDE) model (Quinn, 2018) with information from the Watershed Analysis Risk Management Framework (WARMF) model (Systech Water Resources Inc., 2017) while keeping land use fixed.⁶

The main objective of linking the models is to simulate adaptive policies in a dynamic process that is spatially explicit and influenced by processes operating at different temporal scales. The production inputs that are important for the linkage of the models are the type and quantity

⁶ Keeping land use fixed is a temporary condition that we have inherited from the WARMF model and will be relaxed, by allowing farmers decide on changes to the cropping patterns on their farms over time. Having land use kept fixed is a caveat to the model, leading to sub-optimal results of the optimization process.

of inputs (land and water), and the agricultural management practices (irrigation efficiency and salinity management options). The production outputs are revenue per acre, regional welfare, and water/drainage discharges. The salinity model inputs are the amount of water discharged, and/or cropping land decisions (including fallowed land), and/or parameters that influence the salinity loads. The salinity outputs relate to the amount of discharge and the salinity load levels of those discharges. [Figure 2](#) below shows the flow of the data from the APSIDE model to the WARMF model. The current version of the APSIDE model produces annual output that must be multiplied by a daily scaling factor to produce output that can be used to overwrite daily drainage outputs produced by the WARMF model. One of the unique features of the WARMF model is its ability to accept both real-time flow and water quality data as daily time series inputs or similarly scaled inputs from other models.

5.1 Process for spatial agreement

Initially, the APSIDE model was created to optimize crop production in each model subarea while considering the cost of drainage and the relationship between surface and subsurface drainage and soil rootzone salinity. The model has a detailed database of the cost of various irrigation and drainage technologies and has the ability to perform irrigation technology substitution if the costs associated with this investment compare favorably with the reduced cost of drainage disposal. Drainage cost can be based on salt load or drainage volume (independent of salt load). The APSIDE model can also consider alteration of irrigation water supply salinity, practices such as

land fallowing, reuse of irrigation water, and use of various water sources such as groundwater (Figure 2) as a means of reducing drainage salinity loads.

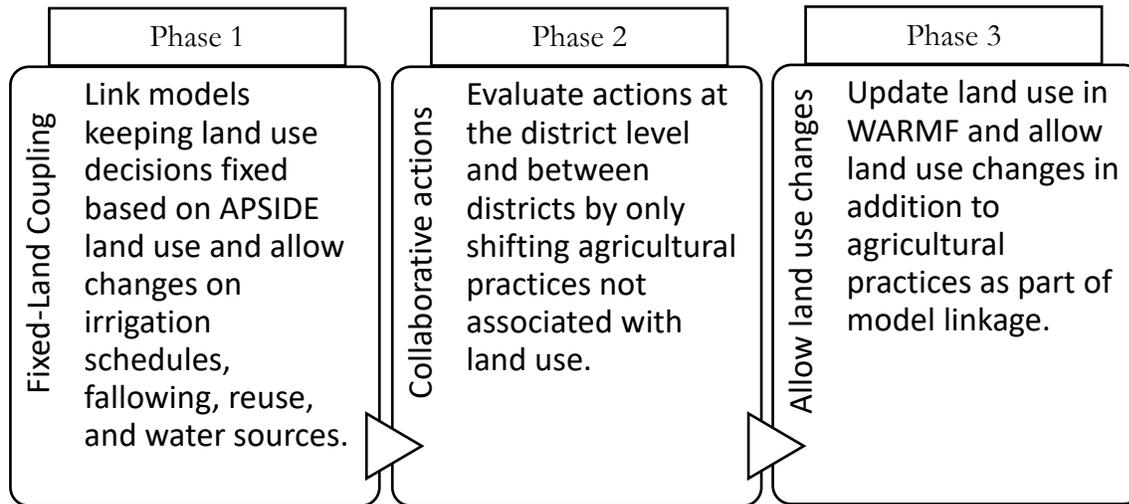


Figure 2. Model linkage process for land-use agreement.

5.3 Process for temporal agreement

The limitations of the WARMF model time series input capabilities for parameters such as compared to the APSIDE model need to be reconciled and the APSIDE model was calibrated to emulate WARMF model drainage and salt load outputs. To do this land use was fixed at 2005/2007 levels to simplify the calibration of the APSIDE model. Temporal agreement refers to both the contemporaneity of the models and the scale at which they are operated. The parameterization and approach for model linkage used the most current year crop data for simulation initial conditions. Similarly, meteorological data for the two models was aligned for scenario modeling and categorized as dry, normal, and wet water year types.

The process for temporal agreement between the two models consists of 3 phases and described in Figure 3.

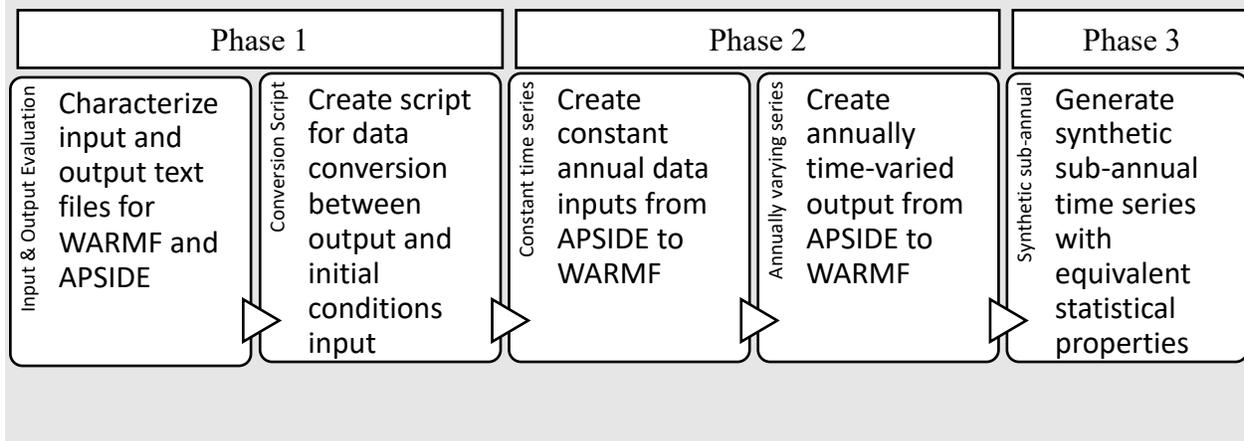


Figure 3. Linking process for temporal agreement between models.

Linkage of the WARMF and APSIDE models required the following assumptions:

- (1) Attention was focused on key common variables and processes in the WARMF and APSIDE models that included applied water, and salt loading to each subarea. Watersheds and political boundaries in the WARMF model were re-aligned and aggregated into the subarea boundaries. The subarea boundaries were more easily accommodated by the lumped APSIDE model.
- (2) The APSIDE model uses simulation output from the WARMF model for calculation of root zone salinity, applied water and salt loading. Salinity impacts and economic outputs are derived from the APSIDE model.
- (3) Irrigated land areas and cropping patterns were fixed in the APSIDE model while allowing drainage salinity management practices to adjust to meet salt load export constraints. Drainage salt loads that are calculated monthly using the APSIDE model are superimposed on WARMF model simulated drainage output for each subarea to assess impacts on compliance with EC objectives at compliance monitoring location on the River.

5.4 Linked Model functions

As previously noted, the version of the APSIDE model used in this study ran on an annual time-step rather than a monthly timestep in the interest of simulation time. This version of the model comprised two modules: an annual economic optimization module and a hydrologic and salinity module that can produce output drainage flow and salt loading monthly or annually (**Error! Reference source not found.**). In the economic optimization the optimal land use and cropped area

are computed first based on current conditions and the applied surface water, groundwater use and drainage return flow quantities are determined at the beginning of each time-step maximizing the net profit objective function. Computation within the hydrologic and salinity module is performed for three model layers – the rootzone, shallow groundwater aquifer and deep groundwater aquifer. A water balance performed within each layer prior to the computation of salinity balances. Fluxes of water and salt between the three layers were derived from prior regional groundwater modeling and checked for consistency with WARMF model estimates.

Specific assumptions and constraints relevant to the solution of the agricultural production model for each subarea are as follows:

- (1) Applied water – surface water and groundwater irrigation applications are decision variables. Groundwater pumping decisions are made annually largely on the basis of pumping cost and the salinity of the pumped groundwater, which remains fixed. The impacts of the more saline water on root zone salinity and crop yields are considered by agricultural production sub-model at the beginning of the next simulation period.
- (2) Salinity estimations –salinity is simulated as a combination of applied saline irrigation water supply and native salts leached from the root zone in each subarea. The gypsum addition applies only to westside sources and primarily to the Grasslands subarea.
- (3) The APSIDE model hydrology includes up-flux from the groundwater, precipitation, surface runoff, applied groundwater and surface water, infiltration from the root zone into underlying aquifers, and drainage through tile drains.

5.5 Modeling regulatory intervention considerations at subarea (R) in the linked model

During periods when salt load assimilative capacity in the San Joaquin River is exceeded stakeholders within each subarea are obliged to provide a collective response to salinity objective exceedances. Stakeholders in one subarea can engage in voluntary agreements with stakeholders in other subareas through their representatives to trade individual subarea salinity load exceedances for a number of management actions to be deployed in the other subregions

The three policy intervention types evaluated in this empirical application with intent to reduce salinity loads, are strict limits on surface water applied, fees on surface water deliveries over a set limit, and fees on total applied irrigation water over a set limit (distinction between surface water and total applied irrigation water recognizes the differences in salinity

concentrations in various sources of irrigation water).⁷ The limits used are based on historical surface water and groundwater use in the subareas applied as increments of 20% from 40% to 100%. Thus, the limits used represent historical surface water and groundwater use in the subareas applied as increments of 20% from 40% to 100%.

