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Managed Aquifer Recharge as a Strategy to Mitigate Drought Impacts in Irrigated Agriculture: Role of Institutions and Policies with Application to California

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Summary:
Managed Aquifer Recharge (MAR) is a set of practices that allow the recharge of water of various types and qualities into a given aquifer. MAR has been practiced in locations that face water scarcity, and is considered a potential strategy to mitigate recurring drought effects in California. Our work is focused on conjunctive use of surface water (fresh and treated wastewater) and groundwater over time by irrigators. Using a dynamic optimization economic model coupled with a hydrologic model applied to the Kings Groundwater Basin in California's Central Valley, we find that the first-best scenario suggests a significant reduction in groundwater use, which is complemented by deficit irrigation, and without inflicting significant changes compared to observed crop-yield levels and land-use decisions. We find that both recharged quantities and methods of recharge applied are sensitive to the type of institutions in place for groundwater management. We also find that a more rigid institution, imposing limitations on groundwater extractions, promotes significant changes in regional land allocation under the optimal strategy with detrimental economic implications. Furthermore, we demonstrate that the regional scale of these implications is dependent upon assumed climate conditions. Thus, our analysis suggests that the impact of future climate uncertainty on the region is highly dependent on the prevailing institutions, and provides an estimated $500 million USD annually as an upper limit for the regional economic costs associated with uncertainty in water availability. Total recharged quantities in the region over the entire planning horizon across policy scenarios and climate simulations are substantial, ranging between 4.88 MAF and 9.54 MAF. In most cases, the calculated value of a unit of water recharged is high with respect to the direct value of water in production. This suggests that recharging groundwater intentionally can indeed benefit the region and help mitigate some of the economic implications associated with future climate uncertainty. Comparing the different policy scenarios analyzed and their hydrologic and economic implications, we find that the Sustainable scenario, in which groundwater overdraft in the region is prohibited, presents a good compromise for the region, between the ideal benchmark (the Social scenario) and the more stringent institutional arrangement (the Credit scenario). Under the Sustainable scenario, groundwater levels increase the most, economic losses are small, and the simulated climate conditions appear to have a small impact on the optimal strategy. The institution imposed in this scenario is constructed according to objectives specified under long-term plans of the stakeholders in the region of interest, derived from the Sustainable Groundwater Management Act (SGMA) legislation. This, in turn, implies that this institution is likely feasible and relatively easy to implement, monitor and enforce, which supports our conclusion.

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Abstract

Managed Aquifer Recharge (MAR) is a set of practices that allow the recharge of water of various types and qualities into a given aquifer. MAR has been practiced in locations that face water scarcity, and is considered a potential strategy to mitigate recurring drought effects in California. Our work is focused on conjunctive use of surface water (fresh and treated wastewater) and groundwater over time by irrigators. Using a dynamic optimization economic model coupled with a hydrologic model applied to the Kings Groundwater Basin in California's Central Valley, we find that the first-best scenario suggests a significant reduction in groundwater use, which is complemented by deficit irrigation, and without inflicting significant changes compared to observed crop-yield levels and land-use decisions. We find that both recharged quantities and methods of recharge applied are sensitive to the type of institutions in place for groundwater management. We also find that a more rigid institution, imposing limitations on groundwater extractions, promotes significant changes in regional land allocation under the optimal strategy with detrimental economic implications. Furthermore, we demonstrate that the regional scale of these implications is dependent upon assumed climate conditions. Thus, our analysis suggests that the impact of future climate uncertainty on the region is highly dependent on the prevailing institutions, and provides an estimated $500 million USD annually as an upper limit for the regional economic costs associated with uncertainty in water availability. Total recharged quantities in the region over the entire planning horizon across policy scenarios and climate simulations are substantial, ranging between 4.88 MAF and 9.54 MAF. In most cases, the calculated value of a unit of water recharged is high with respect to the direct value of water in

production. This suggests that recharging groundwater intentionally can indeed benefit the region and help mitigate some of the economic implications associated with future climate uncertainty. Comparing the different policy scenarios analyzed and their hydrologic and economic implications, we find that the *Sustainable* scenario, in which groundwater overdraft in the region is prohibited, presents a good compromise for the region, between the ideal benchmark (the *Social* scenario) and the more stringent institutional arrangement (the *Credit* scenario). Under the *Sustainable* scenario, groundwater levels increase the most, economic losses are small, and the simulated climate conditions appear to have a small impact on the optimal strategy. The institution imposed in this scenario is constructed according to objectives specified under long-term plans of the stakeholders in the region of interest, derived from the Sustainable Groundwater Management Act (SGMA) legislation. This, in turn, implies that this institution is likely feasible and relatively easy to implement, monitor and enforce, which supports our conclusion.

Keywords: Irrigated Agriculture, California, Central Valley, Managed Aquifer Recharge, Surface Water, Groundwater, Treated wastewater, Groundwater institutions, Climate change, Regional Planning

JEL Codes: C61, Q15, Q25, Q56

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1. Introduction

Managed Aquifer Recharge (MAR) has been a well-practiced policy intervention in many countries. MAR is a set of practices that allow the recharge of water using various types and qualities (surface water, recycled wastewater, and even groundwater from different locations) into a given aquifer. In addition to increasing the stock of underground stored water during years of abundant supply, MAR could also improve quality through natural aquifer purification processes of lower-quality water (Maliva 2014). The benefits of MAR include better ability to manage subsidence damages, increasing water use efficiency, reducing quantity of imported water to the region, creating a seawater barrier and reducing or preventing saline water intrusion, increasing the ability to manage surface and groundwater conjunctively via banking of groundwater and surface water, protecting wetland habitat, providing better flood protection, and increasing water availability (Perrone and Rhode 2016). This helps in providing water in seasons and years of high demand, reducing evaporative losses from storing water in open reservoirs, and avoiding or delaying the need for new dams (Vanderzalm et al. 2015).

California is characterized by growing populations in urban regions developed along the Pacific coast near agricultural regions, widespread underground aquifer systems, and many stochastic flash floods and prolonged drought periods. Water managers at all levels of decision-making in California are permanently planning for drought, even during wet years. In the complex California water system, water policy means designing plans that support a growing economy and population, preserving endangered species, retaining profitable agricultural production, and restoring aquifer levels in 20 years. Such adaptations need to be done with a changing climate that results in a reduced snowpack due to lower and altered precipitation, and with increases in temperatures.

Climate change has been threatening the water supply reliability of California's watersheds. The impacts, though, vary depending on the characteristics of each watershed (He et al. 2019). Climate change impacts the temporal shifts in peaks of river flows, and in the storage volumes of reservoirs. These temporal shifts present costly tradeoffs for water managers (Barnett et al. 2005; Forni et al. 2016; Adams et al. 2017; He et al. 2019; Sun et al. 2019).

Groundwater is a major source for both residential and agricultural activities, supplying nearly 18% of the water used by these sectors (Hanak et al. 2011). Groundwater supported the production of many agricultural areas during drought years when water rights on surface water flows were significantly reduced. With the intensification of drought situations in many regions of the state, water users increase groundwater extractions to a level where aquifer sustainability is on the verge of being jeopardized. Furthermore, after consecutive droughts, several aquifers in California's Central Valley, and around the state were left in critical condition. Groundwater depletion called for a new regulation on groundwater use—the Sustainable Groundwater Management Act (SGMA), which plans to recover sustainable groundwater levels in the next 20 years. The sustainability of groundwater pumping depends to a great extent on recognition of the associated impacts on surface water systems (Wendell and Hall 2015) as water managers try to recover overdraft (Langridge and Daniels 2017). Therefore, understanding the groundwater and surface water interactions are key components in informing decisions around SGMA (Dogan et al. 2019; Langridge and Daniels 2017; Scanlon et al. 2012).

Another phenomenon observed in California, and especially in Southern California, is the increase in actual and planned reuse of treated urban wastewater. This includes use of recycled wastewater for irrigation of agricultural crops, irrigation of public areas, consideration of aquifer recharge with recycled wastewater, and even for direct potable use.

With this background we will focus on the interaction between surface water and groundwater in the context of possible use of these types of water over time. The main use of groundwater and surface water in California is for irrigated agriculture. Understanding the irrigation needs and what that means for the water rights allocation is important to inform decisions that can support surface and groundwater supply sustainability. In other words, being able to understand the economic implications of decisions around water allocation is important to evaluate potential management actions that can be sustained over time. Hanak and Lund (2015) indicate that "agricultural water-use efficiency efforts do not result in net water savings," and that groundwater banking can help overcome problems during droughts, although it "needs more comprehensive basin management mechanisms to limit overdraft and increase conjunctive use operations."

Perrone and Rhode (2016) surveyed and analyzed costs and benefits of proposed MAR projects in California (for the period 2000–2006, in 2015 prices), estimating range and median costs and benefits by type of project. A total of 106 MAR projects have been identified in California. Of these, 57 are for recharge of surface water, 16 are for recharge of storm water, 14 are for recharge of treated wastewater, and 16 are for recharge of blended water types. Of the 106 projects identified, a total of 35 are in Southern California and the rest are in other regions of the state.

Given the potential for MAR in California, we develop in this paper a hydrological-economic model of MAR that refers to the dynamics of aquifer water quantity and includes the surrounding urban and agricultural activities that demand and produce water that can be considered for MAR. In addition, we introduce several institutional arrangements for MAR, such as the concept of "capacity sharing"[1] (and trade) that was proposed by Dudley and Musgrave (1988) as a method of allocating water entitlements to users of reservoir water, and the concept of "water banking."

The paper is developed as follows: In section 2 we discuss previous work on MAR, both internationally and in California. In section 3 we develop the analytical framework to be used in the work. It includes two separate hydrologic (water evaluation and planning—WEAP) and economic optimization model (EOM) components that are integrated into one sequential model. We present in that section also the data needs of both WEAP and EOM, and the calibration procedures applied to the Kings Groundwater Basin, which is the region used for demonstration of the approach. Section 4 displays the rationale and details of the policy runs we adopted for the empirical analysis. In section 5 we present the various sets of results, including the hydrological results (pumping, recharging, irrigating) and the economic results (land use, applied irrigation water from various sources, costs and profits). In addition, we present results of the several institutional arrangements for MAR that we evaluated. Section 6 concludes, discusses the various results, and compares them to results of previous works, and provides several policy implications of interest in general, and to the region in particular.

[1] Capacity sharing of water rights involves allocating shares of inflow, reservoir capacity and reservoir losses among users of water, and letting the users of water operate their capacity shares to satisfy their objectives. Dudley and Musgrave noted that the components of the capacity sharing arrangement could be tradable; however, in their study, equal shares of reservoir capacity, inflow and reservoir losses were allocated to each of four classes of agricultural water users and the operation of the reservoir was simulated over time.

2. Previous work on MAR

Published work on the economics of MAR includes estimates of costs associated with MAR, such as recharge techniques, and estimates of benefits and value of MAR. We will refer to studies that considered three types of water: surface water, storm water, and treated wastewater in the context of MAR. We distinguish between studies conducted internationally and those conducted in California's Central Valley, which is the focus of our work.

2.1 Internationally conducted work

A recent review paper by Dillon et al. (2019) reports the capacity of all major types of MARs from all over the world. Findings suggest that since the 1960s, implementation of MAR has accelerated at a rate of 5% per year, but is not keeping pace with increasing groundwater extraction. At present, MAR has reached an estimated 10 km3/year, ~2.4% of groundwater extraction in countries reporting MAR (or ~1.0% of global groundwater extraction). Authors predict that MAR is likely to exceed 10% of global groundwater extraction, based on experience in which MAR is more advanced, to sustain quantity, reliability, and quality of water supplies.

The definition of MAR appears in Dillon et al. (2009): "Managed aquifer recharge is the purposeful recharge of water to aquifers for subsequent recovery or environmental benefit." Five MAR techniques are usually distinguished from one another; i.e., well, shaft and borehole recharge, spreading methods, induced bank filtration, in-channel modifications, and rainwater and runoff harvesting (IGRAC 2007; Ringleb et al. 2016). The last two techniques refer mainly to water interception methods (Ringleb et al. 2016). A different possibility could be distinguishing MAR application methods between injection wells, infiltration basins, and on-field flooding. Injection wells, or commonly named ASR/ASTR (Pyne 2005), have advantages over infiltration basins through avoided evaporation losses, and shorter travel time needed to reach the groundwater table. However, this method is also associated with significant capital investment and several uncertainties regarding the effect on groundwater dynamics in terms of flows and solute transport, geochemical processes, groundwater levels, and more.

Damigos et al. (2017) apply a contingent valuation method to elicit the value of MAR in a case in Italy. The study obtained monetary estimates and quantified factors influencing people's attitude and willingness to pay (WTP) for MAR. The mean WTP value is equal to €3.4 per household, per month for the total population, respectively. A conservative estimate of the total economic value associated with MAR would be around €50 per household, per year (1€=$US1.2 in 2017). The results show that society holds not only use but also significant nonuse values, which are a part of the total economic value of groundwater according to related research efforts. To this end, MAR valuation highlights its social importance for incorporating its nonmarket benefits into groundwater management policies and assessments.

While many works refer to MAR in terms of surface water recharge, Vanderzalm et al. (2015) present seven case studies from Australia in which treated wastewater is considered for recharge. The work compares the economic cost associated with different recharge techniques of the wastewater. Along this line, Missimer et al. (2014) report results from a study in Saudi Arabia's rural areas that face high water scarcity. They estimate the cost of supplying villages with either desalinated seawater or treated wastewater conveyed via a MAR system. The cost of supplying desalinated water is \$2–5/m^3 (1AF=1235m^3), plus conveyance cost. The cost of supplying treated wastewater via an MAR system is \$0–0.50/m^3, plus conveyance cost. They conclude that MAR and associated reuse systems can solve water supply problems in the rural areas and reduce the economic losses caused by marine pollution, particularly coral reef destruction, from wastewater disposal.

Three recently published works on the economics of MAR in the Mississippi River Valley's Alluvial aquifer highlight several aspects of MAR that could be of relevance to our work. Tran et al. (2019) depart from the observation that past efforts to reduce groundwater overdraft through investment in improved irrigation efficiency has, mostly, failed to reduce aquifer depletion. An alternative on the supply side could be the capture of surface water during high flow events for MAR, or additional surface storage. Using a landscape-level model, they examine optimal management of MAR with interaction to surface reservoir storage, crop choice, and groundwater conservation policies in Eastern Arkansas. Results suggest several relationships between cost of MAR and cost of pumping groundwater to increase water stock in the aquifer, and cost effectiveness of alternative water conservation policies, such as caps or taxes on pumping, compared with MAR cost. Tran et al. (2020a) developed a high spatial resolution hydro-economic model to assess effects of site conditions (natural recharge and proximity to surface water sources), and the agronomic conditions of crops on: optimal MAR, groundwater level, present value of farm net returns, and the cost-effectiveness of a MAR subsidy. They find some general relationships that help determine the appropriateness of MAR to local conditions, such that less irrigation-intensive crops are a substitute for MAR while rice and dryland crops are a complement for MAR; MAR increases groundwater conservation most at the sites with higher net returns to dryland and irrigated soybeans, and lower net returns to corn and cotton; and the cost-effective locations for a MAR subsidy are sites with large net returns to crops, like cotton and soybeans. Tran et al. (2020b) analyze the interaction between levels of groundwater, crop choice and groundwater pumping rates in the context of MAR for various scenarios of drought-severity levels. Using conditions in Eastern Arkansas over a period of 120 years they found drought frequency (risk) has a stronger influence on groundwater pumping and MAR use, compared with drought severity. They were able to identify a high level of slippage (relative increase in groundwater level not related to MAR). But even with such slippage, the total net returns to farms in this region are higher with MAR, and the variability in those returns over the analyzed horizon are less with MAR.

The importance of appropriate institutional arrangements for the success of groundwater recharge and banking (MAR) projects was identified in previous work. Contor (2009) demonstrates the need for a compatible accounting system for groundwater banking that is dependent on the type of aquifer. The author draws a distinction between aquifers with and without hydraulically connected surface water bodies. Maliva (2014) argues that several crucial components contribute to a successful groundwater-banking program. Namely, some favorable hydrogeological conditions to ensure optimal recharge, storage and recovery rates; and efficient institutions with comprehensive accounting systems to maintain water balance between recharge and withdrawals. That would reassure participants that their credits will be respected and prevent spatial and intertemporal externalities to third parties, such as users of adjacent aquifers and future generations.

2.2 Work in the Central Valley, California

The Central Valley of California has been a major region for MAR operations. According to Scanlon et al. (2012), the spatiotemporal variability in natural conditions and the resulting heterogenous groundwater depletion in the Central Valley basins are contributing factors to the conclusion that MAR could be a promising strategy to mitigate the impacts of future droughts on the Central Valley's water balance. The distinction between an infiltration basin recharge and on-field flooding strategy stems mainly from the opportunity costs associated with land reallocation, and possible effects on crop productivity (O'Geen et al. 2015). In a relatively recent survey conducted by the California Department of Water Resources (DWR), a group of 89 water agencies were identified as operating some type of recharge program in their service area (CADWR 2015). Out of this group of agencies, 45 are located within the Central Valley, most belong to the Tulare Lake hydrologic region. According to the survey, recharge in the Central Valley is achieved primarily through infiltration basins.

Further distinction between MAR applications can be made on the grounds of the type of water used for recharge. Perrone and Rhode (2016) compiled and analyzed a database of 106 recharge projects, submitted by different water agencies across California, to be considered under several state funding schemes (Propositions 13/50/84/1E) in the last two decades. According to the authors' distinction, most projects in the Central Valley rely (or will rely) on excess surface water deliveries from the SWP and CVP. The authors also indicate that a respectable number of projects are designed to recharge either storm water or recycled municipal wastewater, or a blend of both. These projects are primarily located in Southern California.

As already mentioned, several recharge projects had been in operation within the Central Valley system for several decades. Faunt et al. (2016) report on substantial amounts of recharge in Fresno and Kern counties over the period 1966 through 2014, using mainly infiltration basins, and based on data gathered from 10 MAR projects. Among these projects, the detailed information of few is well recorded. The Arvin-Edison Water Storage District (AEWSD) banking project, located in the southern edge of the San Joaquin Valley (SJV), holds the capacity to infiltrate over 45,000 acre-feet per year using direct infiltration methods. Since the establishment of this project in 1966, the district had successfully recharged over 1.5 million acre-feet into the underlying groundwater basin. (Thomas 2001; AEWSD 2003). Another significant recharge project is the Kern Water Bank located in Kern County. The project covers 19,883 acres in surface overlying the Kern River Fan, divided approximately in half, and shared between the project's infiltration ponds and natural habitat for wildlife. The recharge capacity of this project is estimated at 450,000 acre-feet per year (Thomas 2001). Located above the Eastern San Joaquin Groundwater Basin, the Farmington Groundwater Recharge Program (FGRP) is led by Stockton East Water District. It is estimated that this project is recharging approximately 11,000 acre-feet per year, mainly through infiltration basins. At completion, the potential recharge capacity is estimated at 35,000 acre-feet per year (FGRP Newsletter 2007).