The scenarios were developed as follows:

- 1) Strict surface water limit by subarea, no groundwater limit, no fees.

$$NSWAT(R) \leq SWLIM(R)$$

where R is the subarea (district), NSWAT is the applied surface water decision variable, and equal to the historical surface water use, it is multiplied by the respective multiples of 20%. SWLIM is the surface water limit. (R replaces in the empirical application the index j that we used in the analytical model.)

- 2) Surface water fees once surface water limit is reached for each subarea, no groundwater limit

$$NSWAT(R) \leq SWLIM(R) + IRRIEXC(R)$$

where, IRRIEXC is the amount of irrigation water above the limit to which a fee is applied (irrigation exceedance).

- 3) Strict surface water limit for each subarea, groundwater limit with fee once total irrigation limit is reached

$$\sum_R (NSWAT(R) + NGWAT(R)) \leq IRRILIM(R) + IRRIEXC(R)$$

$$\sum_R NSWAT(R) \leq SWLIM(R)$$

where NSWAT is the applied surface water decision variable, NGWAT is the applied groundwater decision variable, IRRILIM is the total irrigation limit equal to the sum of the historical surface water and groundwater limits multiplied by the respective multiples of 20%,

⁷ Additional and easier-to-implement technical interventions include temporary pond storage, increased drainage reuse, storage of salt in shallow groundwater by shutting off sump pumps. These could be added to the policy toolkit in our paper, once the technical parameters are identified.

and IRRIEXC is the amount of irrigation water exceeding the constraint to which a fee is applied (irrigation exceedance).

In all scenarios, a reduction of 2.5% per year is applied to the surface and/or irrigation water limits to simulate decreasing water availability that has become common the American Southwest In each of the scenario types 2 and 3, the fee is applied as shown below:

$$NLPROF_{w/fee} = NLPROF_{w/out\ fee} - \sum_R (IRRIEXC(R) \times FEE(R))$$

where NLPROF is the nonlinear profit objective function for the region and FEE is the fee per-acre foot of irrigation exceedance.

Because of the non-linearity of the optimization model, certain combinations of surface water and groundwater use limits resulted in infeasible solutions for land and water use decisions. Those scenarios were excluded from the analysis.

6. Application to water quality issues in the San Joaquin River

The San Joaquin River (SJR), the receiving water body for agricultural drainage in the San Joaquin Basin, is regulated by a regional water quality regulator (Regional Water Quality Board). A TMDL was developed that set load limits for each Subarea (CVRWCB, 2002, 2004) – however the load allocations under the TMDL were overly restrictive and would have resulted in potential annual fines in the order of \$300,000 per subarea based on a 9-year average of salt loads. The Regional Board adopted a real-time, concentration-based schema to substitute for the TMDL salt load-based approach which allowed greater use of the River’s assimilative capacity. Salinity concentration objectives for compliance monitoring stations at Crows Landing bridge, Maze Road bridge and Vernalis were set as 30-day running averages of EC. For Vernalis these salinity concentration objectives were a winter objective of 1,000 uS/cm and a summer objective at 700 uS/cm. The summer, irrigation season salinity objective was considered protective of irrigation agriculture and salt-sensitive crops. A year-round salinity objective of 1,550 uS/cm was set for compliance monitoring stations at Maze Road bridge and Crows Landing bridge (Quinn 2020).

The TMDL set monthly salt load limits for the seven subareas (Figure 4), based on basin hydrography, and existing water district boundaries. Four of these subareas (Northwest Side, East Valley Floor, Grasslands, and San Joaquin River Above Salt Slough) are located on the valley

floor, and drainage from these subareas is dominated by agricultural and managed wetland decision-makers. The other three subareas are watersheds serving three major east-side tributaries to the SJR – namely the Stanislaus, Tuolumne, and Merced rivers. Given the institutional history and management functions within the basin, these seven subareas are the most logical management units and any possible future trade in salinity load permits would initially occur between these entities.

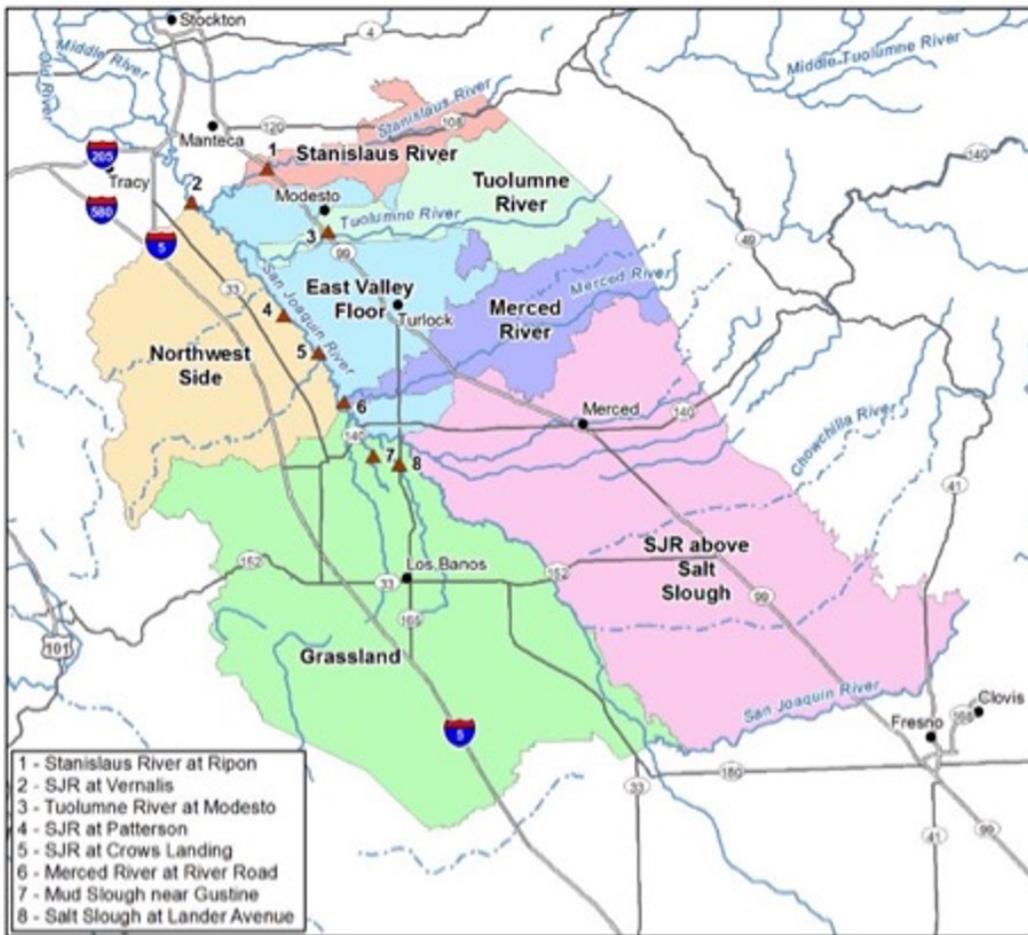


Figure 4. Map of the various San Joaquin River Basin contributing subareas as defined in the 2002 TMDL Regulation Plan.

Note: the 8 red triangles in the Figure that are indicated in the legend by numbers 1-8 are the locations of the salinity load measuring stations.

Source: Quinn (2020).

Table 1 below presents the necessary APSIDE inputs separated according to the dimensions along which they must be defined (e.g. subarea, drainage zone, crop type). Initial conditions include groundwater, applied water, and soil salinity concentrations.

Table 1. Input data required in the APSIDE model.

Crop	Crop-Subarea	Crop-Subarea-Drainage Zone	Subarea	Drainage Zone-Subarea
<ul style="list-style-type: none"> ▪ Max moisture content deficit ▪ Crop price [\$ per ton] 	<ul style="list-style-type: none"> ▪ Irrigation system distribution fractions ▪ Annual total evapo-transpiration [acre-feet per acre] ▪ Effective rainfall [feet per year] 	<ul style="list-style-type: none"> ▪ Subarea yields [tons per acre] ▪ Land rental cost [\$ per acre] ▪ Drainage target 	<ul style="list-style-type: none"> ▪ Surface water deliveries and groundwater pumping [acre-feet] ▪ Porosity in root zone and shallow aquifer ▪ Specific retention in root zone and shallow aquifer ▪ Permanent wilting point in root zone ▪ Distribution system seepage and spill percentage ▪ Max monthly discharge capacity 	<ul style="list-style-type: none"> ▪ Capital requirements [\$ per acre] ▪ Hourly labor requirement [\$ per acre] ▪ Net vertical movement of groundwater [feet per year] ▪ Average depth to and average spacing of tile drains [feet]

Source: Elaborated by authors.

6.1 Subareas

APSIDE and WARMF require a model boundary and catchments through which surface and/or groundwater can flow to the catchment outlet(s). To coincide with current regulatory and modeling efforts, the selected area for analysis starts by matching the Subareas defined in the 2002 TMDL Regulation Plan to facilitate planning and implementation. Next, these boundaries are matched to the exterior boundaries of WARMF to facilitate the linking of WARMF and APSIDE. Finally, we use the National Watershed Boundary Dataset catchments as the delimiting boundaries to allow for spatial analysis of land use, and other datasets necessary for the eventual calibration of the modeling framework.

The final modeled subareas are shown in Figure 5, with a total of seven subareas, of which “Grasslands Wetland”, a sub-subarea within Grassland, will not be modeled within in APSIDE,

because it does not contain any commercial agricultural crop areas and thus cannot produce net revenue based on the calculations in the crop production and economic modeling components. Therefore, we identify $N=7$ as the following subareas: Upper Stanislaus, East Valley Floor, Upper Tuolumne, Northwest Side, Upper Merced, San Joaquin above Salt Slough and Fresno River (SJR), and Grassland Agriculture, in the following order $n=1, 2, 3, 4, 5, 6, 7$.

The spatial designations in APSIDE correspond to Northwest Side (NWS), Grasslands Agriculture (GRA), East Valley Floor (EVF), Merced River (MER), Stanislaus River (STL), Tuolumne River (TLU), and San Joaquin River above Salt Slough (SJR), shown in 5. Irrigable acreage is calculated according to the California Important Farmland dataset (California Department of Conservation, 2018) as including the following categories: farmland of local importance (L), prime farmland (P), farmland of statewide importance (S), and unique farmland (U).

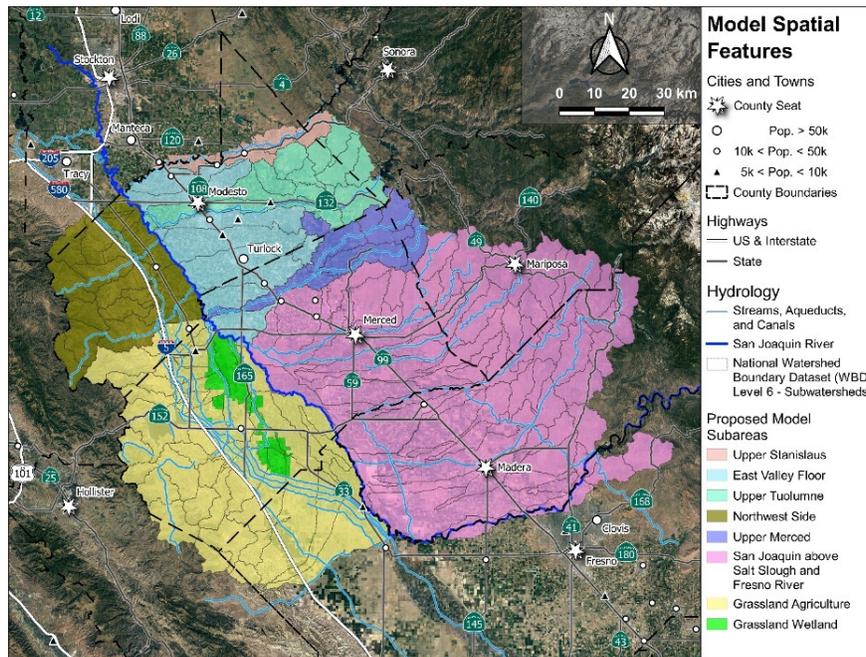


Figure 5. Proposed modeling framework of subareas, based on the national WBD and 2002 TMDL Regulation Plan, shown with local hydrology, cities, towns, counties, and highways.

Source: Elaborated by the authors.

6.2 Drainage zones

The APSIDE model is agnostic to watershed topology and the simulation estimates drainage flow and drainage salt load by simple mass balance performed on each lumped watershed. The WARMF model performs a more geographically informed simulation and drainage return flows to the River are routed to specific drainages, some of which have a history of measurement of both flow and EC. Drainage yield from APSIDE was calibrated to conform to annualized WARMF model drainage discharge summed across all drainage outlets within each subarea (Figure 6).

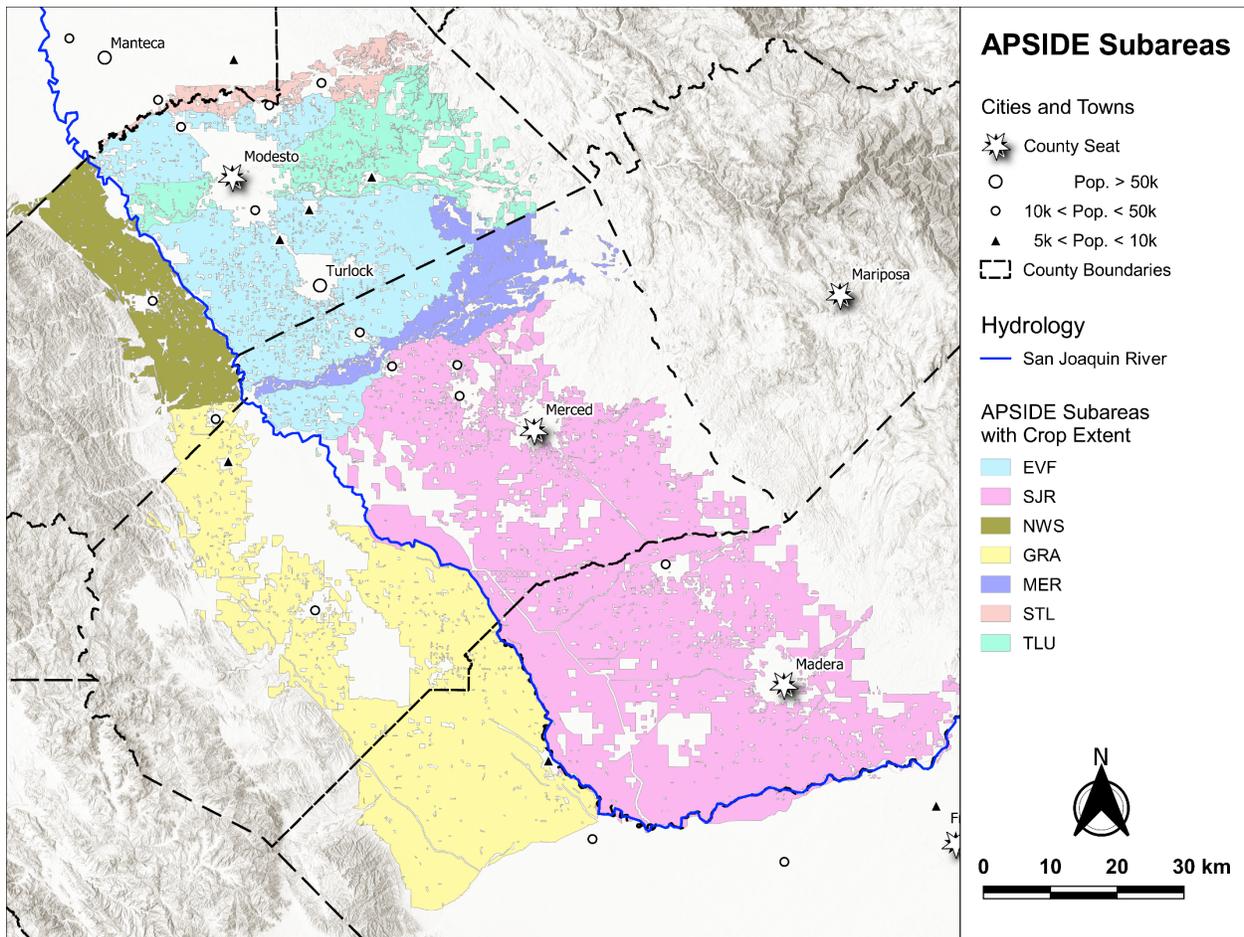


Figure 6. Spatial extent of APSIDE subareas as defined in the 2002 TMDL: Northwest Side (NWS), Grasslands Agriculture (GRA), East Valley Floor (EVF), Merced River (MER), Stanislaus River (STL), Tuolumne River (TLU), and San Joaquin River above Salt Slough (SJR).

Source: Elaborated by the authors.

6.3 Crops

Table 2 presents a summary of the land use categories in WARMF, APSIDE, and DWR (2018) that were used in the model runs.

Table 2. Comparison of land use categories in WARMF and APSIDE with current DWR (2018) crop types or classes.