The Central Valley area is also significantly exposed to occasional floods. The cost of damages from these flood events is estimated at $1.2 billion in current prices (USACE 1999). The adoption of capturing flood water and utilizing on-farm flooding for irrigation and recharge purposes therefore could be a promising strategy. Recent literature has been devoted to study the feasibility of this approach, while addressing several uncertainties associated with it. Bachand et al. (2014) report the results of a feasibility study to capture flood flows for on-field direct recharge over approximately 1,000 acres of Terranova Ranch located in western Fresno County, overlying the Kings Groundwater Basin. Infiltration rates measured suggest that about 15,000 acres would be needed in order to capture median flood flows in the area; however, more permeable soils might decrease the area required. Dahlke et al. (2018) performed a different experiment of managed recharge through winter flooding of alfalfa fields at two sites (Davis in the Sacramento Valley, and Scotts Valley in Siskiyou County) characterized by good soil conditions for recharge (O'Geen et al. 2015). Results indicate that 90% of the water applied had percolated to the groundwater with minimal damage to crop production. In a different study, a modeler approach is adopted in order to evaluate the potential benefits of recharging groundwater through flooding of agricultural lands using excess winter river flows. This study focuses on the east side of the SJV, specifically in Merced, Madera, and Fresno counties. Hypothetical recharge locations are identified based on criteria of required acreage, location along existing conveyance facilities, distance from surface water courses, and recharge suitability index values (RMC 2015). The study estimates that an average of about 80,000 to 130,000 acre-feet per year can be diverted for on-field flooding using existing conveyance infrastructure. This strategy can potentially contribute 31,000 to 52,000 acre-feet per year of recharge to groundwater storage. Recharge potential in the south part of the region (i.e., Fresno County) is higher than in the northern part (Merced and Madera Counties).

Whether the recharge method is on-field flooding or infiltration ponds, concerns have been raised regarding the efficiency of the recharge method and its consequences on the underlying groundwater basin. The main challenges identified are associated with the impact of recharge water on the geochemical structure of underground soil layers, on groundwater gradients and flow direction, and constituents' concentrations within it. Such phenomena were recently observed in two separate studies of recharge projects in the Eastern San Joaquin Groundwater Basin (O'Leary et al. 2012, 2015). Bachand et al. (2014) conclude in their study of on-field flooding that groundwater quality might deteriorate at first, but as more flood flows are diverted for recharge the effect becomes positive.

The distinction between the factors affecting the efficiency of different types of recharge projects is of great importance. Physical and hydrological characteristics, such as the quality of water used for recharge, method of recharge, and soil layers' structure might affect the potential capacity of a project. However, economic institutions and incentives impose different behavioral responses of economic agents, and therefore can affect both the available volume of water for recharge, and the feasibility of the project. For example, under such a distinction in-lieu banking should more appropriately be addressed as an institution, rather than a possible MAR strategy. Further emphasis on the importance of distinction could be drawn by considering the mechanisms (i.e., regulatory, such as taxes and quotas, or property rights arrangements) required to incentivize the implementation of such a strategy among relevant stakeholders. This argument is popular within studies of groundwater recharge and banking projects in California. For example, Thomas (2001) studies multiple conjunctive water management cases in the Central Valley in order to emulate the design features that produce successful projects and avoid those that tend to result in failure. The author focuses primarily on the institutional factors of each project, but also accounts for hydrologic, economic or geographic attributes that appear to correlate strongly with success. The author defines these institutional factors as mechanisms that are designed for: (a) creation and protection of legal rights of the project manager; (b) compensation schemes to relevant stakeholders; and (c) avoidance of unwarranted environmental impacts. Finally, the author concludes that the concurrence of all stakeholders involved is a crucial component of a successful groundwater banking project. The critical role of institutions for a successful recharge project is once more emphasized in Hanak et al. (2018), based on responses for a survey of SJV water districts' experience with groundwater recharge projects in their domain.

Our work builds on the ideas presented in the previous literature. We introduce an analytical framework that builds on an interaction between a hydrologic simulation model and an economic optimization model. We develop a procedure for feedback-input between the hydrologic model and the economic optimization model (EOM) that leads to a steady state level of the hydrology of the aquifer and the surface water sources in the analyzed region. In addition, we include several regulatory policy interventions and a set of possible institutional arrangements that could be introduced in the management of the MAR, based on previously published experience.

3. Methodology

Effective, robust, cost-effective, and sustainable water planning requires analytical tools that capture the physical and natural complexities, the regulatory and water rights allocations, and the agri-economic trade-offs of having a drought water reserve underground and the avoided capital costs of frequent droughts (MacEwan et al. 2017; Medellín-Azuara et al. 2015).

As mentioned, the methodology of this paper is based on the linkage of two models: a hydrologic and water management model, and an economic optimization model (EOM). The hydrologic model is developed using the Water Evaluation and Planning (WEAP) software that includes hydrology and operations across the entire Central Valley, with a detailed representation of the Kings Groundwater Basin and surrounding area. The dynamic-optimization model is based on an integrative approach, combining partial-equilibrium-optimization models of the water and agricultural sectors—calibrated and applied for the same region. This section of the paper provides a description of both models and ends with an explanation of the methodology used for the linkage between the two.

3.1 The hydrologic and water resources management model

We use WEAP for simulating the hydrology consequences of water management decisions in the region. WEAP is a water-planning tool that integrates the hydrological processes of a watershed into a systems model that allocates water among various water users according to a set of user-defined priorities (Yates et al. 2005). The software provides a comprehensive suite of tools for simulating water resources systems, including rainfall-runoff hydrology, water resources infrastructure, agricultural, urban, and environmental demanded quantities, and the ability to apply complex operating rules and constraints to the water allocation problem. WEAP allocates water using linear programming (LP) defined by user-specified water consumption priorities and supply preferences.[2] The integration of natural and managed features makes it ideally suited for evaluating scenarios of managed aquifer recharge.

Since 2006, the California Department of Water Resources (DWR) has used WEAP as part of its regular update of the California Water Plan to assess the potential impact of different climate scenarios. This effort has led to the development of the Central Valley Planning Area (CVPA)

[2] From hereafter, demand and consumption will be used interchangeably.

model, which focuses on water resources originating in the three hydrological regions that comprise the Central Valley: the Sacramento, San Joaquin, and Tulare Lake basins. The CVPA model includes climate-driven hydrology of 25 watersheds flowing into the Central Valley. Crop coverage and demands within the Valley were delineated according to DWR's planning areas, as well as an accounting of the 21 groundwater sub-basins that underlie the valley. The operational rules were included to represent the management of the two largest water projects in the state: The United States Bureau of Reclamation's (USBR) Central Valley Project, and DWR's State Water Project.

Figure 1 is a schematic presentation of the CVPA model in WEAP. Catchments (green dots) represent the physical area of the model and land use that are delineated at the scale of DWR's Planning Areas (PAs). Groundwater objects[3] (green squares) represent aquifers; water demand objects (red circles) represent the domestic water demands. Natural surface water objects (solid blue lines) represent rivers, and human-made surface water bodies (solid orange lines) represent canals. Withdrawal from surface and groundwater sources are presented by transmission links (green lines) to deliver water from the sources to the demands and catchments. Runoff/infiltration links represent return flows (blue dotted lines) from the catchments and demands to groundwater and rivers objects. Consequently, return flows can be analyzed as runoff, interflow, baseflow, or deep percolation. The WEAP software calculates groundwater storage within each of the groundwater objects, based on deep percolation from the catchments and baseflows to the rivers. The CVPA model was modified for this study. The modified model is called CVPAM. The modifications are described in detail in the next section.

[3] Objects are water consumption centers or supply centers, of surface water, groundwater, and treated wastewater.

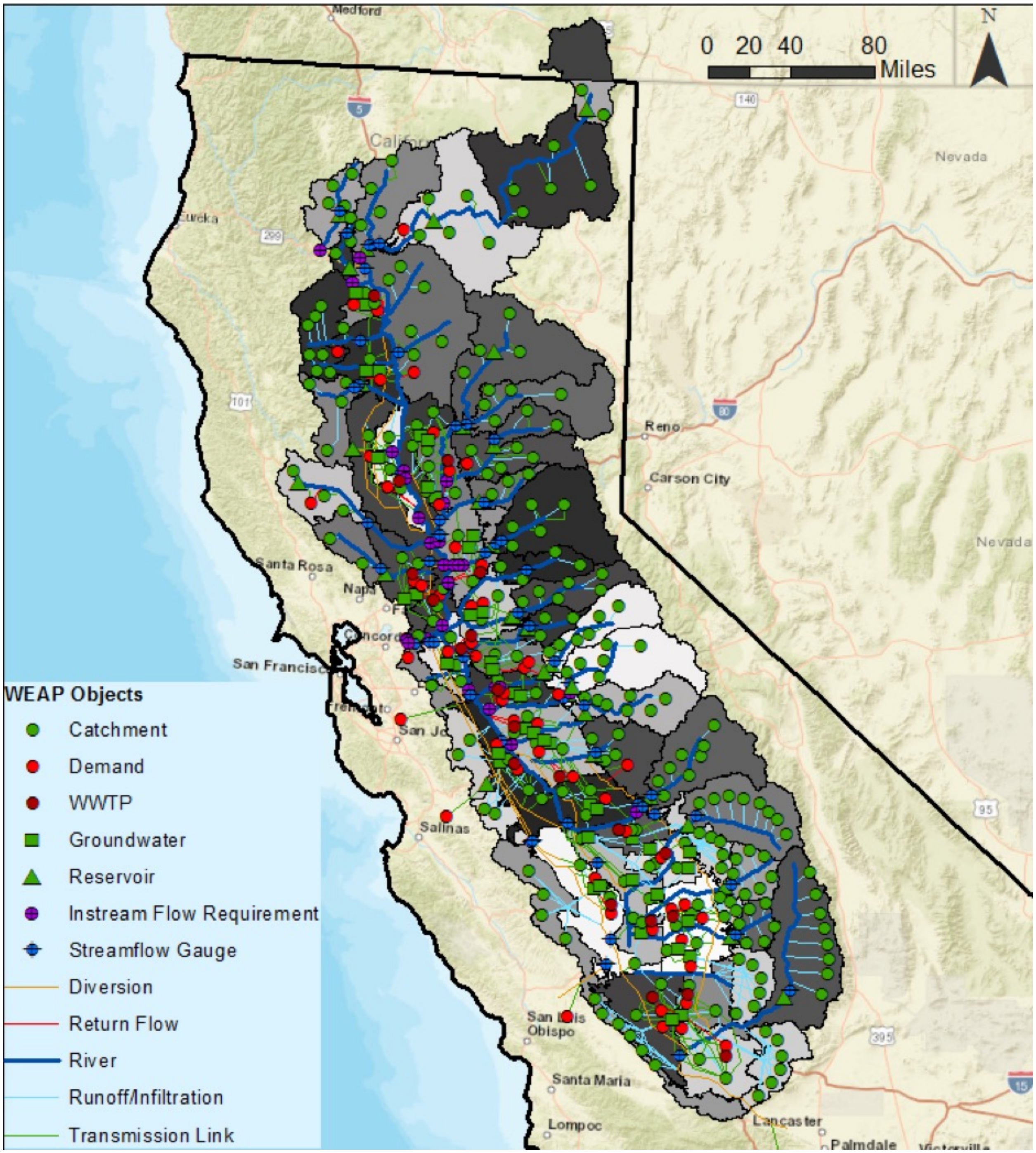

Figure 1. Central Valley Planning Area (CVPA) WEAP Model schematic. Model subregions are shown as grey polygons.

3.1.1 Spatial representation of the model

The modifications of the CVPA model corresponds to the Kings Groundwater Basin portion of the model delimited in Bulletin 118, 2016, and shown in Figure 2. The entire Central Valley is represented in the CVPAM and remains mostly unchanged from the CVPA model. The main modification is a more detailed spatial representation of the study area. Since the PAs of the CVPA model have a coarser resolution than the EOM subdistricts, the PAs were disaggregated to decision analysis units (DAUs).[4] The Kings County Water District is also included as a subregion but does not correspond directly with the DAU boundaries.[5] Figure 3 shows the changes made to the CVPA subregions.

[4] Hereafter, DAUs and subregions are used interchangeably.

[5] The Kings County Water District subregion does not follow the DAU boundaries exactly as it includes portions of two DAUs, but is delineated in order to ensure the WEAP portion of the CVAM maintains the Kings Groundwater subbasin and EOM boundaries, which do not align perfectly with the DAU boundaries.

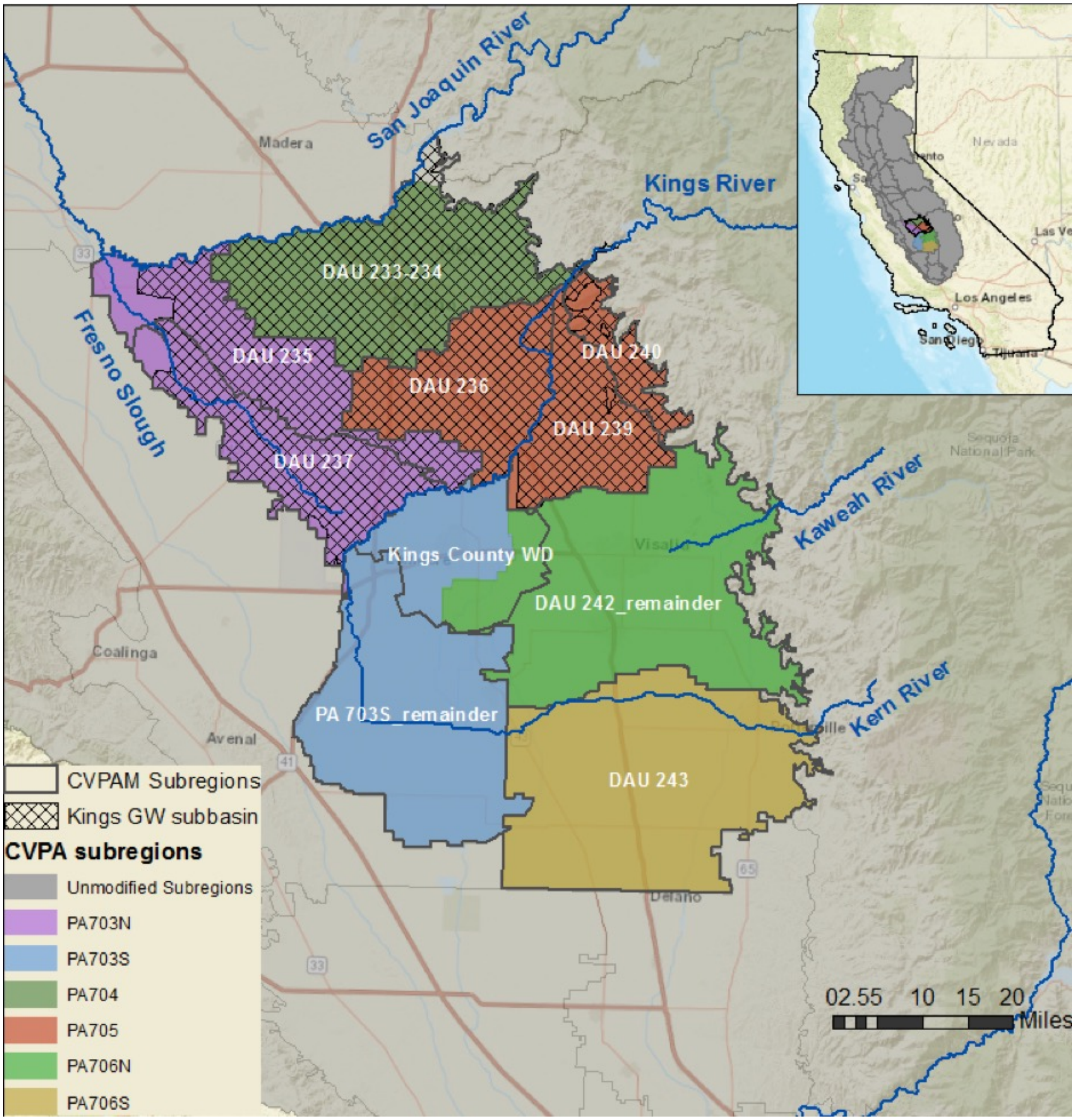

Figure 2. Revised subregions for this study. Colors show the subregions as delineated in the CVPA model (PA stands for Planning Areas) that were modified for this study, grey subregions remained unmodified from the CVPA model, black outlines and white labels show the subregions as revised in the WEAP portion of the CVPAM (DAU stands for detailed analysis unit), which roughly align with the EOM and the Kings Groundwater subbasin. Inset map shows the revised subregions relative to the entire CVPAM model area (grey), and the state of California (outlined in black).

The primary surface water sources in the Kings Groundwater Basin area are the Kings River, Friant Kern Canal, San Joaquin River, Kaweah River, the Mendota Pool, and the reservoirs on these water bodies (Figure 3). The CVPAM includes the entire central valley. Therefore, each model run consists of all water users and surface water sources, as well as operations of the rivers and reservoirs within and outside the study area (Joyce et al. 2011).

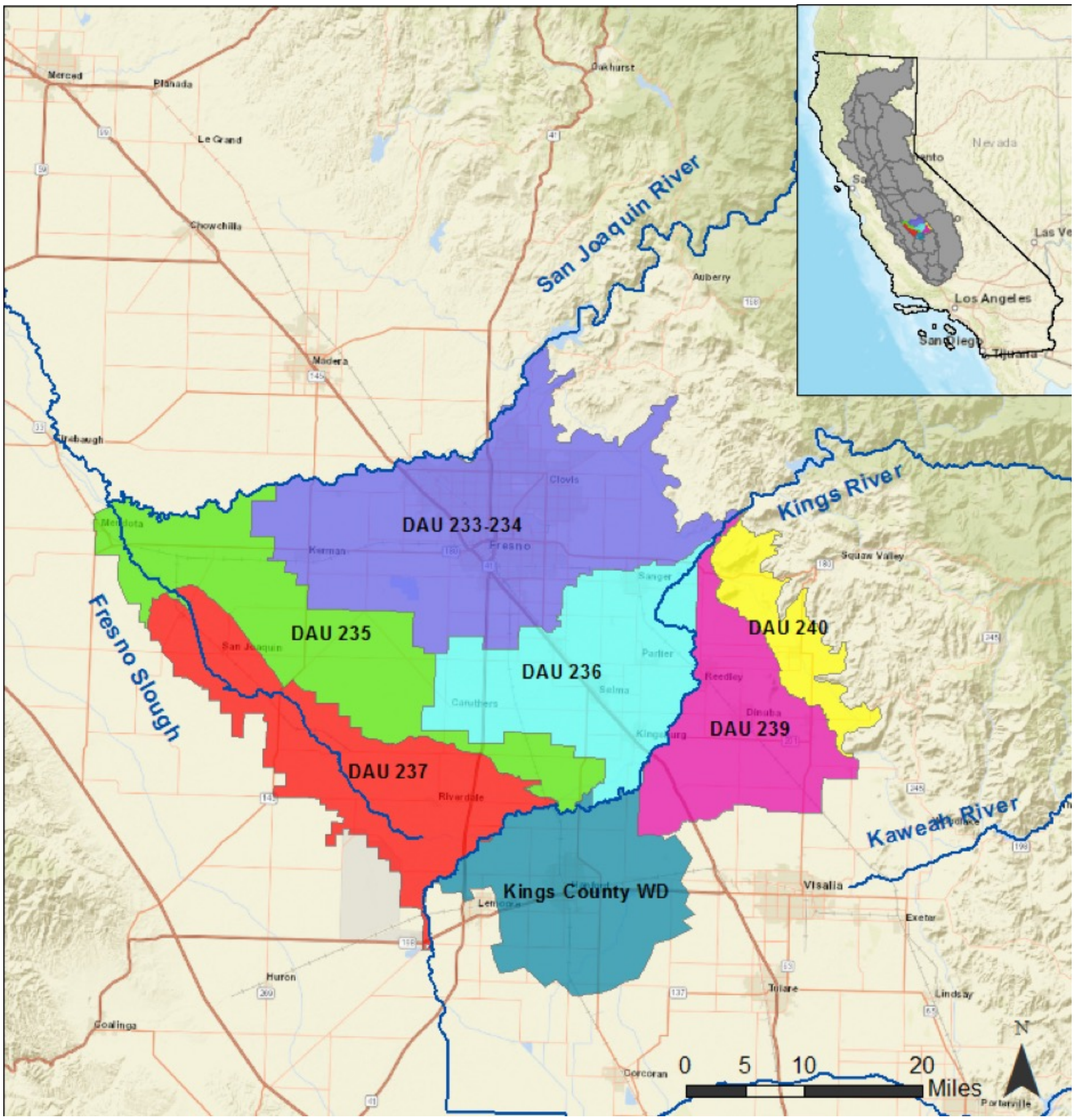

Figure 3. Subregion boundaries within the study area, as delineated in the WEAP portion of the CVPAM. DAU stands for detailed analysis unit. Inset map shows the study area subregions relative to the entire CVPAM model area (grey), and the state of California (outlined in black).

3.1.2 Representation of surface water rights within the study area

The key components affecting water use in California are surface water rights and water management rules that govern water availability to different users. In the study area, water rights are held mainly by water or irrigation districts (districts), making that water available to growers.

State Water Resources Control Board's water rights database,[6] Central Valley Project contracts, and a previously conducted analysis of water supplies in the Kings River Basin[7] were assessed to determine water rights information and available water to each district in the study area (see Figure 4). Water rights are represented on the transmission links model objects reflecting the water available to each subregion from each surface water source. For all surface water sources, except the Kings River, the limits on the transmission links are annual values in acre-feet, as shown in Table 1. Because the model simulates hydrology and inflows to reservoirs based on climate input data, in dry years reservoirs may have less water and may not be able to supply every district with their full water right. Therefore, Table 1 shows the maximum potential water available to each subregion, but actual water available may vary from year to year.

To reflect the operations of the Kings River Water Association, each year's volume of water in the reservoir is portioned out to each subregion, and inflows to the reservoir are modeled each month based on climate input data. With low levels of water in the reservoir, the district's allocation is proportional, based on the water available, using the percentages shown in Table 1.

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[6] https://www.waterboards.ca.gov/waterrights/water_issues/programs/ewrims/

[7] http://www.kingsbasinauthority.org/_documents/reports_papers/Analysis_of_Water_Supplies_in_Kings_Basin_(Phase_1_Task4)_May_2006.pdf

Table 1. Limits on water deliveries to each district and corresponding subregion from each surface water source values are in AF per year unless otherwise noted.

Water District	Kings River*	Friant Kern Canal	Mendota Pool	San Joaquin River	Subregion	Kings River*	Kings River^	Friant Kern Canal	Mendota Pool	San Joaquin River
Fresno ID	521,355	75,000								
Garfield WD		3,500			**DAU 233**	521,355	32.8%	79,700	0	0
International WD		1,200								
Raisin City WD										
Coelho Family Trust			2,080							
Liberty WD		1,000			**DAU 235**	9,264	0.6%	1,000	2,080	0
Mid Valley WD										
Farmers WD										
Liberty Canal Co[3]	9,264									
Consolidated ID	303,959				**DAU 236**	353,583	22.3%	0	0	0
Kings River WD	49,624									
James ID	5,345		35,300	9,700						
Laguna ID	59,503									
Murphy Slough Association	59,339									
Riverdale ID										
Stinson ID	12,722				**DAU 237**	243,103	15.3%	800	55,500	9,700
Tranquility ID	717		20,200							
Laguna WD		800								
Lemoor Canal and Irrigation Co[3]	87,447									
Crescent Canal Co [3]	18,030									
Alta ID	206,779				**DAU 239**	206,779	13.0%	0	0	0
Hills Valley ID		3,346								
Orange Cove ID		39,200			**DAU 240**	0	0.0%	42,946	0	0
Tri-Valley WD		400								

Water District	Kings River*	Friant Kern Canal	Mendota Pool	San Joaquin River	Subregion	Kings River*	Kings River^	Friant Kern Canal	Mendota Pool	San Joaquin River
Kings County WD[1]	Via stocks in other companies (see below)	8,600		Purchase short term excess water[5]	Kings County WD	221,541	14.0%	8,600	0	0
Kaweah Delta WCD[2]										
Peoples Ditch Co	153,985									
Last Chance Water Ditch CO	67,556									
Lakeside Ditch Co										
Corcoran Irrigation Co[4]	17,665				Outside the study area	32,403	2.0%	0	0	0
Burrel Ditch Co[4]	8,944									
John Helen Mutual Water Co[4]	5,794									

[1] This district also has water rights to the Kaweah River, but due to lack of information on water supply to various districts from Lake Kaweah, the water in the lake is divided simply by 80% to districts to south of Lake Kaweah, 20% to Kings County WD catchment.
[2] The majority of the area of this district is outside of our study area, so these water rights were not revised
[3] The location where this water is used is unknown, so it was assumed the water is used within the district closest to the diversion point with the same name
[4] The location where this water is used is unknown or outside of the study area, so it is included outside of the study area in the model.
[5] The details of these purchases are unknown and assumed to not occur often, therefore are not included in the model
*As average annual deliveries based on the Kings Basin water allocation analysis
^As percent of total average annual deliveries

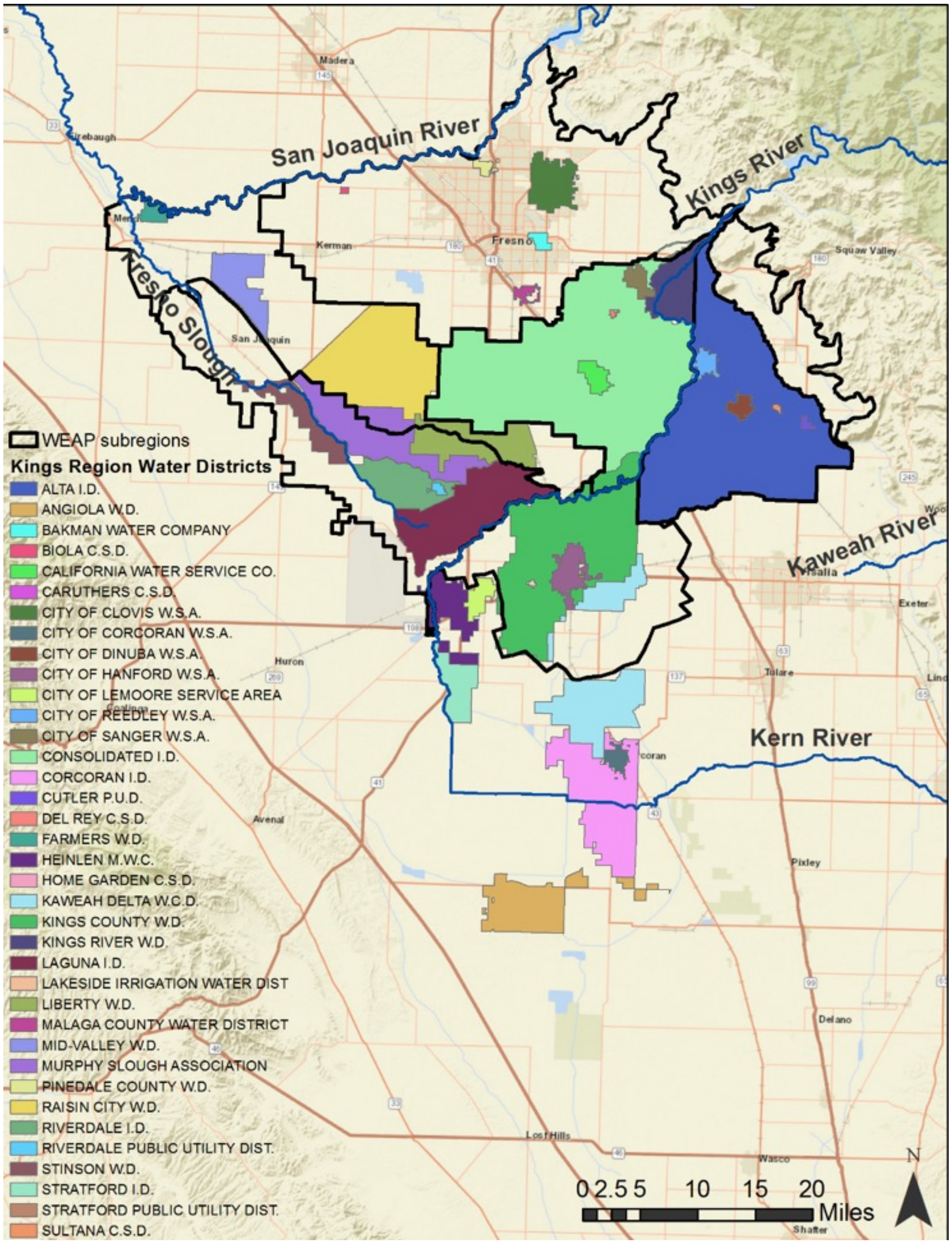


Figure 4: Map of water districts within the study area.

3.1.3 Representation of groundwater

In the CVPA model, there was only one object representing the region's groundwater. As part of the modifications, a groundwater node was created for each subregion containing values for storage and specific yield, which together are used to estimate the groundwater head—with specific yield of 10%, which is consistent with DWR estimates (CADWR 2006). Lateral flows between groundwater objects are represented using runoff/transmission links (Figure 5) calculated using Darcy's Law and the difference in head between adjacent subregions (see Equation (5) in section 3.2.1).

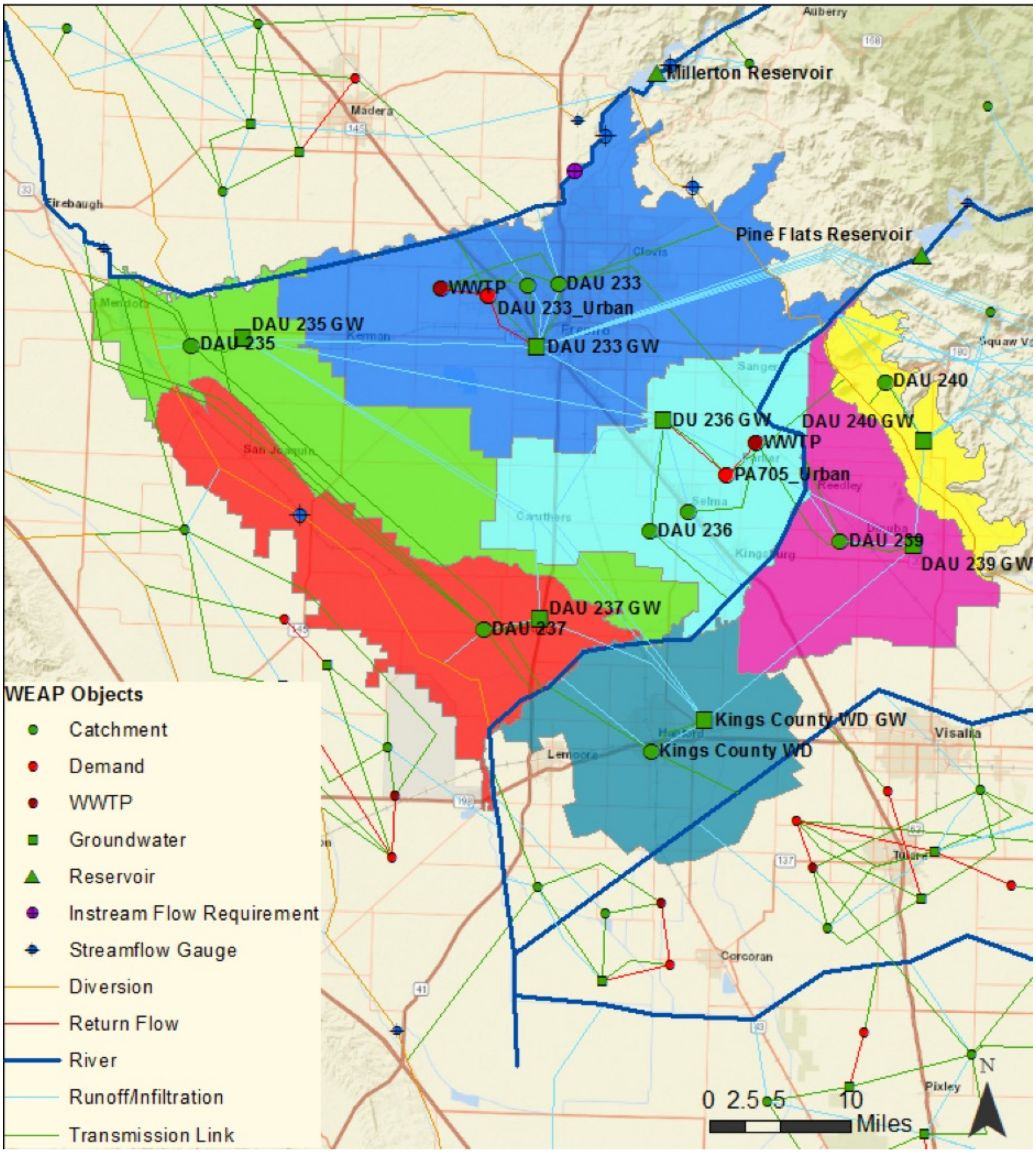


Figure 5: Schematic of the WEAP portion of the CVPAM model within the study area. WEAP objects directly related to the study area are enlarged and labeled.

3.1.4 Wastewater supplies

Based on available information, 10,000 acre-feet per year assumption of treated wastewater from the Fresno wastewater treatment plant was applied to agriculture in the surrounding area in the baseline scenario. The available volume of treated wastewater in each subregion is equivalent to 70% of the supplied water to the residential sector (Sato et al. 2013). Additional wastewater treatment within the study area is included in the model for scenario analysis based on increases in treated wastewater.

3.1.5 Calibration

The original calibration of the CVPA model remained unchanged for the streamflow data upstream of Pine Flats Reservoir. A comparison of observed and simulated streamflow on the single gauge of the Kings River is shown in Figure 6. Reservoir operations for Pine Flats Reservoir also remain the same as in the original CPVA model, and observed and simulated reservoir volume comparison is shown in Figure 7.

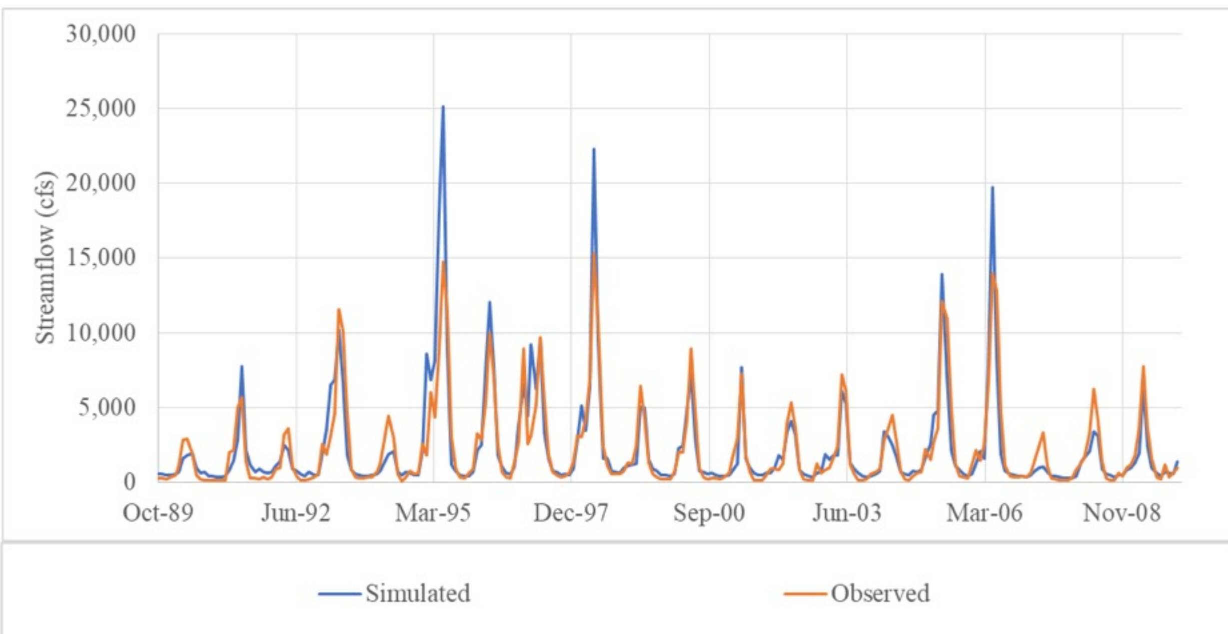


Figure 5. Observed (yellow line) and simulated (blue line) streamflow in the Kings River, upstream of Pine Flats Reservoir.