WARMF (2005/2007)	DWR (2018)		APSIDE					
Land Cover	Crop Type or Class (Code Class)	Area (acres)	Crop	Area (acres)				
Cotton	Cotton	70,834	COT	70,834				
Olives, citrus, and subtropicals	C CITRUS AND SUBTROPICAL	9,687	OCS	9,687				
Orchard	D DECIDUOUS FRUITS AND NUTS	706,835	TFN	706,835				
Rice	R RICE	3,001	RIC	3,001				
Vines	V VINEYARD	97,556	VIN	97,556				
Perennial forages	Alfalfa	91,350	PFG	152,750				
	[P PASTURE] - Alfalfa	61,399						
Winter grains and safflower	Wheat	35,561	WGS	79,230				
	Miscellaneous Grain and Hay	42,676						
	Safflower	992						
Warm season cereals and forages	Corn, Sorghum, or Sudan	173,369	CEF	173,369				
Other row crops	Beans	11,239	ROW	127,417				
	Sunflowers	192						
	Miscellaneous field crops	596						
	[T TRUCK NURSERY AND BERRY CROPS] - Nursery	115,391						
Flowers and nursery	Flowers, nursery, or Christmas tree farms	3,897	NUR	39,097				
	Y YOUNG PERENNIAL	35,200						
Paved areas	U URBAN	179,621						
Urban commercial								
Urban industrial								
Urban landscape and open space								
Urban residential								
Sewage treatment plant								
Farmsteads								
Barren land	X NOT CROPPED OR UNCLASSIFIED	2,541,301						
Deciduous forest								
Evergreen forest								
Fallow								
Grassland/ herbaceous								
Irrigated wetland								
Marsh								
Mixed forest								
Native classes unsegregated								
Other CAFOS								
Shrub/scrub								
Perennial forages DLA					-	-		
Double crop DLA					-	-		
TOTAL		4,180,699		1,459,776				

In this empirical application, a total of ten crop types were considered: cotton (COT), citrus and subtropical orchards (OCS), fruit and nut trees (TFN), rice (RIC), vineyards (VIN), perennial forages (PFG), winter grains and safflower (WGS), cereals and sudan (CEF), row crops (ROW), and flowers and nursery (NUR). Crops with less than 5% of the total crop area in DWR (2018) were excluded to avoid infeasibility due to edge effects, specifically, citrus, and subtropical orchards (OCS), rice (RIC), and flowers and nursery (NUR). The remaining crop types and their acreage by subarea are shown in [Table 3](#).

Table 3. Main crops represented in APSIDE in each of the seven subareas (acres).

Crop	COT	CEF	WGS	VIN	PFG	ROW	TFN	Total
Subarea								
EVF	-	58,436	4,725	6,437	27,405	10,797	109,471	217,271
NWS	-	5,861	6,033	1,229	5,517	16,993	41,432	77,066
SJR	10,919	57,495	27,496	70,713	51,545	28,895	317,230	564,292
GRA	59,584	26,465	28,153	4,269	41,979	58,709	88,706	307,866
STL	-	1,140	925	1,211	2,733	400	18,105	24,514
TLU	-	6,209	2,637	3,696	7,049	163	60,264	80,018
MER	-	6,829	1,766	7,604	4,490	1,064	36,855	58,608

Crop type is used to determine a number of parameters that are necessary for determining crop response to salinity and crop water use, which in turn determines overall yields and salinity in the various media modeled in APSIDE (e.g. drainage, root zone, groundwater). The effects of salinity on crop production is parameterized in APSIDE through the use of two concepts, the salinity at which crop yield is 50% of ideal conditions (Ayers and Westcot, 1989) and the Maas and Hoffman coefficients (1977), describing the yield level as a function of salinity. Yield quantities under ideal conditions and price per ton (in 2002 dollars⁸) for each crop type were taken from US Bureau of Reclamation (2002) and *Quick Stats* (NASS/USDA, 2021) by averaging over crops with available information within each crop type weighted by crop area within the model

⁸ The price values were left in 2002 dollars because the original costs and prices in the model were determined for that year and the proof of concept did not require updated values.

area.⁹ Maximum root zone depth and maximum allowable soil moisture deficit (MAD) are used as part of the soil salinity and water balance and were taken from previous versions of APSIDE where available (Quinn, 2018) or the literature where necessary (Datta et al., 2017 and NRCS/USDA, 2005). A final crop related parameter for the water and salinity balance is the irrigation system distribution fraction (%) which was developed in an earlier version of APSIDE using data from CH2MHILL (1990) to determine the share of applied water attributed to each of beneficial use, deep percolation, uncollected runoff, evaporation loss, and the proportion of applied water that effectively leaches salt.

6.4 Salinity inputs

While WARMF and APSIDE determine time-varying salinity based on the hydrologic and nutrient needs of the land cover and/or crop types that are defined in the respective models. However, the input needs of each model are distinct, and APSIDE is the one among the two that also produces crop production yields as a model output. In this application, WARMF model output was used specifically to provide initial values for salinity in surface water sources and soils within the model area.

Output salinity data was averaged over each water year from 2000 to 2019, the period for which data was available for all tributaries in WARMF, with the exclusion of any years in which data were not available for the entire water year (The WARMF model has been run prior to the work on this paper, from the 1980's onward, and APSIDE (annual model) has been run for 50 years simulations). The averaging was conducted as a weighted average for catchments and river segments by area and segment length, respectively, for each subarea. Additionally, salinity input was necessary for each of the four soil layers modeled in the crop production model. The salinity gradient was taken from a previous version of APSIDE and multiplied by the initial conditions given in the surface water salinity determined by the river segment average for each subarea. The results using this methodology are shown in Table 4.

⁹ One of the problems with crop delineation is that the DWR and USBR crop categories are quite different – so cannot exactly map one to the other. Note that the USBR data is what farmers think they will plant – not what they have actually planted.

Salinity values were calculated as a weighted average using the length of the river segment or the area of the sub-catchment to act as the weight. Results of River and Catchments are presented in Columns (2) and (3) of Table 4, respectively.

Table 4. Salinity shown as total dissolved solids (TDS) in ppm for surface water (River), shallow groundwater (Catchment), and soil quarters as determined from WARMF output for the period 2001-2018.

(1) Subarea	(2) River Weighted Average	(3) Catchment Weighted Average	(4) Soil Layer Quarter			
			1	2	3	4
EVF	808	1896	800	1400	2450	4300
NWS	1448	2643	1450	2550	4450	7800
SJR	1820	3508	1800	3150	5500	9650
GRA	1849	3819	1850	3250	5700	10000
STL	547	850	550	950	1650	2900
TLU	650	815	650	1150	2000	3500
MER	854	1341	850	1500	2650	4650

Note: Layer 4 concentrations seem relatively high for the Merced, Tuolumne and Stanislaus watersheds.

Then, we determined the model salinity inputs by scaling the values in columns (2) and (3) of Table 4 using the inputs from the original WARMF model that was provided to us. The original inputs for salinity in the WARMF model were (Table 5):

Table 5: WARMF subarea initial salinity values (ppm)

WARMF Subarea	Soil Layer Quarter			
	1	2	3	4
BVW.DR	500	800	1100	2400
PAN.DR	850	1300	1900	2500
PCH.DR	850	1300	1900	2500
SLW.DR	850	1300	1900	2500
WW1.DR	1000	1700	5000	8000
WW2.DR	1000	1700	5000	8000
WW3.DR	1000	1700	5000	8000
WW4.DR	1000	1700	5000	8000

Source: WARMF original data files.

Based on these ratios we generated the values for each of the subareas in the new model we used in this working paper (Table 4, Column (4) layers 1, 2, 3, and 4).

Other salinity inputs were calculated in a similar fashion (using the values included in the original WARMF model and scaling them by the relative salinity calculated from the WARMF output for the 2000-2019 period).

6.5 Hydrologic Inputs

Most of the hydrologic inputs such as effective precipitation, evapotranspiration, irrigation system distribution fractions, were determined and left as default values from previous studies (Quinn, 2018), as was described earlier. However, surface and groundwater availability limits needed to be determined based on the different delineated areas that we evaluated in the current study. These were adapted from the values determined for various regions in the Central Valley in the 2000 version of the Statewide Agricultural Production Model (SWAP) (Marques et al., 2005). The regions outlined in the SWAP model were overlain on top of the APSIDE subareas for the current model to determine a weighted percentage of the groundwater and surface water availability based

on land area. These values, shown in Table , comprise the limits that are assumed for the base case scenario.

Table 6. Historical limits on surface water and groundwater by subareas (Acre Feet).

Subarea	SW	GW
NWS	197,554	73,196
GRA	777,046	287,904
STL	63,523	4,148
TLU	185,076	12,087
EVF	680,762	166,998
MER	159,669	43,998
SJR	1,186,600	854,800
Total	3,249,630	1,443,131

Source: Marques et al., 2005.

7. Results

We present results of several policy intervention scenarios, including the base case, and various policies that were described earlier in the paper.

7.1 The base case scenario

The base case scenario presents the model results without any regulation intervention. Figure 7 presents crop acreage (top panel), crop share (middle panel) and crop yields (bottom panel) by type of crops cultivated in each of the subareas. On the west side of the region, (NWS and GRA), GRA is the largest subarea while on the east side (STL, TLU, EVF, MER and SJR), SJR is the largest subarea (Figure 6). Both SJR and GRA are likely to affect the total salinity load.

Scrutiny of the results in Figure 7 indicates major differences among the subareas with regards to land use. STL and TLU subareas have most of the land (>90%) cultivated with TFN while all other subareas are much more crop-diversified. This could have some interesting bearing on the flexibility of the different subareas to respond to policy interventions aimed at reducing salinity loads.