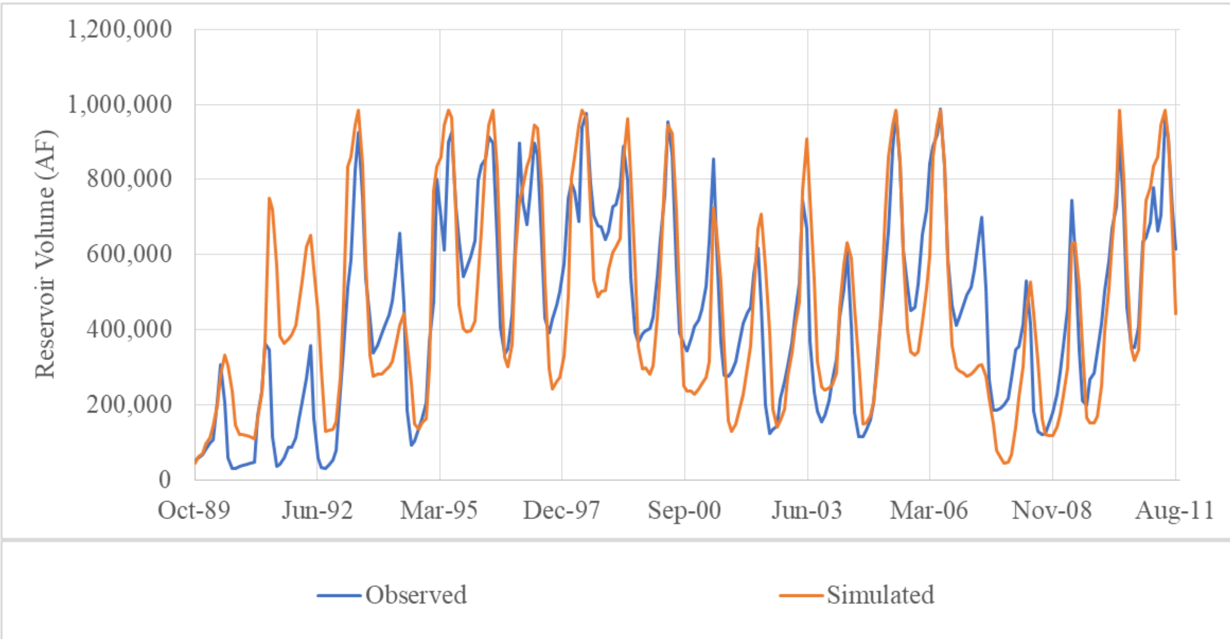


Figure 6. Observed (yellow line) and simulated (blue line) volume of Pine Flats Reservoir.

In addition to surface hydrology, evapotranspiration and applied water were calibrated against DWR's land and water use estimates[8] from 1998 to 2010. All evapotranspiration and applied water values were averaged across all subregions (except the Kings County Water District subregion because the boundary of this subregion does not match the DAU boundaries) and compared with available information from DWR, shown in Figure 8, Figure 9, and Table 2.

[8] https://water.ca.gov/Programs/Water-Use-And-Efficiency/Land-And-Water-Use/Agricultural-Land-And-Water-Use-Estimates

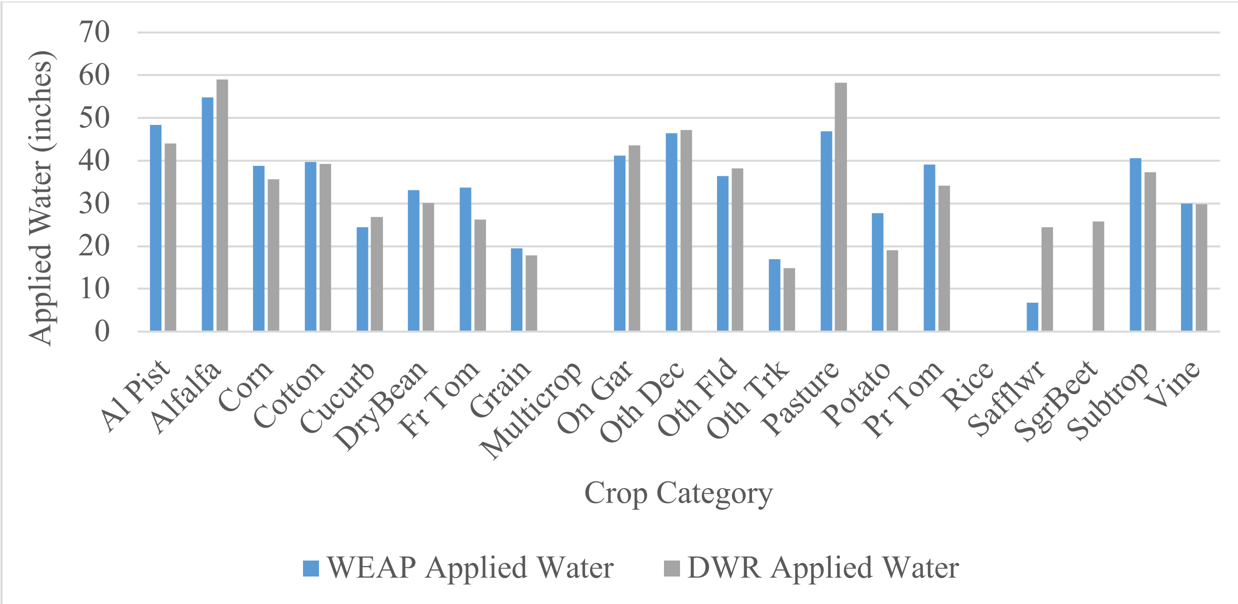


Figure 7. Comparison of simulated average annual applied water in the WEAP portion of the CVPAM (averaged over all subregions except the Kings County Water District subregion, from 1998 to 2010), with that of DWR (averaged over the same area and years)

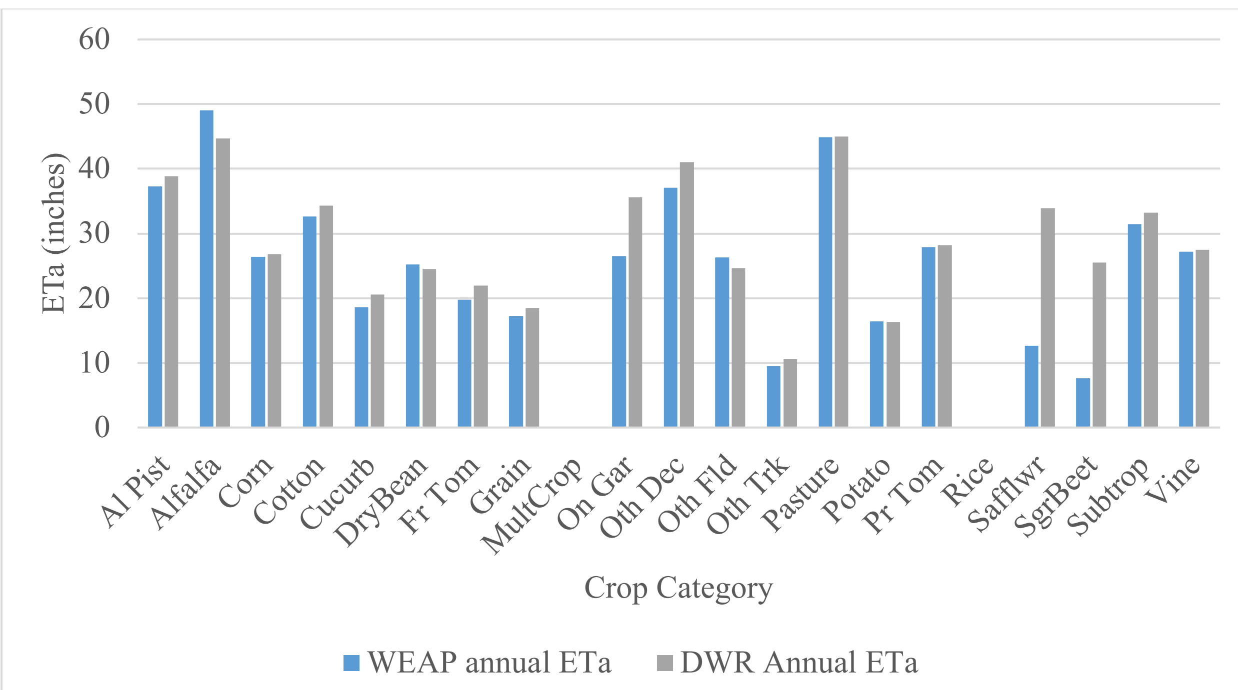


Figure 8. Comparison of simulated average annual actual ET in the WEAP portion of the CVPAM (Eta, averaged over all subregions except the Kings County Water District subregion, from 1998 to 2010), with that of DWR (averaged over the same area and years).

Table 2. Calibration statistics for the CVPAM and DWR for applied water and Eta (evapotranspiration), averaged over all subregions except the Kings County Water District subregion, from 1998 to 2010.

Crop	Average Area	WEAP Average Annual Eta	DWR Average Annual Eta	Percent Difference Eta	WEAP Applied Water	DWR Applied Water	Percent Difference Applied Water
Al Pist	93887	37.3	38.9	3.9	48.3	44.0	-8.9
Alfalfa	229471	49.0	44.7	-9.7	54.8	59.0	7.6
Corn	104657	26.4	26.8	1.3	38.8	35.6	-8.2
Cotton	231641	32.6	34.3	4.8	39.6	39.2	-1.1
Cucurb	2601	18.6	20.5	9.4	24.5	26.8	9.3
DryBean	8722	25.2	24.5	-2.7	33.1	30.1	-9.1
Fr Tom	15795	19.7	21.9	10.0	33.7	26.2	-22.1
Grain	107247	17.2	18.5	7.2	19.5	17.8	-9.0
MultCrop	0						
On Gar	4067	26.5	35.6	25.6	41.2	43.7	5.9
Oth Dec	181877	37.0	41.0	9.7	46.4	47.2	1.7
Oth Fld	212959	26.3	24.6	-7.1	36.4	38.1	4.9
Oth Trk	23014	9.5	10.6	10.3	17.0	14.9	-12.3
Pasture	22612	44.9	45.0	0.2	46.9	58.2	24.0
Potato	150	16.4	16.4	-0.2	27.7	19.0	-31.3
Pr Tom	7096	27.9	28.2	1.0	39.1	34.1	-12.7
Rice	0						
Safflwr	5345	12.6	33.9	62.8	6.8	24.4	260.0
SgrBeet	4453	7.6	25.5	70.1	0.0	25.8	
Subtrop	158741	31.4	33.2	5.4	40.5	37.3	-8.0
Vine	274949	27.1	27.5	1.2	30.0	29.8	-0.7

Note: The calibration target was to get simulated values within 10% difference of DWR values, for the crop categories that cover the majority of the study area.

Groundwater storage and head were also calibrated, by comparing simulated values in CVPAM with C2VSIM[9] simulated storage and observed water well data from DWR's Water Data

[9] C2VSim stands for "California Central Valley Groundwater-Surface Water Simulation Model." It is the software developed and used by the California Department of Water Resources to assess policy interventions on groundwater in the Central Valley of California. https://water.ca.gov/Library/Modeling-and-Analysis/Central-Valley-models-and-tools/C2VSim

Library[10], respectively. All of the available wells within the study area (2,431 wells) were used in the calibration (Figure 10). Calibration was conducted by adjusting flows between aquifers until storage and groundwater head matched within ranges of C2VSIM storage and observed groundwater heads, respectively, in each subregion. Figure 11 shows the comparison of groundwater storage between CVPAM and C2VSIM across all subregions. Figure 12 shows the comparison of simulated and observed groundwater head for DAU 236 subregion. Figures for the remaining subregions are included in Annex B.

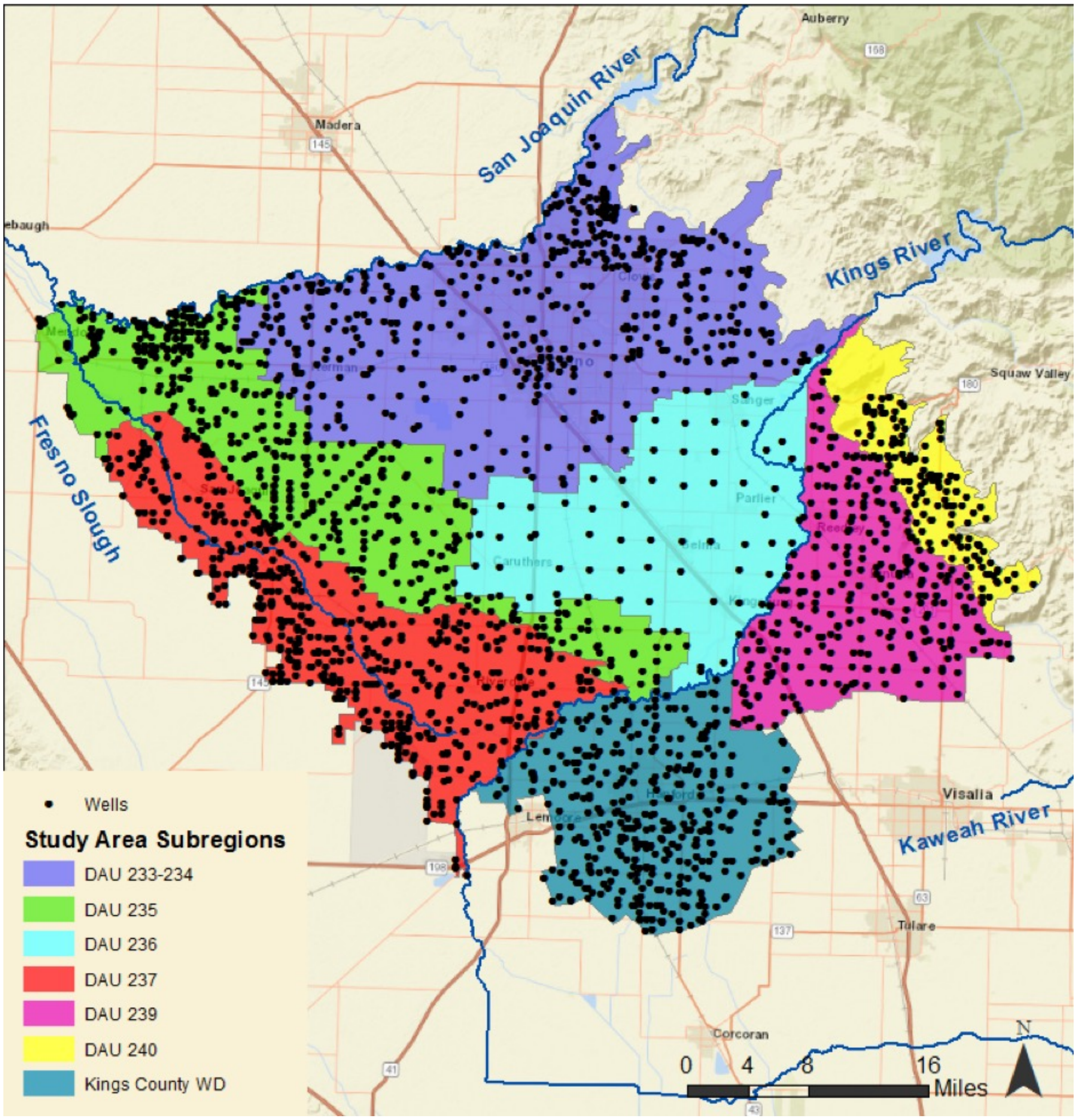


Figure 9. Map showing all wells within the study area, relative to study area subregions.

[10] http://wdl.water.ca.gov/waterdatalibrary/

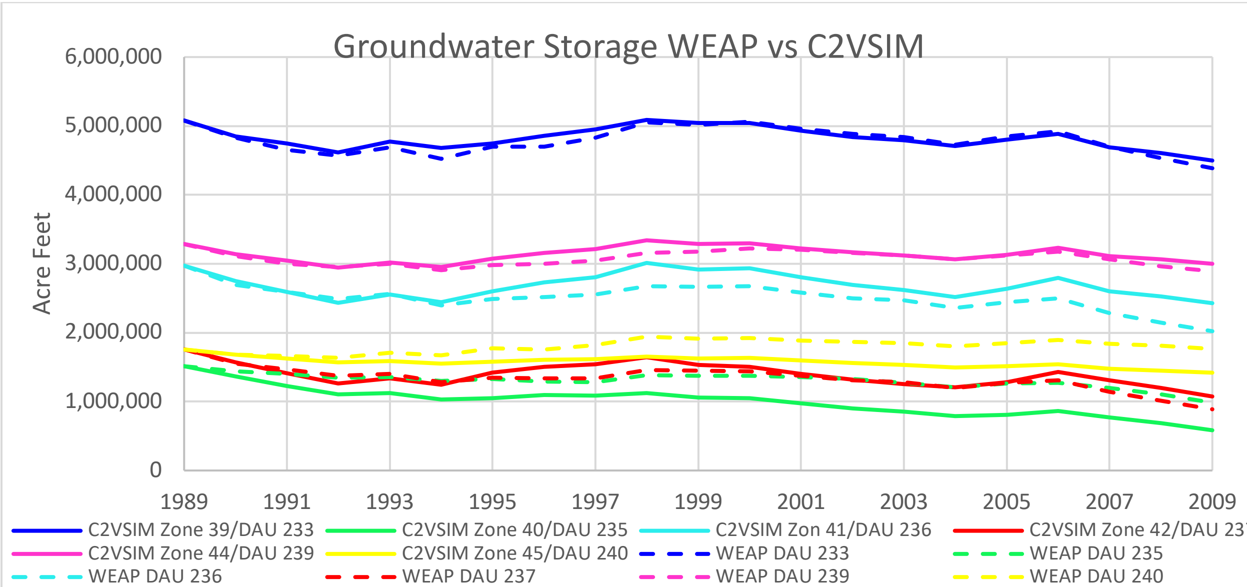
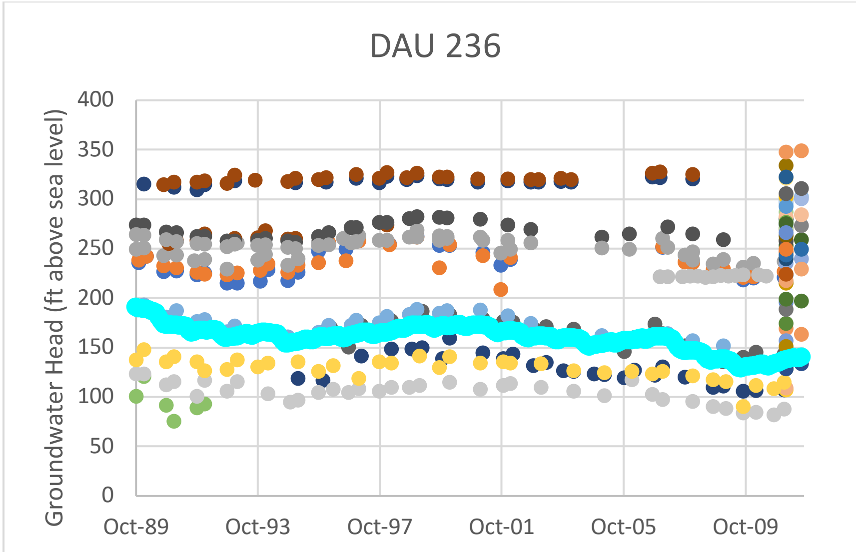


Figure 10. Simulated storage in the WEAP portion of the CVPAM (broken lines) and C2VSIM (solid lines) for each subregion, except Kings County Water District subregion. This subregion is missing because its boundaries do not match boundaries with a corresponding zone in C2VSIM.



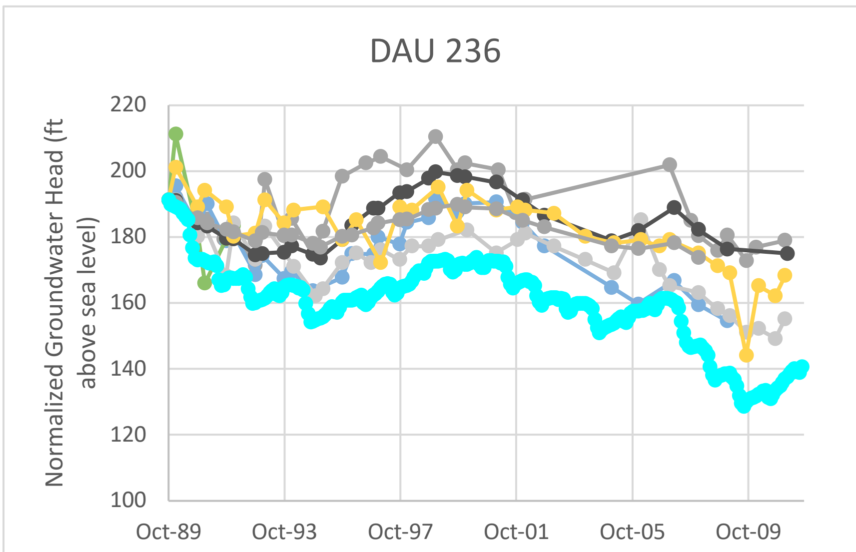


Figure 11. Simulated groundwater head within the DAU 236 subregion (light blue), compared to observed groundwater head from various wells within the subregion, one color per well record (top), and the same observed values, normalized to initial head as set in the WEAP portion of the CVPAM (bottom).

3.2 The economic optimization modeling framework (EOM)

The economic optimization-modeling framework uses an integrative approach to combine dynamic-partial-equilibrium-optimization models of the water and agricultural sectors. The integrated framework endogenizes both land-use decisions and farm management practices, as well as water resource management variables such as water allocations from different sources (surface water, groundwater, and treated wastewater), groundwater dynamics, potential infrastructural development and, most importantly in our context, intentional recharge into groundwater aquifers.[11] Instead of developing the modeling capacity required from scratch, we adopt and modify to our needs two modeling frameworks, previously developed in the context of the state of Israel. The models used are the hydro-economics model MYWAS (multi-year water allocation system) (Reznik et al. 2017) and the positive mathematical programming (PMP) VALUE (vegetative agriculture land-use economics) model (Kan and Rapaport-Rom 2012), and we rely on the integration approach presented in detail in Slater et al. (2020). Our analytical framework differs from the one shown in Slater et al. (2020) by explicitly representing the hydrogeological principles. These principles include: (1) the inclusion of intentional recharge using designated infrastructure (e.g. infiltration basins); (2) deep percolation (that originates from irrigation or treated wastewater discharge), which is included in our groundwater stock equation of motion; and (3) accounting for lateral flows between sub-basins. The following subsection presents the analytical framework in formal notation.

3.2.1 *The model*

Let an agricultural region be composed of several decision-makers u, such that $u \in (1, \dots, U)$, and let each of these decision-makers control an area L_u, which is subdivided to the subdistrict level $d \in (1, \dots, D)$. Each subdistrict d is then characterized by different climate (i.e., precipitation and temperature), soil characteristics (water-holding capacity that influence plant growth and groundwater dynamics), and the availability of water sources of different types φ, which include groundwater (g), surface water (s), and treated wastewater (r). At each time step t of the planning horizon $t \in (1, \dots, T)$, each decision maker u can allocate her cultivable land area under each subdistrict L_{ud} among $j \in (1, \dots, J)$ crops, a decision that we notate by x_{udjt}, and decide on the amount of water applied per unit of land w_{udjt} to each crop in each subdistrict at each time step.

[11] The term intentional recharge is used interchangeably with MAR, and distinguishes all forms of MAR from natural recharge occurring from rainfall, river runoff and other natural processes, in which there is no human intervention.

A regional social planner is then faced with the problem of maximizing the present-value net gains from agricultural production, given a set of constraints, as depicted in problem (1).[12]

$$\max_{x_{udjt}, w_{udjt}, q^{\varphi}_{udt}, R^{M}_{udt}} \sum_t \rho_t \cdot \sum_{u,d,j} \pi\left(x_{udjt}, w_{udjt}, \boldsymbol{q}^{\varphi}_{udt}, R^{M}_{udt}\right)$$

$$s.t.$$

$$(1) \quad x_{udjt}, w_{udjt}, q^{\varphi}_{udt}, R^{M}_{udt} \in \boldsymbol{\Omega} : \boldsymbol{\Omega} \equiv \left\{\mathbf{H}\left(x_{udjt}, w_{udjt}, \boldsymbol{q}^{\varphi}_{udt}, R^{M}_{udt}, \boldsymbol{z}\right)\right\}$$

Where ρ is the discount factor, and $\pi(\cdot)$ represents net benefits from crop production, which we will define in detail shortly. $\boldsymbol{\Omega}$ is the set of constraints $\mathbf{H}$, ensuring that the optimal levels and paths of decisions and states of the system comply with all hydrological, engineering, and feasibility conditions in the region. $\boldsymbol{q}^{\varphi}_{udt}$ is the vector of water quantities allocated to each subdistrict at each time step from the different water sources. R^{M}_{udt} represents intentional recharge quantities at the subdistrict level through infrastructure developed for the sole purpose of recharge (e.g., infiltration basins), and $\boldsymbol{z}$ are the different parameters of the system (e.g., pumping capacities, rainfall, available cultivable land and others, as is described below).

Starting with the objective function of problem (1), we define net gains from agricultural production $\pi(\cdot)$ in equation (2):

$$(2) \quad \pi\left(x_{udjt}, w_{udjt}, \boldsymbol{q}^{\varphi}_{udt}, R^{M}_{udt}\right) = x_{udjt} \cdot \left[p^{y}_{jt} \cdot y\left(w_{udjt}, \boldsymbol{q}^{\varphi}_{udt}\right) - \gamma_j - (\delta_{1j} - \delta_{2j} \cdot x_{udjt})\right] - C\left(\boldsymbol{q}^{\varphi}_{udt}, R^{M}_{udt}\right)$$

In equation (2), revenues from crop sales are defined as the periodic market price of each crop p^{y}_{jt} multiplied by the per-acre yield, which is the function $y\left(w_{udjt}, \boldsymbol{q}^{\varphi}_{udt}\right)$. These are then deducted by the crop-specific variable costs of production (excluding water costs), γ_j, and the economic costs quadratic function $x_{udjt} \cdot (\delta_{1j} - \delta_{2j} \cdot x_{udjt})$, representing optimality considerations of farmers, which is manifested by observed land allocation to crops (Howitt 1995). Finally, we account for the costs of water supply and intentional recharge in each district, as represented by the function $C\left(\boldsymbol{q}^{\varphi}_{udt}, R^{M}_{udt}\right)$ in equation (2).

[12] We ignore benefits accumulated from water consumption in the urban sector. We therefore assume domestic water demand to be perfectly inelastic, and denote the quantity consumed in that sector as Q_{udt}, which we assume increases according to population and income growth trends.

We follow Kan et al. (2002) and Kan and Rapaport-Rom (2012), and define per-acre yield as a linear function of evapotranspiration, which in turn is a non-linear function of applied water quantity, w_{udjt}, and salinity level, $\psi\left(\boldsymbol{q}_{udt}^{\varphi}\right)$, as depicted in equation (3):

$$y\left(w_{udjt},\boldsymbol{q}_{udt}^{\varphi}\right)=\theta_{1udj}+\theta_{2udj}\cdot\frac{\bar{e}_{udj}}{1+\alpha_{1udj}\left[\alpha_{2udj}\cdot\psi\left(\boldsymbol{q}_{udt}^{\varphi}\right)+\alpha_{3udj}\cdot(w_{udjt}+\tilde{w})^{\alpha_{4udj}}\right]^{\alpha_{5udj}}} \tag{3}$$

Salinity level itself is a function of all blended water sources at the subdistrict level. In equation (3), $\bar{e}_{udj}$ is the potential evapotranspiration level, θ_{1udj} and θ_{2udj}, and α_{1udj} through α_{5udj} are crop and subdistrict specific parameters. The costs of water supply, wastewater treatment and intentional recharge $C\left(\boldsymbol{q}_{udt}^{\varphi},R_{udt}^{M}\right)$, will be explicitly formulated and described in detail in the calibration section that will follow.

Groundwater dynamics is included in the set $\boldsymbol{\Omega}$ of constraints $\mathbf{H}$. We define groundwater changes at the temporal and spatial dimensions according to equation (4):

$$G_{udt}-G_{ud(t-1)}=\frac{R_{udt}^{M}+\sum_{j}x_{udjt}\cdot\left(w_{udjt}+\tilde{w}-et(\cdot)\right)+(\kappa\cdot Q_{udt}-q_{udt}^{r})+\bar{l}_{udt}-q_{udt}^{g}}{\nu\cdot L_{ud}} \tag{4}$$

Where G_{udt} is groundwater head in each subdistrict at each time step. Therefore, change in groundwater level between time periods in the model is increasing with intentional recharge from infiltration basins (R_{udt}^{M}), deep percolations resulting from agricultural irrigation ($\sum_{j}x_{udjt}\cdot\left(w_{udjt}+\tilde{w}-et(\cdot)\right)$, where $et(\cdot)$ is evapotranspiration function as defined in equation (3)), and deep percolation of treated wastewater quantities that are not reused ($\kappa\cdot Q_{udt}-q_{udt}^{r}$, where κ is a fixed share of sewage out of the quantity consumed in the domestic sector). Groundwater head decreases with pumping (q_{udt}^{g}). The net of all flows in and out of the basin are divided by the term of subdistrict land area (L_{ud}) multiplied by the basin specific yield (ν). Note that all forms of surface water contributions to groundwater storage in our model fall in the broad definition of MAR. Therefore, we distinguish between intentional recharge through infiltration basins, which is the diversion of water away from production for the sole purpose of recharging groundwater, and between deep percolations resulting from excess irrigation levels of agricultural crops. The third form of recharge is deep percolations of treated wastewater that are not reused in agricultural irrigation, and due to lack of other safe disposal alternatives are left to percolate to the ground in various methods (e.g., evaporation ponds, spread fields, and others). The latter form resembles intentional recharge through infiltration basins since it also diverts water away from production.

Lateral flows are also affecting groundwater head in the model. The net of lateral flows to, and out of the subdistrict are denoted in equation (4) as $\overline{l}_{udt}$, where lateral flows are defined as in equation (5):

$$l_{udd^{-1}t} = f_{dd^{-1}} \cdot b_{dd^{-1}} \cdot \left(G_{ud^{-1}(t-1)} - G_{ud(t-1)} \right) \quad (5)$$

Thus, lateral flows at each period are determined based on groundwater head difference between adjacent sub-basins (subdistricts) in the previous time step, multiplied by the border length between subdistricts ($b_{dd^{-1}}$) and a factor $f_{dd^{-1}}$, that its calibration is a crucial part that is achieved through the integration with the CVPAM model.

Equation (6) specifies the limitation on surface water deliveries to each subdistrict:

$$q^s_{udt} \le S_t - \sum_{u^{-1}} \sum_{d^{-1}} q^s_{u^{-1}d^{-1}t} \quad (6)$$

Such that, quantity delivered to a specific subdistrict cannot exceed the periodic availability of each source S_t deducted by upstream diversions to all other connected subdistricts. Equations (7) and (8) are common input use constraints in the agricultural production process. Equation (7) caps land use by the total land area in each subdistrict, whereas equation (8) limits the use of water in each subdistrict according to water quantities delivered to that subdistrict from all sources:

$$\sum_j x_{udjt} \le L_{ud} \quad (7)$$

$$\sum_j x_{udjt} \cdot w_{udjt} \le q^g_{udt} + q^s_{udt} + q^r_{udt} - R^M_{udt} - Q_{udt} \quad (8)$$

Further specifications of constraints and their parametrization are described in the data collection and calibration section that follows.

3.2.2 Data and calibration of the EOM

The calibration process of the EOM included several steps and was validated in each step using the calibration tests suggested by Howitt et al. (2012). First, we divided the region of interest to the subdistrict level, and based on existing land allocation analysis, decided on crop representation in the model. Based on the assumption that under similar growing conditions (soil, climate, water quality) the agronomic growth process for each crop remains the same, we import the parameters for the evapotranspiration functions defined in equation (3) from previous work conducted in Israel (i.e., $\bar{e}_{udj}$ and α_{1udj} through α_{5udj}). In order to do so, we performed a detailed comparative analysis of soil structure and climate between regions in Israel and in our own Kings Groundwater Basin study area to validate that indeed there are similar growing conditions in both regions. Once we assign these parameters for each crop-district combination in our model, we turn to the calibration of the production function parameters (θ_{1udj} and θ_{2udj}). This stage required collection of crop-level data from the University of California Cooperative Extension "Cost and Return Studies" (UCCE, n.d.), relevant to our region of interest. The next step was to calibrate the quadratic cost function based on the PMP approach (Howitt 1995), which required using land allocation data that was collected through the CADWR Land Use Viewer (n.d.). We used official reports from state agencies and stakeholders in our region of interest to determine the levels of model parameters that characterize the hydrological, engineering, regulatory, and other conditions that comprise the optimization problem. In the next three subsections we describe each of the data collection and model calibration steps.

3.2.2.1 Delineation to subdistricts, crop representation, and importing values for evapotranspiration function

As described above, yield of all crops included in the model is defined as a nonlinear function of water quantity and quality (equation (3)). According to agronomic principles, yield is considered to be linear with respect to evapotranspiration, which itself is a nonlinear function of water quantity and quality. This nonlinear relationship is complex and the calibration process of all parameters for all crops covered in the model would require significant resources and fine resolution data (Kan and Rapaport-Rom 2012). Instead, we imported values calibrated by Kan and Rapaport-Rom (2012) for similar crops in Israel. To do so, we compared climatic conditions and soil texture classifications—the two determining factors in the calibration process of parameters in Kan and Rapaport-Rom (2012) evapotranspiration function—between our region of interest—Kings Groundwater Basin, and respective regions in Israel, from which that data was taken.

We first divided the Kings Groundwater Basin area to 30 subdistricts (Figure 13), based on differences in hydrological and climatic conditions, as well as crop patterns and irrigation district affiliation. Subdistricts are then grouped according to the delineation to DAUs (presented in Figure 3) to match the spatial resolution in the CVPAM model. We then collected data on soil taxonomy for each subdistrict in the Kings Groundwater Basin from the Natural Resources Conservation Service of the United States Department of Agriculture (NRCS-USDA). Specifically, for soil comparison we used the Great Group classification (Hirmas 2019). This classification of soils in each subdistrict is presented in Figure 14. As we explained, the division to the subdistrict level also accounted for hydrogeological conditions. Hence, most of the subdistricts are quite homogeneous in terms of the variation in soil types within the district—for 26 out of 30 subdistricts in the region, 90% of land area covered, on average, is classified into only four soil classification groups (different classifications for each subdistrict). In order to find a matching region in Israel in terms of soil characteristics, we used previous work conducted by the International Arid Land Consortium (IALC) which, based on existing soils map of Israel (Dan et al. 1975), translated soil classifications in Israel to the Great Group classifications commonly used in the USDA (Figure 15). With respect to Kan and Rapaport-Rom (2012) delineation to regions, we identified four regions in Israel with similar soil characteristics to different subdistricts in the Kings Groundwater Basin. Comparing long-term monthly averages of precipitation and evapotranspiration levels between these four regions and the Kings Groundwater Basin, we could not find statistically significant differences in either (Figure 16).

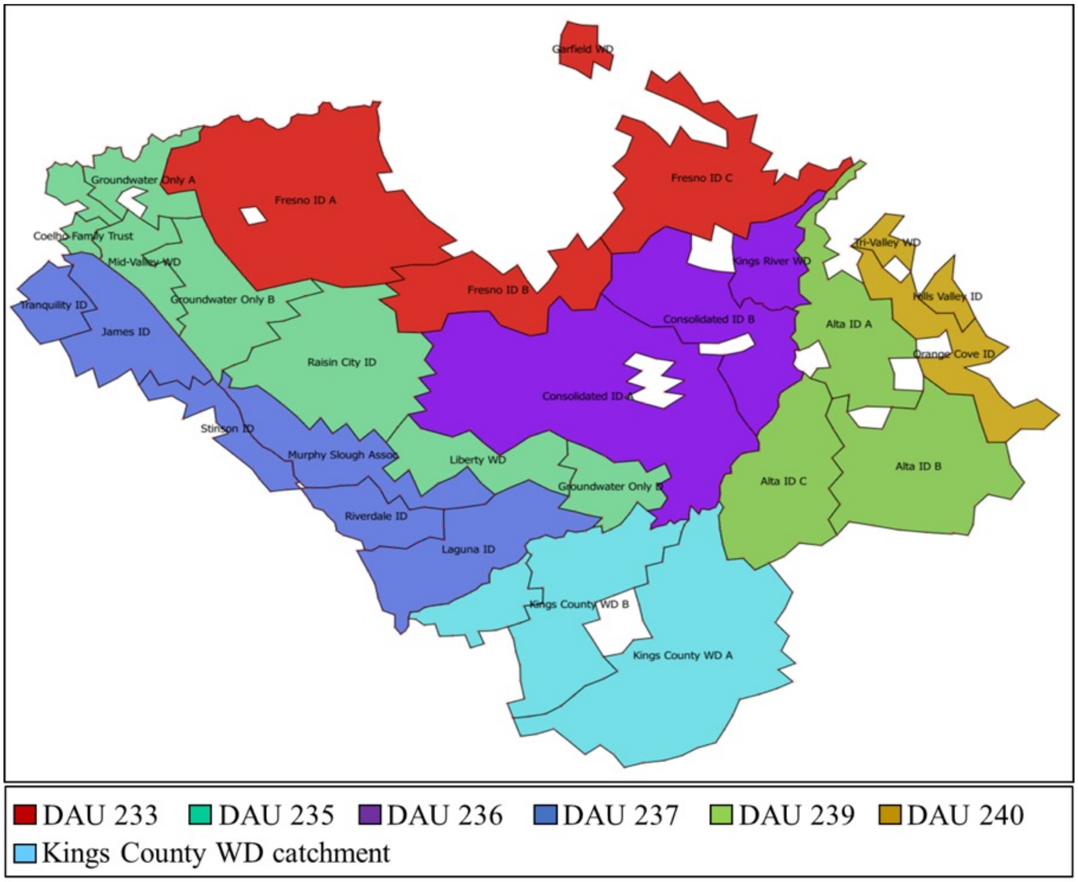


Figure 13. Subdistrict division in the model for the Kings Groundwater Basin.