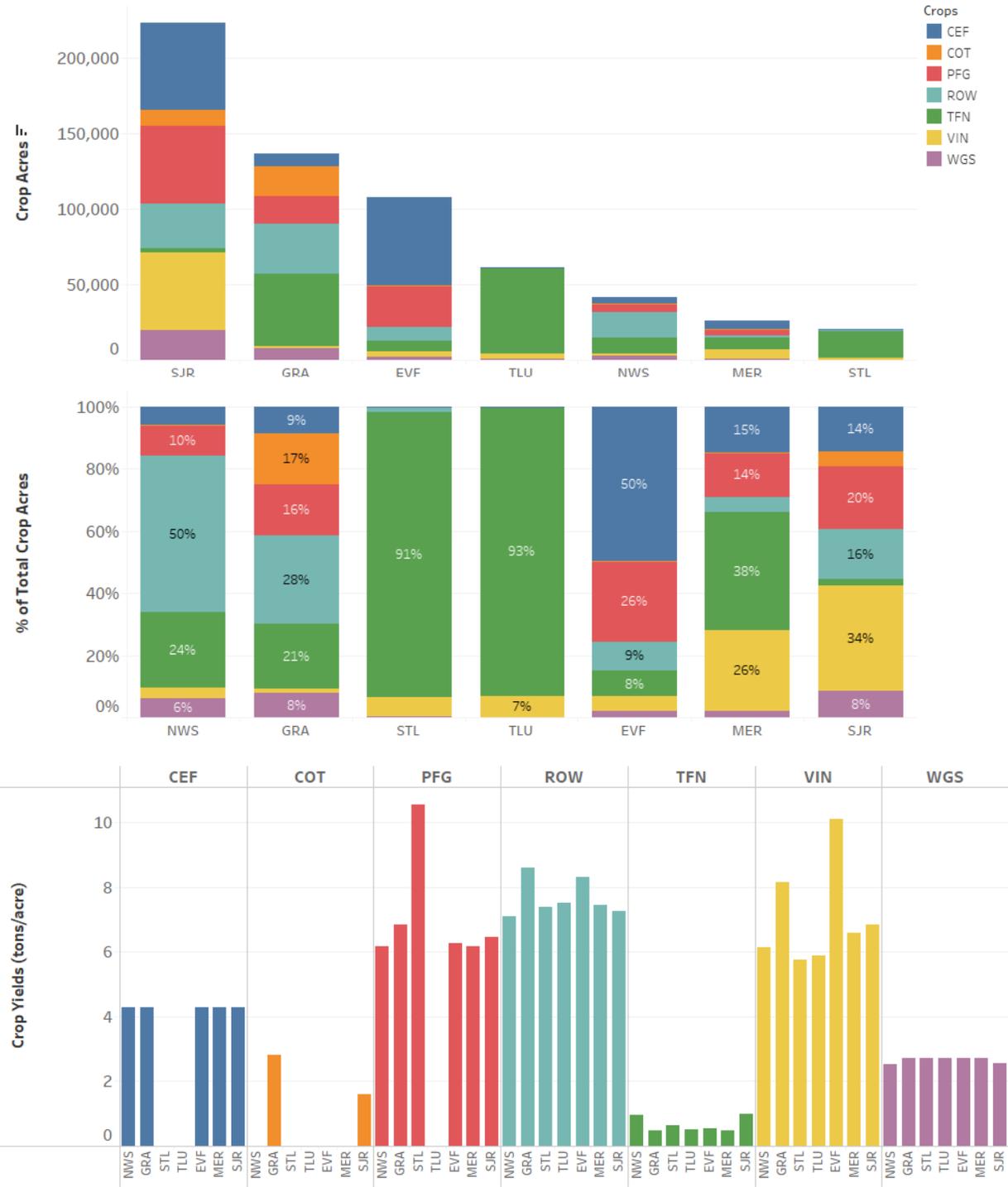


Figure 7. Cultivated land and crop yield for the base case scenario.

Figure 8 presents base case scenario solution per subarea of additional variables. Total applied water volumes (in acre-feet), total volume of drainage water (in acre-feet), and the share of the subarea salinity load disposed to the river (in ton per acre). These results indicate that SJR has the largest quantity of applied water and drainage water per acre and the largest share in the total salinity load (due to its cultivated area), among all subareas. ¹⁰



Figure 8. Volume of applied water by source (Upper Panel), volume of drainage water (Middle Panel), and share of salinity load in drainage water (Bottom Panel) for the base case scenario.

¹⁰ Regional Board data show that Mud and salt Sloughs (downstream of SJR) account for 65% of the salt load.

An important factor in determining the performance of policy scenarios with respect to the base case is the combination of profitability of a given optimal crop mix and water supply availability. This depends upon the yield reduction due to salinity, but also on the revenue for each crop type. While the WARMF model is typically run on a daily timestep, the analysis in our paper is on annual basis. Therefore, it is assumed that farmers adjust their land use decisions once a year, as they get the signal of their salt overage fine.¹¹ Figure 9 presents the profit per acre for each subarea as well as the profit per acre-foot of applied water. In the profit per acre, we can see that the high revenue per acre of crops dominate which subareas perform the best, particularly vineyard (VIN) and row (ROW) crops in the San Joaquin subarea, and the row (ROW) and tree (TFN) crops in the Grasslands subarea.¹² Alternatively, profit per acre-foot of applied water, helps to better understand the water requirements of the various crops. The Northwest Side subarea shows the highest profit per acre-foot of applied water, indicating that the crop mix in the subarea does not require a high volume of applied water per unit of yield.¹³

Salinity concentrations in the model subareas are an important indicator of overall productivity and thus profitability of the region. [Figure 10](#) presents the total dissolved solids concentration in various water sources by subarea. In all water sources, the salinity is highest in the Grasslands, Northwest Side, and San Joaquin subareas,¹⁴ which is consistent with the initial conditions derived from WARMF output (Table 4). However, the model-calculated salinity of the applied water, which is equal to the weighted average of concentrations and volume of the surface water, groundwater, and recycled water applied ([Figure 10](#)), is highest in the Stanislaus and Tuolumne subareas, because the high salinity of groundwater and recycled water use that make

¹¹ Farmers growing orchards, vineyards and other semi-permanent crops choose crops based on returns to acre and on potential profit even if they were faced with fines one a year - this does not mean they will change what they grow. Their degrees of freedom in adjusting their cropping patterns are more limited.

¹² Among the TFN, almonds provide the best return throughout the Valley except in areas with poor drainage and high rootzone salinity.

¹³ Yields are highest here no doubt because they can get water from the Delta Mendota Canal, San Joaquin River and local pumping of groundwater.

¹⁴ Salinity is highest on the westside due to the fact that surface water delivery is from the Delta.

up a large percentage of water applied in these subareas,^{15, 16} since they are the subareas with lower surface water sources available for irrigation. As seen in Figure 7, yields per acre are much lower in the Stanislaus and Tuolumne subareas for PFG and WGS crops, mainly due to having soils that are less fertile (very sandy and low in natural salts and nutrients) than in the other subareas, which include both crops that use some recycled water for irrigation. However, in the case of VIN, which are not irrigated with any recycled water, their productivity is not affected to the same degree by water quality. This may be attributed to the salinity of the applied water being lower than in the crops that are watered in part with recycled water, thus avoiding the same magnitude of negative effects on productivity (Figure 10, lower panel).

¹⁵ However, return flows from these subareas and the EVF are of relatively high quality because the bulk of water supply is from the Sierras.

¹⁶ However, WARMF runs show that salts are produced by the Grasslands subarea.