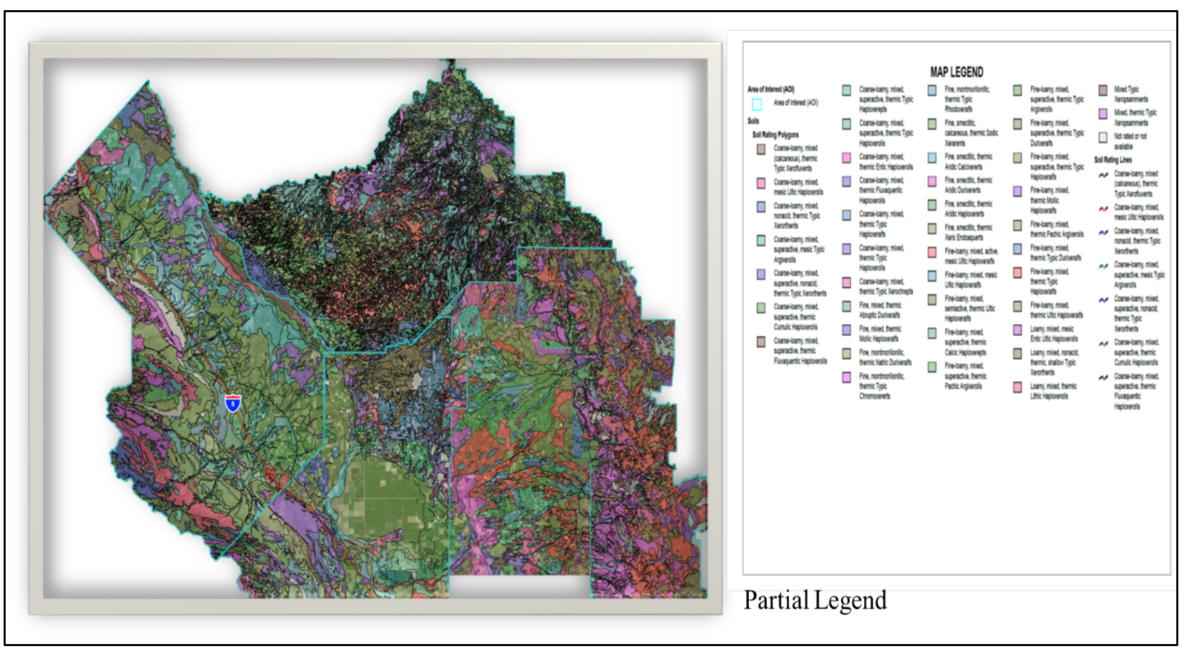
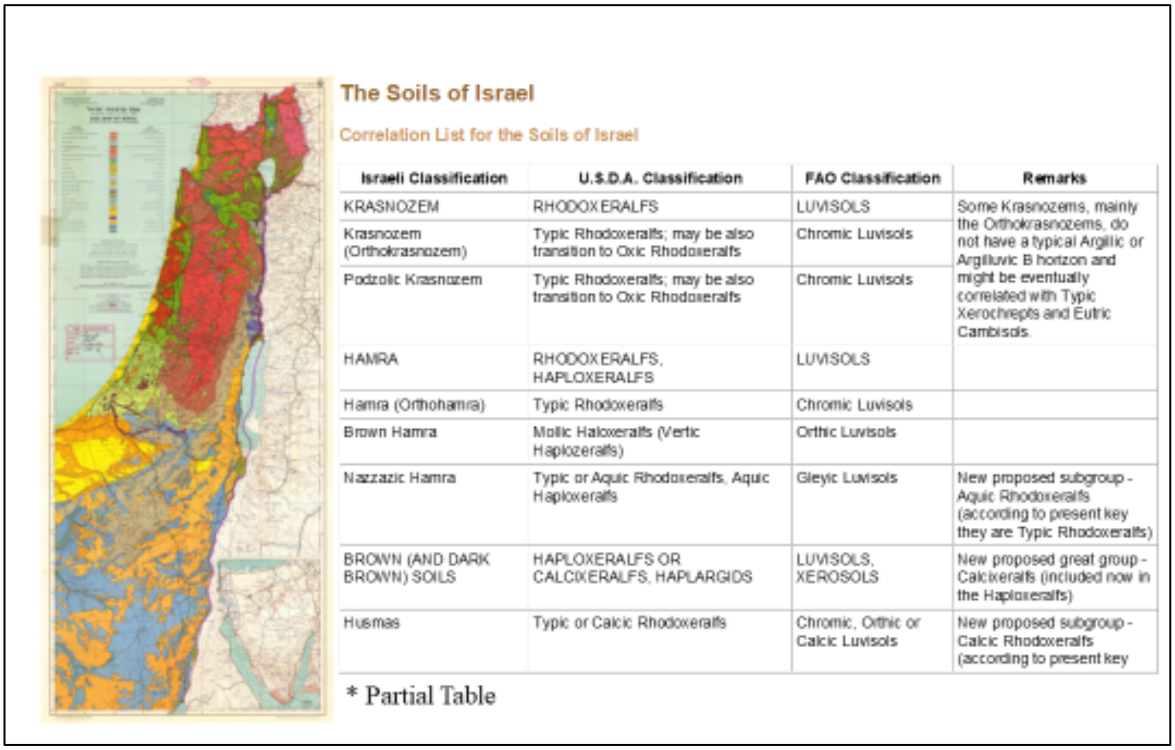


Figure 14. Soil classification map of Kings Groundwater Basin (Source: NRCS-USDA, n.d.).



The Soils of Israel

Correlation List for the Soils of Israel

Israeli Classification	U.S.D.A. Classification	FAO Classification	Remarks
KRASNOZEM	RHODOXERALFS	LUVISOLS	Some Krasnozems, mainly the Orthokrasnozems, do not have a typical Argillic or Argilluvic B horizon and might be eventually correlated with Typic Xerochrepts and Eutric Cambisols.
Krasnozem (Orthokrasnozem)	Typic Rhodoxeralfs; may be also transition to Oxic Rhodoxeralfs	Chromic Luvisols	
Podzolic Krasnozem	Typic Rhodoxeralfs; may be also transition to Oxic Rhodoxeralfs	Chromic Luvisols	
HAMRA	RHODOXERALFS, HAPLOXERALFS	LUVISOLS	
Hamra (Orthohamra)	Typic Rhodoxeralfs	Chromic Luvisols	
Brown Hamra	Mollic Haloxeralfs (Vertic Haplozeralfs)	Orthic Luvisols	
Nazzazic Hamra	Typic or Aquic Rhodoxeralfs, Aquic Haploxeralfs	Gleyic Luvisols	New proposed subgroup - Aquic Rhodoxeralfs (according to present key they are Typic Rhodoxeralfs)
BROWN (AND DARK BROWN) SOILS	HAPLOXERALFS OR CALCIXERALFS, HAPLARGIDS	LUVISOLS, XEROSOLS	New proposed great group - Calcixeralfs (included now in the Haploxeralfs)
Husmas	Typic or Calcic Rhodoxeralfs	Chromic, Orthic or Calcic Luvisols	New proposed subgroup - Calcic Rhodoxeralfs (according to present key

* Partial Table

Figure 15. Map of soils of Israel and correlation table to soil classification of USDA and FAO (Sources: Map (Dan et al. 1975); Table of Correlation (IALC n.d.)).

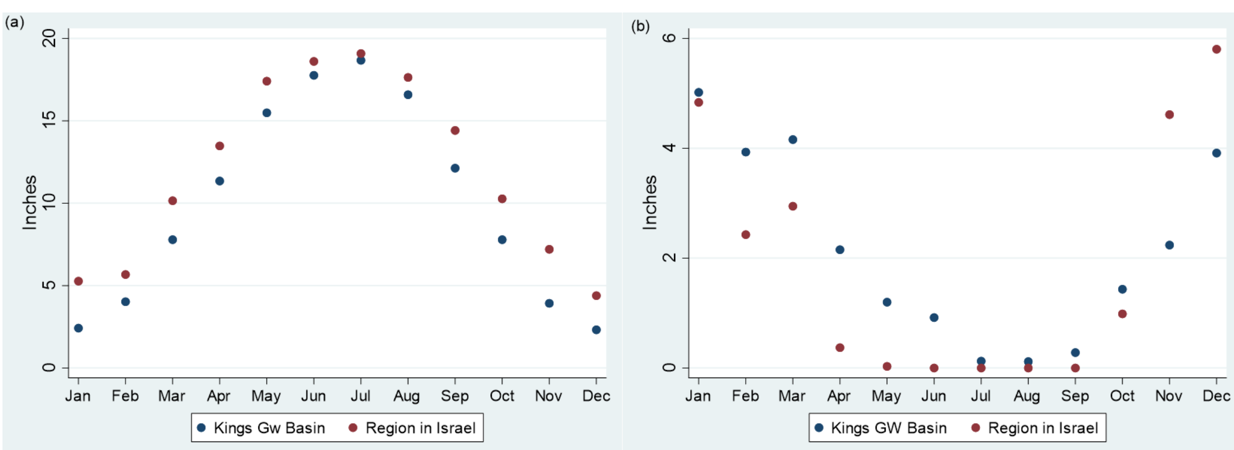


Figure 16. Monthly averages of potential evapotranspiration (Panel a) and precipitation levels (Panel b) in Kings Groundwater Basin and a region in Israel.

Based on the described comparison above, Table 3 presents the assignment of functions imported from four regions in Israel to each of the subdistricts in the Kings Groundwater Basin. The values for parameters of each of the evapotranspiration functions imported (Function A through Function D) is detailed in Annex Tables A.1 through A.3 by crops. We model 20 different land categories in the study area, including land fallowing (detailed description of categories, crops included in each one, and the equivalent land category according to DWR and the CVPAM model definitions is presented in Annex Table A.4). Data on land allocation for the different crops was collected from the CADWR Land Use Viewer (n.d.) for the year 2014, and is presented in Figure 17, according to DAUs delineation and by DWR land categories.

Table 3. Subdistrict division according to imported evapotranspiration functions from regions in Israel.

Function A	Function B	Function C	Function D
Alta ID B	Alta ID A	Fresno ID C	Kings County WD A
Alta ID C	Consolidated ID B	Garfield WD	
Consolidated ID A	Kings River WD	Kings County WD B	
James ID	Fresno ID A	Laguna ID	
Tranquility ID	Fresno ID B	Hills Valley ID	
	Groundwater Only E	Tri-Valley WD	
	Murphy Slough Assoc	Mid-Valley WD	
	Riverdale ID		
	Stinson ID		
	Orange Cove ID		
	Coelho Family Trust		
	Groundwater Only A		
	Groundwater Only B		
	Groundwater Only C		
	Groundwater Only D		
	Liberty WD		
	Raisin City ID		

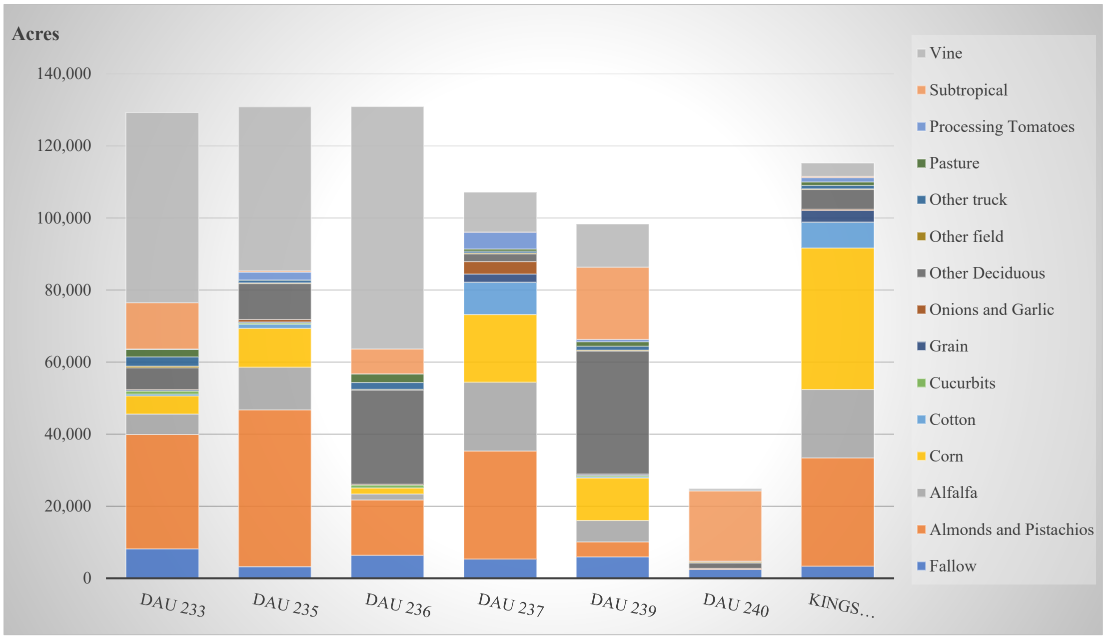


Figure 17. Land allocation in the Kings Groundwater Basin by DAUs (Source: CADWR Land Use Viewer, Statewide crop mapping, 2014).

3.2.2.2 Calibration of the linear crop production and quadratic PMP cost functions

In order to calibrate the production function parameters, we follow Kan and Rapaport-Rom (2012) procedure. First, to extract θ_{2udj} from equation (3), we equate, for each crop, the value of marginal product (VMP) with the price of water. Once calibrated, we use θ_{2udj} and observed yield, and applied water quantity and quality per acre to find θ_{1udj}. This procedure requires knowledge of output prices, yield per-acre, and quantity, quality, and price of applied water per-unit of land. For yield and output prices, we relied on data for the year 2014 from California County Agricultural Commissioner's reports published by the U.S. Department of Agriculture for Fresno, Kings, and Tulare counties (see Table 4). We also used regional Cost and Return Studies (UCCE, n.d.) for cross-reference purposes. Applied water quantities are adopted from the CVPAM model (Table 2, column 5). Water quality, measured by salinity (dS/m) is calculated as a weighted average, based on subdistrict water use by source (i.e., groundwater extractions and surface water deliveries). For that calculation, we used data on surface water and groundwater use in each subdistrict taken from the baseline calibration of the CVPAM model, as well as from the Kings River Watershed Coalition Authority (KRWCA) Groundwater Assessment Report (2014). Salinity levels for each water source were collected from KRCWA (2014) and the State Water Resources Control Board (SWRCB) Groundwater Ambient Monitoring and Assessment Plan (n.d.).

To determine water price, we used the cost and return studies from UCCE (n.d.). Data related to cost of an acre-foot of water in the cost studies indicates some variation. We assume that it is unlikely that neighboring farmers from the same subdistrict are paying significantly different tariffs, which also vary by their crop choice, for surface water supplied by their water district. Hence, we calculate an average water price at the subdistrict level, also acknowledging the difference between surface water price and groundwater supply costs. The calculated surface water price is the average of all water prices reported in the cost studies (by crop), weighted by observed land allocation to each crop at the subdistrict level. The cost associated with groundwater use in each subdistrict is the sum of pumping and conveyance costs. We use fine resolution well-level data, as presented in Figure 10 to determine lift, and use estimates on energy costs from the literature (MacEwan et al. 2017) to compute pumping costs per acre-foot at approximately 27.5 cents. Conveyance costs are calculated based on average distance of conveyance from each well within the subdistrict. To construct a single water price to each subdistrict we use again reported water use by type as weights to calculate an average price for the subdistrict.

Calibration of δ_{1j} and δ_{2j} parameters of the quadratic cost function in equation (2) is performed using the two-stage PMP calibration procedure developed by Howitt (1995). For that purpose we also collected per unit of land variable costs of production (excluding water costs) from the UCCE (n.d.) cost and return studies, which is assigned to the parameter γ_j from equation (2). We report in Table 4 and Table 5 the data used for the calibration of the different production and cost functions' parameters, distinguishing between data at the crop level (fixed for all subdistricts) and data at the subdistrict level (fixed for all crops), respectively.

Table 4. Crop yields, prices, and variable costs of production for the baseline year (2014)

Crop	yield (tons/acre-yr)	crop price ($/ton)	Other variable costs ($/acre)
Almond	1	7331	2095
Alfalfa	8	237	607
Corn	25	64	787
Cotton	2	1364	969

Melon	19	330	1308
Wheat	3	256	581
Onion	29	321	7634
Peach & Nectarine	10	1327	5035
Plum	9	1251	9877
Cherries	4	5063	13866
Pomegranate	5	1576	5552
Apples	17	1150	14764
Sorghum	16	50	379
Broccoli	7	1000	5414
Pasture	5	192	239
Tomatoes	53	83	2601
Oranges	15	516	5119
Olives	4	1074	3328
Grapes	13	1496	16725

Table 5. Subdistrict average water price and salinity for the baseline year (2014)

Subdistrict	Av. Price ($/AF)	Av. Salinity of applied water (dS/m)
Alta ID A	46.87	0.26
Alta ID B	46.36	0.38
Alta ID C	47.62	0.28
Consolidated ID A	95.74	0.19
Consolidated ID B	74.05	0.35
Kings River WD	81.20	0.13
Fresno ID A	104.97	0.25
Fresno ID B	94.85	0.20
Fresno ID C	80.93	0.30
Garfield WD	96.54	0.11
Groundwater Only E	100.77	1.49

Kings County WD A	86.80	0.42
Kings County WD B	110.26	0.51
James ID	70.79	0.30
Laguna ID	66.64	0.62
Murphy Slough Assoc	92.18	0.33
Riverdale ID	78.84	1.23
Stinson ID	78.54	0.93
Tranquility ID	67.96	0.31
Hills Valley ID	21.25	0.68
Orange Cove ID	20.73	0.61
Tri-Valley WD	15.47	0.66
Coelho Family Trust	20.18	0.67
Groundwater Only A	27.55	0.49
Groundwater Only B	54.43	0.73
Groundwater Only C	26.01	0.67
Groundwater Only D	28.39	0.81
Liberty WD	44.97	0.81
Mid-Valley WD	34.03	0.73
Raisin City ID	60.35	1.38

3.2.2.3 Data and specification of regional conditions and constraints

We move now to complete the specification of all relevant model parameters and constraints. First, with respect to the costs of supply, we distinguish between costs of groundwater pumping (which we already described), surface water deliveries, wastewater treatment and intentional recharge through infiltration basins. We attribute the cost of conveyance to all water sources available for each region. Groundwater is obviously levied additionally with pumping costs, as we already described. Cost of wastewater treatment is assumed monotonically, increasing with quantity treated at a decreasing rate. We use the parameters estimated by Fraas and Munely (1984). Intentional recharge through infiltration basins does not carry additional costs other than conveyance.

Considering the magnitude of variation in historical river flows in the region, and acknowledging that diversions are limited such that on extreme wet condition not all flow is being diverted for irrigation, we cap extraction from each of the surface water supply sources by their maximum historical record. These maximal quantities are 2,314, 233, and 92 (TAF) for the Kings River, Friant-Kern canal, and the San Joaquin River, respectively (WRIME 2006).