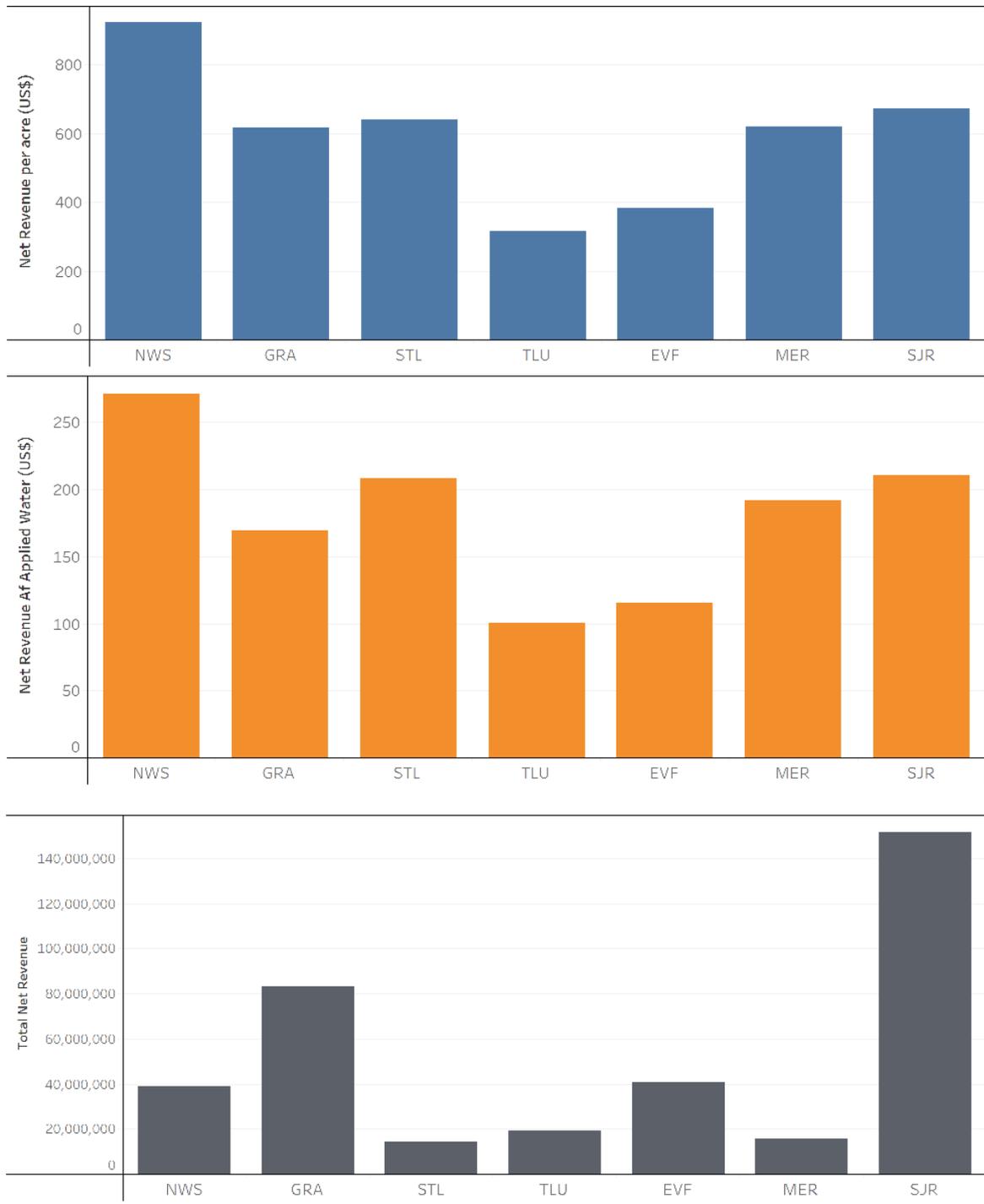


Figure 9. Net revenue per acre (Upper Panel) and per unit of applied water (Middle Panel), and total net revenue by subarea (Bottom Panel) in the base case scenario.

Figure 10 presents the results of the model-produced concentrations of salinity as total dissolved solids (TDS) for the various input and output components, including the salinity of the water sources within the model. These segments include deep percolation, recycled water, root zone, shallow groundwater, and tile drain (drainage water), which are disposed to the river.

Model-produced results suggest that even if the salinity of the irrigation water in the Stanislaus and Tuolumne subareas are the highest (861 and 693 TDS, respectively), yet the salt concentration in the drainage tiles is the lowest among all subareas (6,312 and 6,269 TDS, respectively).¹⁷ The main polluting subareas in terms of salt concentrations are NWS, GRA, and SJR. We will return to these differences in the discussion on policy results.

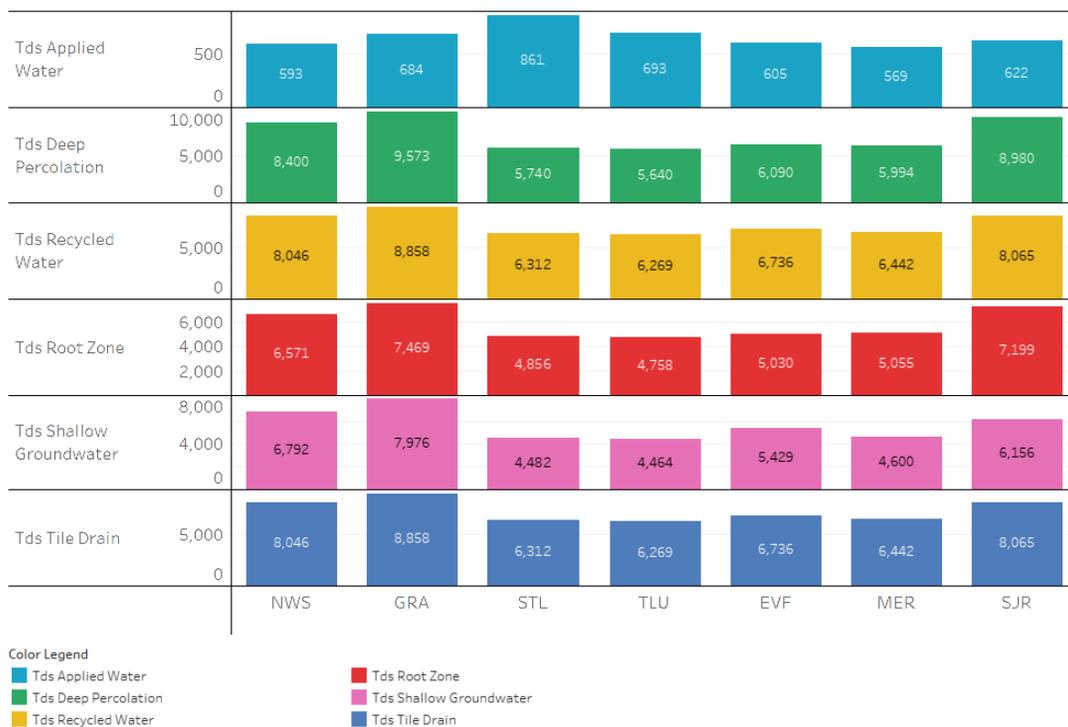


Figure 10. Model-produced concentration of salinity as total dissolved solids (TDS) for water sources within the model including all applied water, deep percolation, recycled water, root zone, shallow groundwater, and tile drain (drainage water).

¹⁷ This result is in disagreement with actual water supply data. Stanislaus and Tuolumne subareas get irrigation water from snowpack in the Sierra's with EC around 50 uS/cm. Delta Mendota Canal water can range from 300-1,000 uS/cm EC and is typically in the <350 ppm TDS range because it comes from the salt impacted Delta.

Model results allow the calculation of the annual salt load disposal (ton/year) to the river from each of the subareas. Results suggest that on average, each AF of drainage disposed to the river carries nearly 10 tons of salt. Two of the subareas are major contributors of salt load pollution—The GRA alone contribute about 60 percent of the salt load disposed into the river.¹⁸These findings can be useful in setting a regional policy aimed to regulate the salinity pollution across the subareas,The establishment and operation of a market for pollution permits is not the focus of this paper, however.

Table 7. Annual drainage and salt loads calculated in the model from individual subareas in the region under study.

Subarea	^a TDS of Drainage Water (ppm)	^b Annual Drainage Volume (rounded AF)	Share of Subarea in Total Annual Regional Drainage Volume (%)	^c Annual Salt Load Disposal (ton)	Share of Subarea in Total Annual Salt Load Disposal (%)
NWS	8046	22,000	6	244,560	6.3
GRA	8858	80,000	21	879,061	22.6
STL	6312	18,000	5	156,972	4.0
TLU	6269	38,000	10	329,129	8.5
EVF	6736	62,000	16	577,003	14.9
MER	6442	18,000	5	160,205	4.1
SJR	8065	138,000	37	1,537,686	39.9
Total	N/A	376,000	100	3,884,616	100

^aFrom Figure 10, bottom panel.

^bFrom Figure 8 middle panel.

^cNote: Calculation of tons of salt per year=[AF per year/365/1.983]×TDS (AF and TDS are taken from data in the table).

7.2 Allocation of joint exceedance fee on salt load disposal to the river

For simplicity we refer to the entire region that is comprised of all seven subareas (GRA, STL, TLU, EVF, MER, and SJR). We refer to the annual salt load of 3,884,616 tons disposed to the

¹⁸ Data prior to the Grassland Bypass project showed about 60% of salt load coming from Mud and Salt Sloughs. That has changed with GBP and current data may show higher contributions from SJR and NWS.

river (Table 7). The question is, of course, what scheme should be used to charge the subareas for the disposal of the total salt to the river.

To determine the variable to be used in such calculation let us first analyze the correlations between the historical values of surface water, groundwater and total water allocated to the farmers in the region, and the model-calculated total applied water, drainage values and salt disposed. Table 8 below presents the results of a correlation analysis of water drainage and salt input and output among the subareas. The assumption behind such correlation analysis is that high correlation among these variables will help justify their use in the calculation of the regional tax distribution across the various subareas. Due to the difficulty to observe exactly how much water (surface water, groundwater, or total water) was used by each subarea, and due to the high correlation among all these variables, we decided to use the values produced by the model of total applied water.

Table 8: Correlation between water used, drainage, and salt disposed to the river.

	Historical SW	Historical GW	Historical Total Water	Model Total Applied Water	Model Total Drainage	Total Salt
Historical SW	1					
Historical GW	0.919	1				
Historical Water	0.985	0.972	1			
Model water	0.986	0.932	0.983	1		
Model drainage	0.975	0.957	0.987	0.992	1	
Model Total Salt	0.969	0.970	0.990	0.989	0.996	1

We also need to determine the tax rate by which the salt disposing subareas will be charged per ton of salt disposed. We used the values of \$10 and \$20/ton (Quinn 3/9/2022—personal communication).¹⁹ The salt tax was charged to the amount of salt exceeding a cap of 354,743, 142,610, and 98,390 ton per year for wet, dry, and critical years (Table Annex A1). These values are the sum of the monthly or part-monthly calculated allowance levels (ton) for each subarea in

¹⁹ Quinn suggested the use of \$10/ton based on a comparison with the standard fine of \$1,000/day typically imposed by the Regional Board for exceedance of numerical pollutant objectives. This number has not been suggested by any regulatory agency.

the region. In this paper we apply two charging approaches: (1) assuming that given the non-point source pollution, it is harder to follow the salt load created by the individual subareas, we rather use the total annual salt load for the entire region as a basis for the salt exceedance charges. We then allocate the total regional salt charges to the individual subareas, using the annual water used for irrigation, which is an easier observable variable. Then (2) we assume that there is an outlet with measuring stations for each subarea, we use the subarea salt load as a basis for the salt exceedance charges. The difference between the total exceedance tax charges between (1) and (2) can be used as the value of information for establishing monitoring stations for individual subarea. Results of this analysis can be found in Table 9 and 10 for two states of nature—wet and dry. In Table 9 we calculate the per acre charges and net revenue per acre following the charge for salt exceedance from the entire region subject to the salt regional allowance, and allocating these charges to the individual subareas using their share in total applied irrigation water, and for two levels of the tax.

Table 9: Charging by entire region exceedance of regional salt allowance and use of irrigated water share as weight.

	Wet Year		Dry Year	
Annual regional salt allowance (ton)	354,743		142,610	
Annual regional salt disposal (ton)	3,884,616		3,884,616	
Salt load to be charged (ton)	3,529,873		3,742,006	
Total charge using \$10/ton (\$)	35,298,730		37,420,060	
Total charge using \$20/ton (\$)	70,597,460		74,840,120	
Net revenue and charges to individual subareas (only in the case of \$10/ton)				
	Charge per acre (\$)	Net revenue per acre (\$)	Charge per acre (\$)	Net revenue per acre (\$)
NWS	80.59	919.41	85.43	914.56
GRA	7.29	578.42	7.72	577.98
STL	85.96	764.03	91.12	758.87
TLU	61.40	210.02	65.09	206.33
EVF	64.47	268.85	68.34	264.98
MER	68.77	571.23	72.90	567.09
SJR	67.74	606.17	71.81	602.09

Scrutiny of Table 9 suggests that the use of the total regional allowance in salt load and subarea water applications for calculation of the weights for the allocation of the joint tax results in minor differences in all, but GRA subarea. It would be interesting to compare the results in Table 9 to those in Table 10 in terms of regional net revenue and distribution of salt load tax payments and net revenue.

Table 10: Charging by subarea data exceedance of subarea salt allowance.

	Wet Year		Dry Year	
Subarea annual allowance and salt load disposal (ton)				
	Allowance	Disposal	Allowance	Disposal
NWS	8,926	244,560	5,275	244,560
GRA	222,087	879,061	87,585	879,061
STL	3,966	156,972	2,344	156,972
TLU	3,920	329,129	2,317	329,129
EVF	16,259	577,003	9,609	577,003
MER	7,085	160,205	4,187	160,205
SJR	92,500	1,537,686	31,293	1,537,686
Net revenue and charges to individual subareas (only in the case of \$10/ton)				
	Charge per acre (\$)	Net revenue per acre (\$)	Charge per acre (\$)	Net revenue per acre (\$)
NWS	58.91	941.09	59.82	940.18
GRA	46.93	538.79	56.53	529.18
STL	76.50	773.50	77.31	772.69
TLU	46.46	224.97	46.69	224.74
EVF	46.73	286.60	47.28	286.05
MER	61.25	578.75	62.41	577.59
SJR	62.83	611.08	65.50	608.42

Table 10 indicates a much lower level of charges per acre for salt load exceedance under subarea-level allowances compared to charges based on total regional exceedance and allocation of the joint cost by using regional irrigation water share for calculating weights to be used for allocation of the joint regional tax charges. Table 11 presents the annual regional net benefits per acre after salt exceedance tax of \$10/ton for wet and dry years.

Table 11: Subarea and regional welfare under two tax exceedance (\$10/ton) charging approaches.

Subarea	Wet		Dry	
	Net Revenue Based on Regional Allowance (\$/acre)	Net Revenues Based on Subarea Allowance (\$/acre)	Net Revenue Based on Regional Allowance (\$/acre)	Net Revenues Based on Subarea Allowance (\$/acre)
NWS	919.41	941.09	914.56	940.18
GRA	578.42	538.79	577.98	529.18
STL	764.03	773.50	758.87	772.69
TLU	210.02	224.97	206.33	224.74
EVF	268.85	286.60	264.98	286.05
MER	571.23	578.75	567.09	577.59
SJR	606.17	611.08	602.09	608.42

An interesting finding in Table 11 is that under the mechanism of charging based on overall regional allowance and allocation of tax among subareas according to share of applied irrigation water, the net revenue per acre of agricultural land was always lower than under the mechanism of charging based on subarea allowance. This difference in net benefits per acres was held for all subareas, except for subarea GRA.

There are several implications to these results. First, the difference in the total regional net revenue between the two charging mechanisms (with net revenue under charging by subarea allowance greater than charging by total regional allowance and allocation of the tax amount by the share of the irrigation water applied on each subarea) suggests that it is preferable to work with subarea allowances. This means that investment in 7 subarea monitoring stations needs to be made, and the difference between the two salt load tax charges can provide an indication of what would be the justified investment in monitoring stations. Second, the differences in per acre charges and the resulting differences in the per acre net revenues between the two charging mechanisms across all 7 subareas may lead to dissatisfaction among the subarea stakeholders.

7.3 Impacts from policy intervention scenarios

Quotas and fees on inputs (land and water) used for irrigation are common policy intervention in the case on nonpoint source pollution, where the level of pollution cannot be assigned to a particular polluter (Helfand and House, 1995; Gardner and Young, 1990; Larson et al., 1996). The policy scenarios evaluated consist of restrictions to surface water and groundwater sources use, and the incorporation of fines and fees when applied water exceeds the established restrictions (quotas). Figure 11 compares the scenarios to the base case for the policy evaluation analyses. Subareas were aggregated to save reporting space: Northwest—NW (NWS), Southwest—SW (GRA), Northeast—NE (STL, TLU, EVL, MER), and Southeast—SE (SJR).

Policy intervention scenarios are listed on the left hand-side of Figure 11. Following the principles discussed in Helfand and House, (1995), Gardner and Young, (1990), and Larson et al., (1996), we introduced 64 combinations of policy interventions, consisting of fees and resource-use restrictions. Strict limits on surface water use with no limit on groundwater use (scenarios 0 to 3) result in increases of pumping, particularly for the Northwest (NW), and in salinity level increases. Introducing a surface water fee (scenario 5 to 14) with no limit on groundwater, reduces pumping and salinity levels while maintaining net revenue. If surface water is 100% of the historical levels, the changes in revenues for all regions are minimal, i.e., close to the base case with very low changes in salinity levels. Strict limits on surface water with no fee, and varying limits on groundwater with varying fees that allow increases in pumping (scenarios 29 to 63) mimics exploration of policy scenarios under droughts and SGMA. When surface water is restricted, results show that the Northwest (NW) can cope better with these restrictions by paying increasing pumping, paying exceedance fees and paying for increasing salinity drainage loads. Similarly with the Southwest region. Surface water reductions of 40% (scenarios 53 to 64) result in lower net revenue compared to the base case for the NW region with highest increases in salinity levels and groundwater use. East side regions can maintain or increase net revenue values with respect to the base case. While we discuss reduction in net revenue comparing policy scenarios with the base case scenario, none of the policy intervention scenarios were associated with negative net revenue, by allowing following, using more groundwater, and shifting to high revenue crops.

In extreme cases, such as in scenario 41 and 52, where surface water reductions are set to 60%, the West Side could maintain or increase net revenue by paying irrigation water exceedance fees; however, the East Side shows reductions or smaller increases with respect to the base case scenario.