Noticing the fact that significant acreage in the region is covered with perennial crops (Figure 3), we include further structure on land allocation decisions. We do so by forcing lower yield in early years of perennials, if expansion of land devoted to these crops occurs within the planning horizon of the model. This yield constraint is set to 50% of the yield of a mature plantation (orchard). Number of years until maturity vary by crop and is calibrated based on data from the UCCE cost and return studies.

The share of sewage generated in urban centers out of the quantity consumed by city inhabitants is calibrated to 70%. A value of 0.113 is used for specific yield (CADWR 2006), and is assumed fixed for the entire basin. Motivated by the objectives presented in SGMA, we set the planning horizon of the model to 20 years—starting at the baseline year of 2014.

3.3 The iterative process between WEAP and EOM

Understanding the irrigation needs and what that means for the water rights allocation is important to inform decisions that can support surface and groundwater supply sustainability. Hanak and Lund (2015) indicate that groundwater banking can help overcome problems during drought, although it "needs more comprehensive basin management mechanisms to limit overdraft and increase conjunctive use operations." Linking the CVPAM and EOM model can support the evaluation of conjunctive use and cooperative actions.

Figure 18 shows a schematic of the iterative process between the two models that builds from work described in Forni et al. (2016). The main variables in this process are water availability from the different sources (surface water, groundwater, and treated wastewater), and cropland allocation responses from the available water (and related costs) from these sources.

The iteration process starts with CVPAM, run at a monthly time step from 1990 to 2011 with fixed land allocation used (CADWR 2016). Available water supply for each year is based on climate-driven availability, the system constraints, and the water requirements from all demands in the Central Valley.

In the first iteration, CVPAM model variables for surface water deliveries, groundwater pumping, lateral groundwater flows volume, groundwater depth, and treated water deliveries are manually transferred to the EOM model. Given groundwater head and lateral flow data from CVPAM, the calibration factor ($f_{dd^{-1}}$) in EOM was adjusted to include the lateral flows formula, as defined in equation (5). The optimization model then incorporates water deliveries from CVPAM, aggregated to annual values, and runs to estimate the optimal cropland allocation for each decision unit by year. These yearly values of cropland are then sent to and included in CVPAM, replacing the fixed values from the previous run. CVPAM runs again to go through the next iteration.

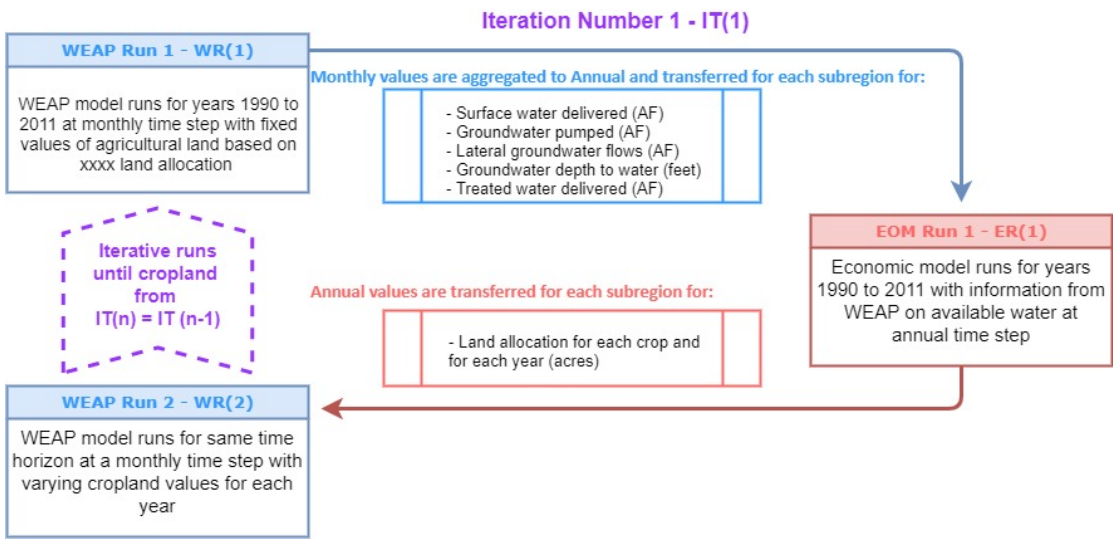


Figure 18. Schematic for iterative process between WEAP and the EOM.

Arriving at a convergence between the CVPAM and EOM truncated the iteration process by reaching an “epsilon” difference between the values calculated by EOM and CVPAM in each iteration, which was introduced by the programmer. It took the iterative process six iterations to reach such convergence. Table 6 below shows the share of regional land that meets the conditions of percentage change between rounds of iteration. The list of (epsilon) conditions is given in the first column, where percent change is measured at the crop and DAU level. The table indicates that for the majority of DAUs, changes in land allocation for each crop, on an annual average, in the entire subregion area were less than 0.5%, between the second and third rounds of iterations.

Table 6. Convergence criteria according to land allocation.

Condition on Percentage Change of Land Allocated to Each Crop Between Iterations in Each DAU	Share (percent) of Land Allocated in DAU that Meet Condition (Annual Average)	
	Between Round 1 and Round 2 of Iterations	Between Round 1 and Round 2 of Iterations
DAU 233		
Under 0.5%	96	99
Under 1%	1	0
Under 5%	2	0
Under 10%	1	0
Over 10%	0	0
DAU 235		
Under 0.5%	99	100
Under 1%	0	0
Under 5%	0	0
Under 10%	0	0
Over 10%	0	0
DAU 236		
Under 0.5%	98	100
Under 1%	0	0
Under 5%	1	0
Under 10%	1	0
Over 10%	0	0
DAU 237		
Under 0.5%	84	97
Under 1%	5	1
Under 5%	9	1
Under 10%	1	0
Over 10%	1	0
DAU 239		
Under 0.5%	93	100
Under 1%	1	0
Under 5%	5	0
Under 10%	1	0
Over 10%	0	0
DAU 240		
Under 0.5%	98	100
Under 1%	0	0
Under 5%	1	0
Under 10%	0	0
Over 10%	1	0
Kings County WD		
Under 0.5%	58	91

Under 1%	18	5
Under 5%	20	3
Under 10%	3	1
Over 10%	1	0

The importance and benefit of this iterative process, and the lateral flow formula calibration exercise included in it are demonstrated using Figure 19. The trends presented in Figure 19 are for regional average groundwater head distinguished by the mode of operation of the EOM. In one mode (termed *Ignorant*), the EOM performs optimization, ignoring lateral flows completely (corresponding to the EOM prior to integration with CVPAM), whereas in the other mode (termed *Educated*) the model optimizes when lateral flows are endogenized (corresponding to the calibrated EOM after convergence). With respect to results of the *Ignorant* EOM, we compute the groundwater head when either ignoring or accounting for lateral flows in the calculation. Values in the figure are normalized to one according to regional average groundwater head in the baseline year.

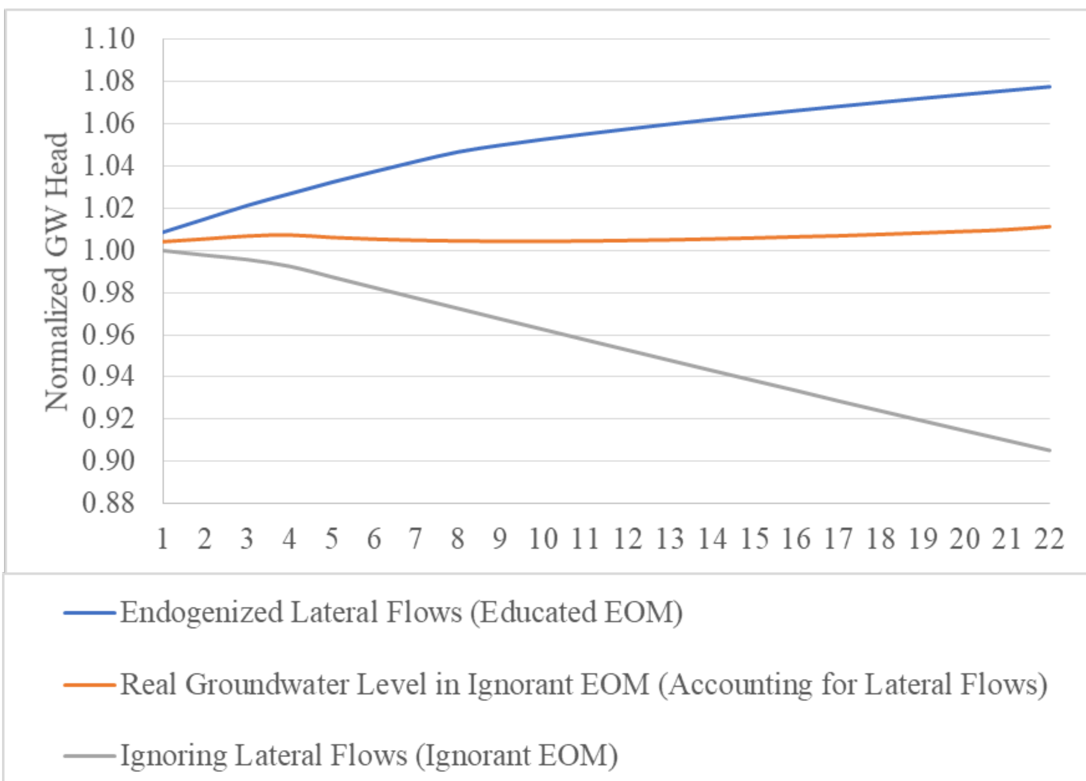


Figure 19. Comparison of groundwater head between an *Educated* EOM versus an *Ignorant* EOM.

The differences between trajectories are prominent. In the case of the *Educated* EOM, it is recommended according to the optimal results that the groundwater head in the region should rise by 8% on average. Whereas, according to the results of the *Ignorant* EOM, actual groundwater level (accounting for the impact of lateral flows) rises by less than 1%. Finally, if lateral flows impact groundwater head is ignored completely (which is how the model objective function is formulated in the *Ignorant* case), groundwater head plunges by 10% on average in the region over the course of the entire planning horizon.

Measuring the benefits associated with the integration with CVPAM and endogenizing lateral flows, we calculate the difference in objective function values between the *Educated* and *Ignorant* EOM results. This calculation yields a positive annual benefit of approximately $120 million USD in favor of the *Educated* EOM.[13] This figure is equivalent to about 2.5% of the annual agricultural revenue for the Fresno County.[14]

4. Set of policy runs

We introduce three alternative scenarios in terms of water management practices in the region. The first, which sets the benchmark for the other institutional arrangements, is the social planner solution (referred as *Social*). This solution corresponds to the optimization problem defined under equation (3), where all decision and state variables of the system are determined to maximize the present value of net gains of the entire region, ignoring income distributional implications. The second scenario is called *Sustainable*, and is constructed in the spirit of SGMA. In this scenario, we impose minimal thresholds for groundwater head at the end of the planning horizon, at the subdistrict level. For these end conditions, we adopt the criteria set in the groundwater sustainability plans (GSP) of the two largest (in terms of land area) groundwater sustainability agencies (GSA) in the region—Central Kings GSA (CKGSA-GSP 2019), and North Kings GSA (NKGSA-GSP 2019). That is, we require that groundwater head at the end of the planning horizon will be greater or equal to its baseline initial level at the onset of the planning horizon. This scenario

[13] Annual economic welfare values are defined as the annuities of the objective function distributed over the entire planning horizon at the assumed discount rate.

[14] Agricultural land in Fresno County and our region of interest—the Kings Groundwater Basin, overlap almost completely.

also draws on previous work conducted in California. Specifically, it is similar to the "no overdraft" scenario in Harou and Lund (2008), who examined potential strategies to end groundwater overdraft. The third scenario, referred to as *Credit*, uses the principals of "capacity sharing" laid out by Dudley and Musgrave (1988). According to this scenario, each DAU holds a credit account that limits the annual amount that can be extracted from the groundwater storage. An initial endowment of annual credit is assigned for each DAU, which increases with intentional recharge (through infiltration basins) to the basin and decreases with pumping, throughout the planning horizon. Table 6, reports the initial credit endowment assumed in the analysis. This endowment is based on annual regional MAR capacity, which is divided to DAUs as an average between their own observed MAR capacity level, and a division of regional recharge capacity according to DAU size, which we measure by land area.

Table 6. Initial credit endowment for annual groundwater pumping

DAU	Initial Credit Endowment (TAF/year)
DAU 233	134
DAU 235	115
DAU 236	360
DAU 237	104
DAU 239	109
DAU 240	20
Kings County WD	343

For each of the policy scenarios described, we simulate three time-series of exogenous conditions in terms of regional rainfall and surface water availability. Under the first simulation, termed *Average*, we assume average conditions in terms of rainfall and river flows throughout the entire planning horizon. The second, termed *Hist1*, simulates regional climate conditions prevailing in the period 1975-1996. The third simulation, termed *Hist2*, copies the climatic conditions in the region for the period 1983-2004. Figure 20 depicts these conditions for each of the three simulations specified. The two historical periods were chosen to represent long-term rainfall and surface water flow patterns in the region. The main difference between the two simulated water availability scenarios is in the timing of high- and low-availability events.

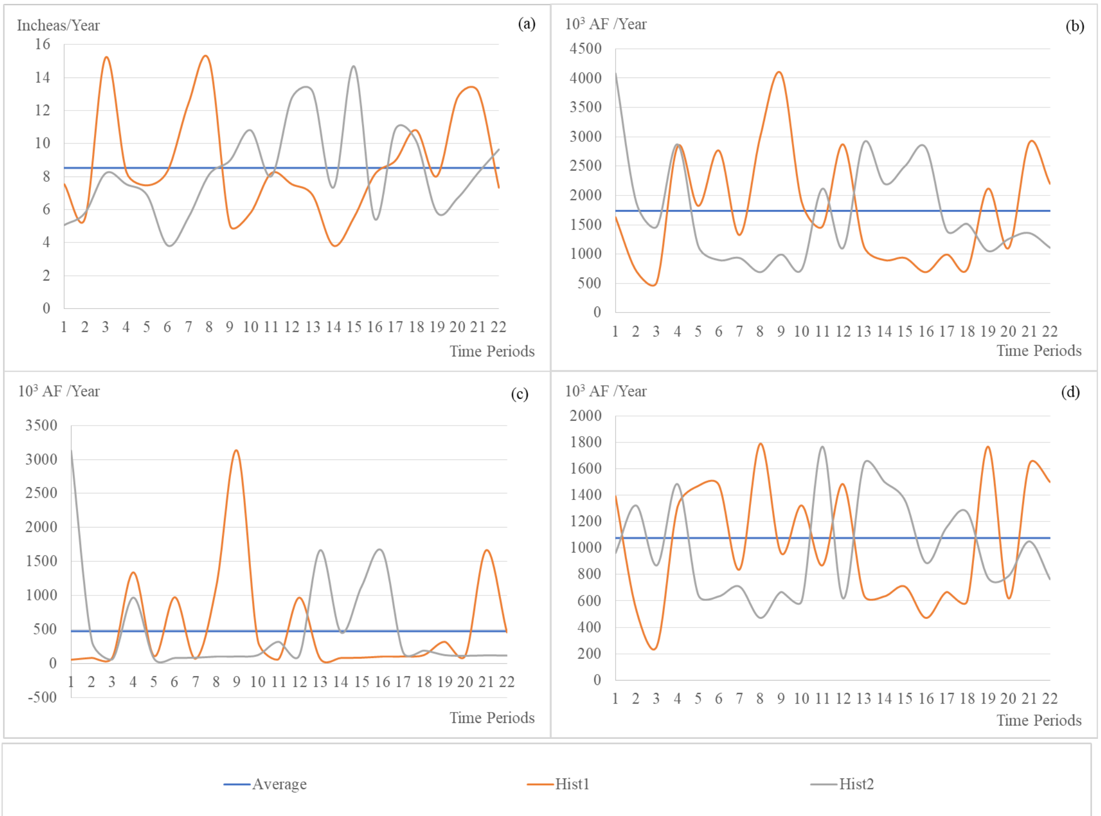


Figure 20. Simulated annual surface water availability and rainfall in the region. (a) regional rainfall; (b) Kings River flow; (c) San Joaquin River flow; (d) Friant-Kern Canal flow.

5. Results

After reaching convergence between the EOM and CVPAM simulations, we use the hydrologically educated EOM to run all policy scenarios, under the different simulated rainfall and river-flow trajectories presented in Figure 20. We first present detailed outcomes from the benchmark *Social* scenario.

5.1 Socially optimal plan

In Table 7, we present for the *Social* scenario under *Average* conditions the annual average optimal land allocation to crops as percentage of observed land allocation levels, according to DAU delineation and aggregated to six general crop categories. Nut crops and grapes (vine) are separated from all other fruit crops, as these are the two largest crop categories in the region.

It can be noticed that in most regions an increase in field crops and vegetables is suggested on the expense of fallowed land according to the model results, and with respect to baseline conditions. Land devoted to permanent crops is similar to observed levels. The exception is DAU 235, in which land fallowing and field crops share increase, and land allocated to fruit crops and grapes shrinks, with respect to observed levels. Interestingly, these land allocation results remain robust in most policy scenarios and climate simulations performed in our analysis.

Table 7. Annual average land allocation to each crop category as percentage of observed levels by DAU

	Fallow	Almonds and Pistachios	Field Crops	Fruit	Vegetables	Vine
DAU 233	83	99	109	100	109	100
DAU 235	166	97	111	91	99	95
DAU 236	76	99	128	99	110	100
DAU 237	70	99	104	98	101	99
DAU 239	73	100	108	100	105	100
DAU 240	58	99	630	96	113	97
Kings County WD	88	99	101	99	105	100

The time-paths of water application levels, averaged for each DAU are presented in Figure 21. With respect to calibrated values as presented in Table 2, according to the model results deficit irrigation is found optimal across most of the region and throughout the majority of the planning horizon. However, there are noticeable differences in time trends of irrigation practices between DAUs. As presented in Figure 21, in DAU 233, DAU 237, and Kings County WD water application levels are higher than for all other DAUs, and demonstrate a decreasing trend over time. The time-trend of water application levels in DAU 235 also stands out—being the lowest in the region, yet also demonstrating a decreasing trend.