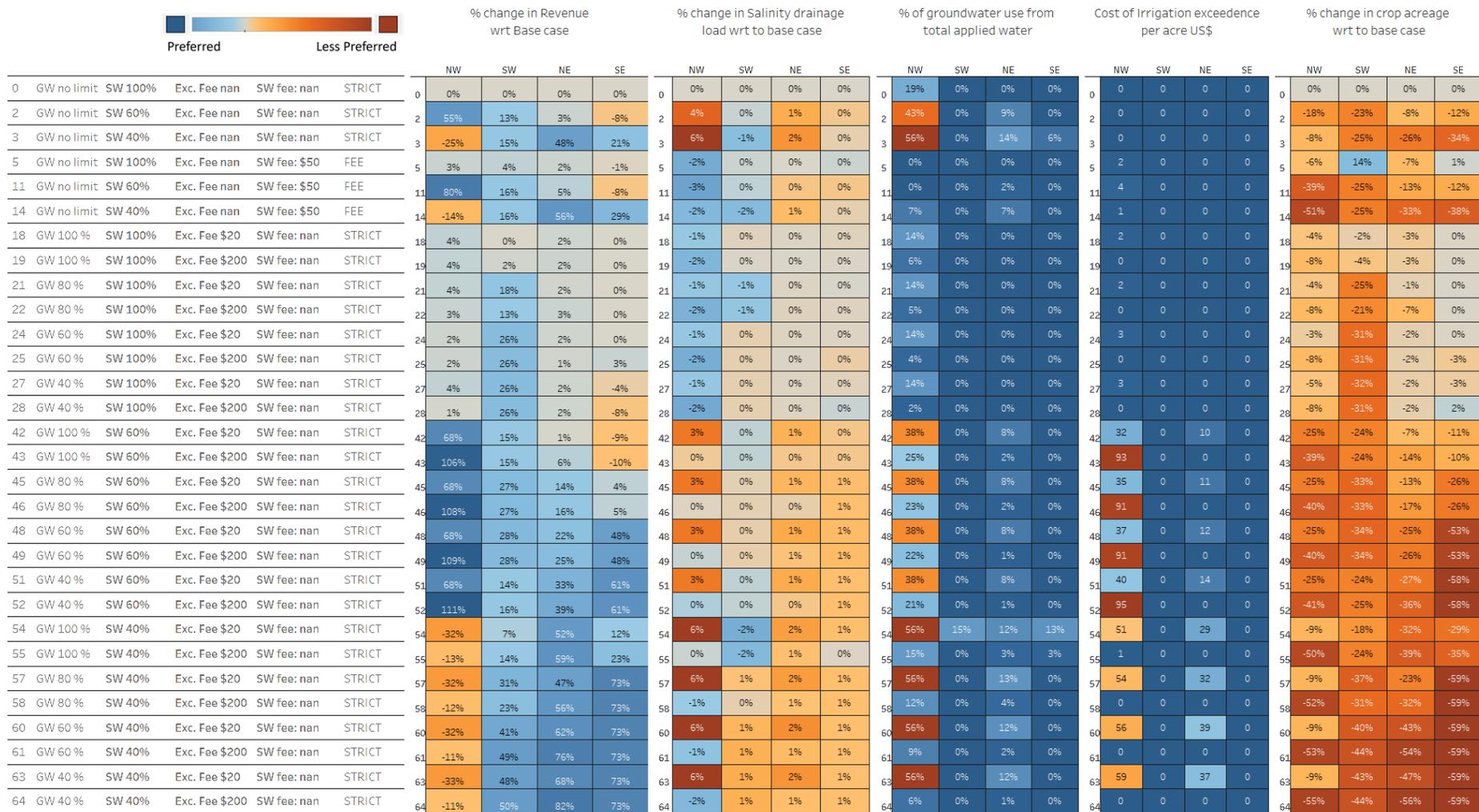


Figure 11. Policy scenario results in comparison to the base case scenario (#0) for net revenue per acre, salinity per acre, groundwater share from the total applied water, and irrigation exceedance fee paid.

8. Discussion, conclusion, and future work

Agricultural production under saline conditions and environmental externalities in the form of nonpoint source pollution of water ways is one of the main challenges related to managing water resources to maximize productivity under environmental constraints on surface and groundwater sources. Designing policies that can respond to this challenge requires an understanding of two aspects: the biophysical implications of salinity concentrations in agriculture, as well as the economic implications of restricting use of irrigation water and promoting innovative management practices to reduce such pollution. In this paper, we demonstrated how the two models, APSIDE and WARMF, can be linked to capture these aspects and allow evaluation of the implications of such policies.

Linking the models required a careful consideration of the spatial and temporal aspects of each model, as well as how “flexible” each of the models are in allowing to make changes to key variables, such as crop land use. Because APSIDE’s flexibility in the programming, most of the changes made to make this integration work, happened in APSIDE. The structure and routines of WARMF were kept intact. The linked WARMF-APSIDE models were applied on annual intervals over a period of 20 years.

We followed previous work (Helfand and House, 1995; Gardner and Young, 1990; Larson et al., 1996) which applied and compared different direct and indirect policy interventions, and their advantages and disadvantages. The scenario analysis focused on three key aspects of policy options, designed for the case of nonpoint source pollution in irrigated agriculture, such as the restrictions on surface water use to represent drought conditions with no limits on groundwater, restrictions on groundwater use to represent SGMA-related policies, and the incorporation of different levels of fines and fees when water use exceeds the established quotas.

We evaluated 64 combinations of policy interventions, consisting of fees and use-restrictions. While reductions in net revenue are observed across all policy intervention scenarios, compared with the base case scenario, none of the policy intervention scenarios were associated with negative net revenues, by allowing each of the subareas to fallow land, use more groundwater, and shift to high revenue crops.

Strict limits on surface water use, but with no limit on groundwater use result in increases of pumping and in elevated salinity load levels. Introducing a surface water fee with no limit on groundwater, reduces pumping and salinity levels while maintaining net revenue compared with the base scenario. When surface water availability is kept at historical levels of supply, the net revenues for all regions are as in the base case with very small changes in salinity levels. Therefore, policies that limit GW pumping are also sought. Referring to policy scenarios under droughts and SGMA by imposing strict limits on surface water with no fee, and varying limits on groundwater with varying fees resulted in significant differences across the subareas, suggesting the Northwest (NW), comprising of NWS, and Southwest (SW), comprising of GRA, can cope better with these restrictions by paying increasing pumping cost, paying exceedance fees and paying for increasing salinity drainage loads. Reduction of surface water availability by 40% results in reduction of net revenues compared to the base case for the NW region with highest increases in salinity levels and groundwater use. East Side regions can maintain or increase net revenue values with respect to the base case. These results suggest that the East Side faces less stringent abatement cost and might be willing to sell salinity permits under certain levels of surface water reductions, if trade in pollution permit is established. The differences among the subareas in terms of salinity abatement cost and agricultural production profitability stem from their hydrogeological situation, access to surface water and groundwater, and types of crops grown. These results point to the possibility of collaboration among all subareas in the form of trade in pollution permits that we will refer to at a later stage of the analysis (regional trade in salinity permits is not analyzed in this paper).

All in all, the results indicate that, as expected, surface water restrictions cause increases in salinity loads as more groundwater is used. The incorporation of fees for imported water is a potential policy option that can help farmers maintain lower levels of salinity loads and retain level of profit. In more restrictive cases of surface water availability, results indicate that collaborative responses could provide a way for farmers to maintain revenue levels by selling/buying pollution permits. While this paper addresses the impacts on salinity loads from water management options at the individual level, i.e., for each water district, the results suggest

that a more detailed analysis with the incorporation of collaborative options and trading actions could be very informative for decision makers in this region.

Future work and refinement should focus on potential collaborative responses. The results of the analysis in this paper suggest that there are some patterns that emerged that could indicate relative advantage among subareas abatement cost, and profitability that some regions would be better off purchasing pollution permits rather than abating the salinity load themselves. For example, in policy scenarios where surface water reductions are set at very high levels the results in this paper suggest that the West Side may benefit from purchasing pollution permits from the East Side. This opportunity to trade faces a reduction in attractiveness to both subareas as the availability of surface water continues to increase (climate change) and as SGMA restrictions on pumping groundwater become more restrictive.

The results presented in this paper help illuminate the need for a more robust integration of the level of salinity loading as part of the optimization to establish reasonable revenue-making and environmentally sustainable policies. An operational model is needed that can calculate salinity loading and optimize revenue internally and in more frequent decision-making junctures (weekly, monthly).

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Annex: Schedule of salt load permissions for each of the subareas per month or parts of a month, and annual values.

Table annex A1: Maximum allowable salt loads by month and subarea (ton)

															Total Regional by Scenario		
Year type	January	February	March	April1	April2	May	June	July	August	September	October	November	December	Annual	Wet Total	Dry Total	Critical Total
San Joaquin River (SJR)																	
Wet	6657	13623	18379	3623	11556	4995	0	0	740	6930	15456	5453	5088	92500			
Dry	4695	6398	1817	0	0	0	0	0	0	3770	5859	4284	4470	31293			
Critical	3059	2445	1817	0	0	0	0	0	0	2798	4633	3929	3677	22358			
Grasslands (GRA)																	
Wet	15645	32020	43197	8515	27160	11741	0	0	1739	16289	36327	16202	13252	222087			
Dry	11036	15036	9411	1631	9270	342	0	0	0	8862	11420	10070	10507	87585			
Critical	7189	5746	4270	0	0	0	0	0	0	6576	10888	9235	8643	52547			
Northwest Side (NWS)																	
Wet	4310	8820	11899	2346	7482	3234	0	0	479	4487	10007	4463	3651	8926			
Dry	3040	4142	2593	449	2554	94	0	0	0	2441	3146	2774	2894	5275			
Critical	1980	1583	1176	0	0	0	0	0	0	1811	2999	2544	2381	9031			
East valley (EVF)																	
Wet	7851	16067	21676	4273	13629	5891	0	0	873	8173	18229	8130	6650	16259			
Dry	5538	7545	4723	819	5652	171	0	0	0	4447	5730	5053	5272	9609			
Critical	3608	2883	2143	0	0	0	0	0	0	3300	5463	4634	4337	5959			
East valley (EVF)																	
Wet	1915	3919	5287	1042	3324	1434	0	0	213	1994	4446	1983	1622	3966			
Dry	1351	1840	1152	200	1135	42	0	0	0	1085	1398	1232	1286	2344			
Critical	880	703	523	0	0	0	0	0	0	805	1333	1130	1058	3956			

Merced (MER)																	
Wet	3421	7001	9445	1826	5939	2567	0	0	380	3562	7943	3543	2898	7085			
Dry	2413	3288	2058	357	2027	75	0	0	0	1938	2497	2202	2297	4187			
Critical	1572	1256	934	0	0	0	0	0	0	1438	2381	2019	1890	3493			
Toulumne (TLU)																	
Wet	1893	3874	5226	1030	3286	1420	0	0	210	1971	4395	1960	1603	3920			
Dry	1335	1819	1139	197	1122	41	0	0	0	1072	1382	1218	1271	2317			
Critical	870	695	517	0	0	0	0	0	0	796	1317	1117	1046	1046	354743	142610	98390

Source: California Environmental Agency (2002: Table 4-15)