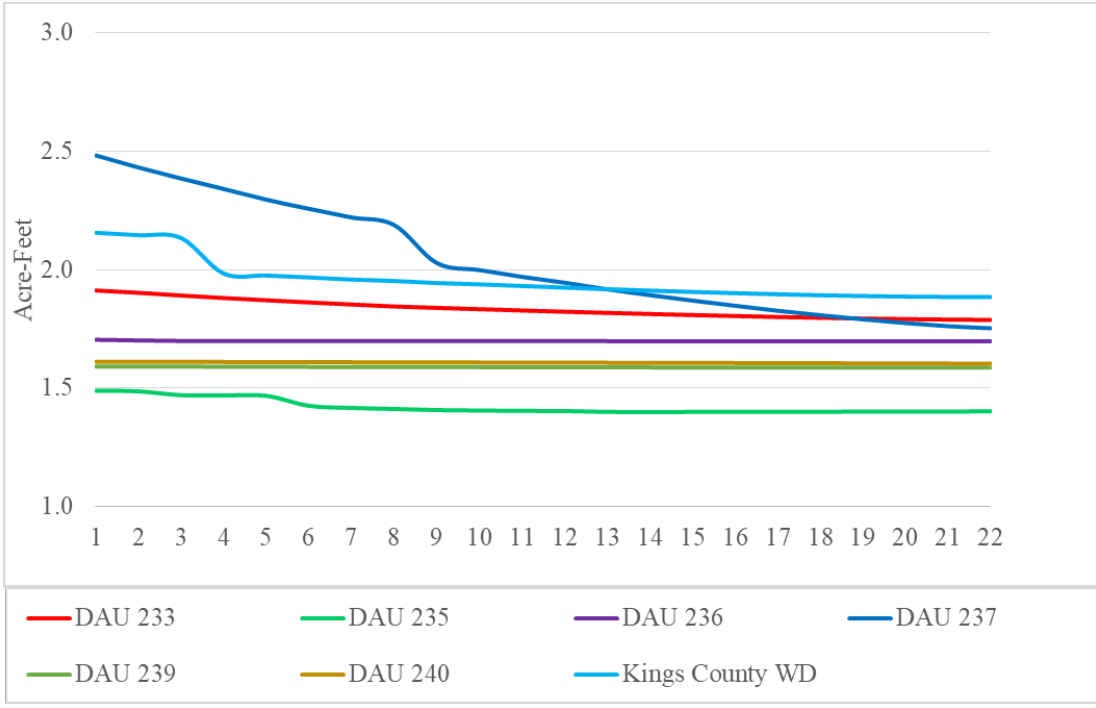


Figure 21. Average water application level per-acre in each time-step, by DAU.

In order to complement these results, we present in Figure 22 the time-paths of regional water use according to the aggregated crop categories from Table 7. Corresponding to the trends observed in Figure 21, it is noticeable that only for field crops and vegetables the regional water use decreases with time, whereas for all fruit crops it remain constant. Considering that the regional land share of vegetables is very small, and that field crops are predominantly grown in DAU 237 and Kings County WD (see Figure 17), the results highlighted by figures 21 and 22 combined is that field crops are excessively irrigated in these subregions at the beginning of the planning horizon, with a decreasing trend. As mentioned, water application level in DAU 235 also demonstrates a decreasing trend. Interestingly, in this subregion excess irrigation is also practiced, and even flooding of fallowed land, however on smaller acreage, hence the subregion average water application is low. Figure 22 indicates that total annual agricultural water use in the region declines from about 1.4 MAF to about 1.2 MAF over the planning horizon.

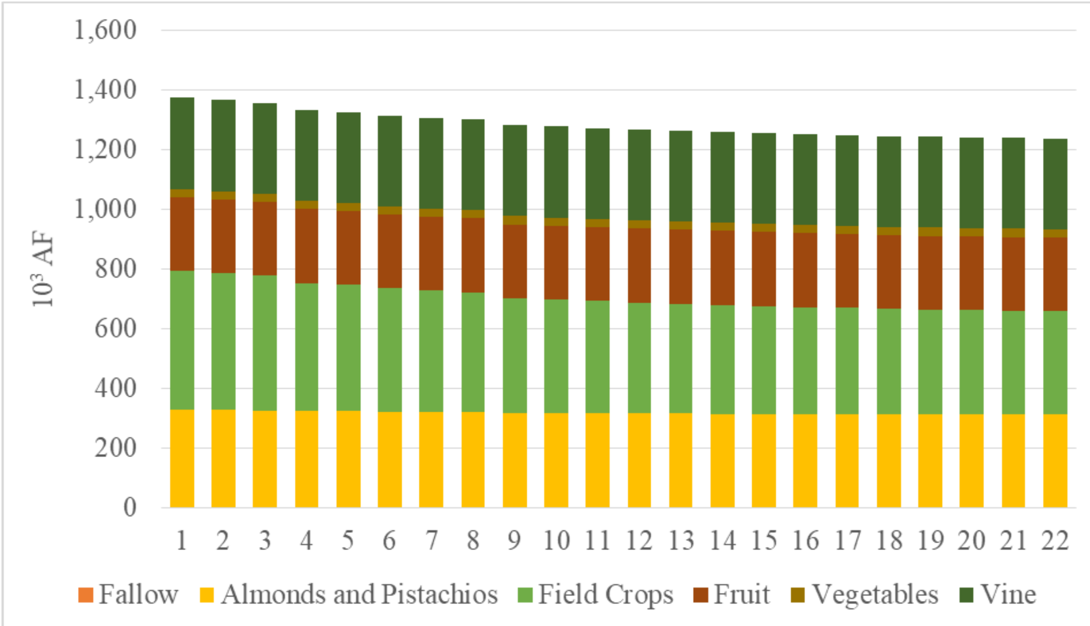


Figure 23 depicts inflows to groundwater storage by DAU and according to the three sources of deep percolation as listed in equation (4). According to results displayed in Figure 23, recharge of groundwater is achieved primarily through deep percolation from irrigated crops, specifically, field crops in subregions DAU 237 and Kings County WD as demonstrated in figures 21 and 22. Another prominent source of recharge are unused treated wastewater (effluent) in DAU 233. This corresponds to the prevailing discharge practices in our region of interest, where almost all treated wastewater discharge happens through evaporation ponds and spread fields (or basins) by regulation, as can be learned from the National Pollutant Discharge Elimination System (NPDES) database (State Water Resources Control Board n.d.). Deep percolation from irrigation of crops (and fallowed land) in DAU 235 are also non-negligible according to results presented on Figure 23. In total, according to the optimal plan, annual recharge from all sources to groundwater for the entire region amounts to 345 TAF at the beginning of the planning horizon, and decreases monotonically to about 270 TAF.

Figure 24 depicts groundwater extractions over time by DAU. According to trends presented in Figure 24, total groundwater extraction in the region is increasing from 150 TAF per year to about 200 TAF per year, throughout the planning horizon, and is concentrated primarily in DAU 235. This subregion has minimal access to the surface water sources in the region. Therefore, this outcome is not very surprising. With respect to results described earlier of deficit irrigation, it is clear after reviewing water resources use in the region, that the reduction in irrigated quantity with respect to observed values is attributed to a decrease in regional groundwater extractions.

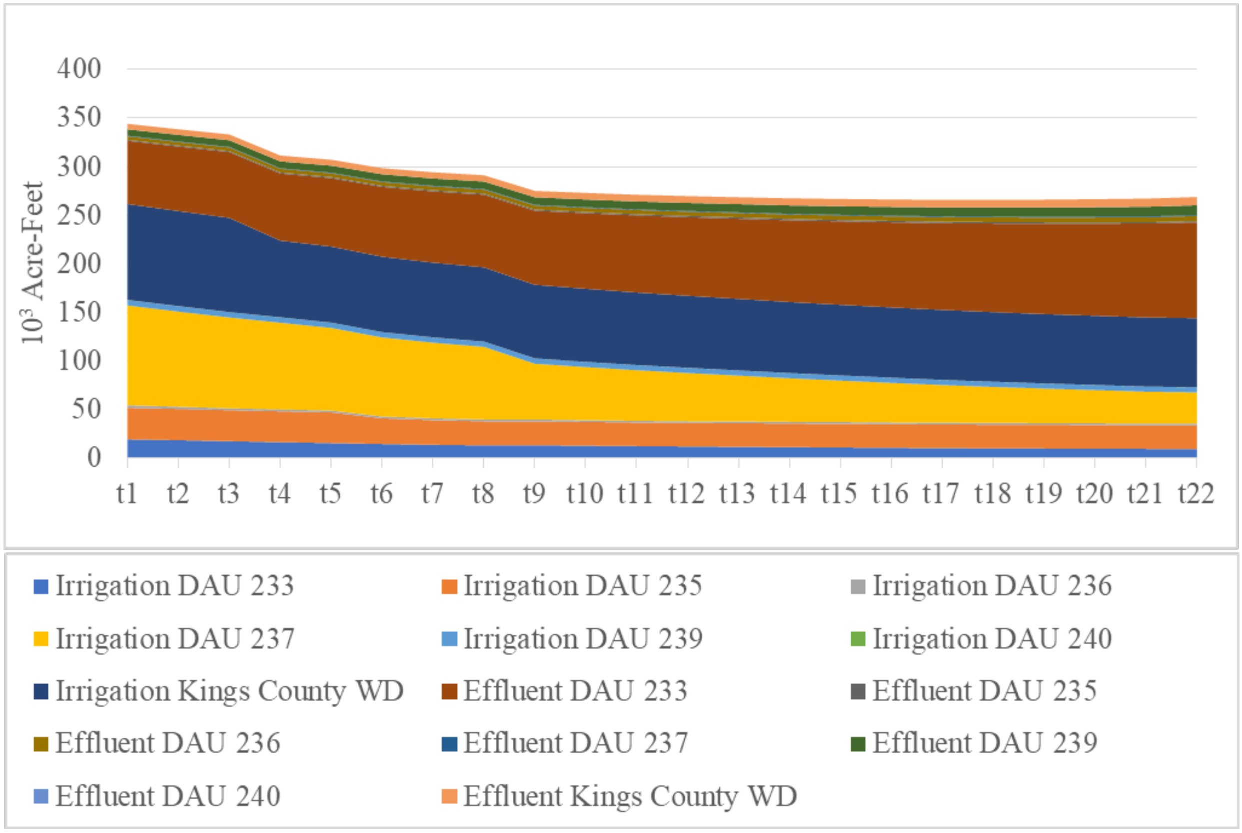


Figure 23. Time path of regional deep percolation to groundwater, by DAU and source.

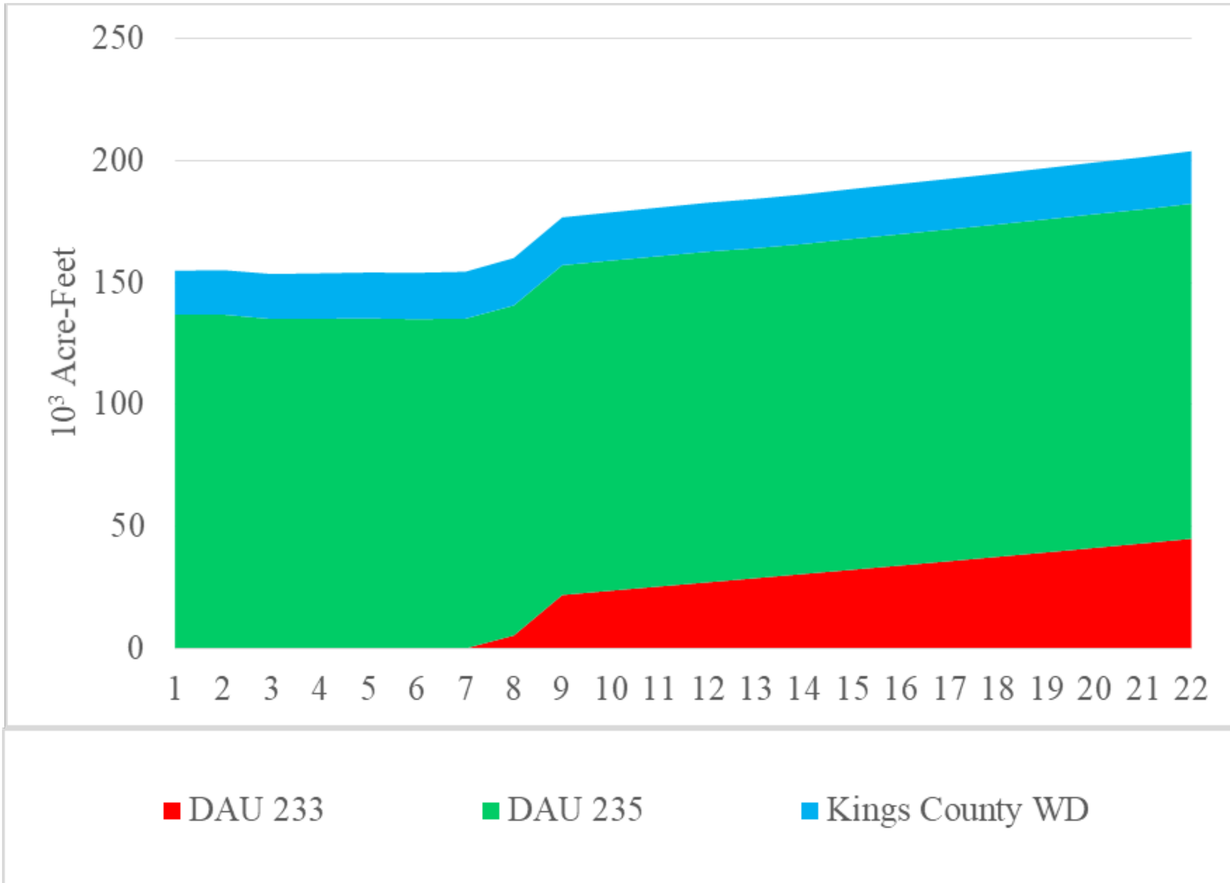


Figure 24. Time path of regional groundwater extraction by DAU.

The resulting impacts of these water management and farming practices on groundwater levels in the region are depicted in Figure 25. Increasing trends in groundwater head can be observed in DAU 237 and in Kings County WD, and to a smaller magnitude in DAU 233 and DAU 239. Groundwater level in DAU 236 and DAU 237 demonstrate a decreasing trend throughout the planning horizon. Again, standing out is DAU 235, in which groundwater head remains constant through time. On average, groundwater head in the region increases by 10%.

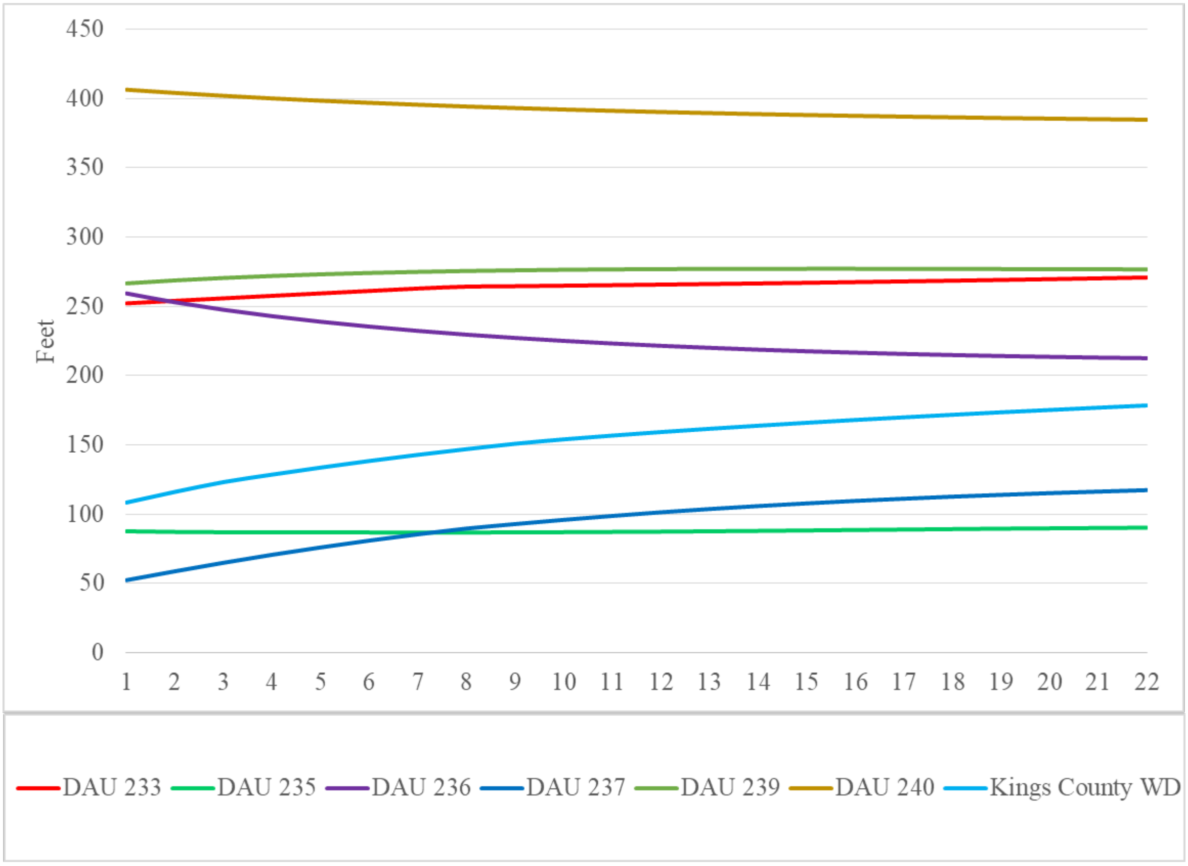


Figure 25. Time path of groundwater head by DAU (feet above sea level).

With reference to equation (5), we examine groundwater lateral flows between subregions in light of the trends depicted in Figure 25, in terms of groundwater head difference between adjacent subregions. Starting with the northeastern part of the region, groundwater flows from DAU 240 to DAU 239 remain almost constant through time. Groundwater generally flows out from DAU 239 to its adjacent subregions; however, flow volumes change significantly. Flow between DAU 239 and DAU 233 is mostly insignificant; flow to DAU 236 increases with time; whereas flow to Kings County WD decreases with time. Flow between DAU 233 and DAU 236 is insignificant at the onset of the planning horizon, and changes direction with time. By the end of the planning horizon significant flows are measured from DAU 233 to DAU 236. Groundwater flows from DAU 236 southwest to all adjacent subregions decrease with time. However, more so to DAU 237 and Kings County WD due to the increasing trend in groundwater head in these subregions. The same increasing trend is also responsible of changing the direction of groundwater lateral flows between DAU 235 and DAU 237, and for increased flow volumes from Kings County WD to DAU 235.

Figure 26 summarizes these trends in lateral flows. For each DAU, the figure depicts net lateral flows, accounting for flows between subdistricts that belong to the same subregion, and flows between subdistricts from different subregions. Negative net flows imply that groundwater exit the subregion, whereas positive values imply net inflows to the subregion. It is clear that except DAU 235 all other subregions, regardless of their baseline conditions become exporters of groundwater flows as time progresses, whereas DAU 235 remains the sole recipient of net flows. This suggests that according to the optimal plan the cone of depression created from trends in groundwater head and lateral flows in the subregion is augmenting groundwater storage in DAU 235. Considering that groundwater head remains constant in this subregion, and the limited access to surface water sources of that subregion, leads to the conclusion that asymmetry in access to water resources in the subregion is a significant driver of the results we obtain.

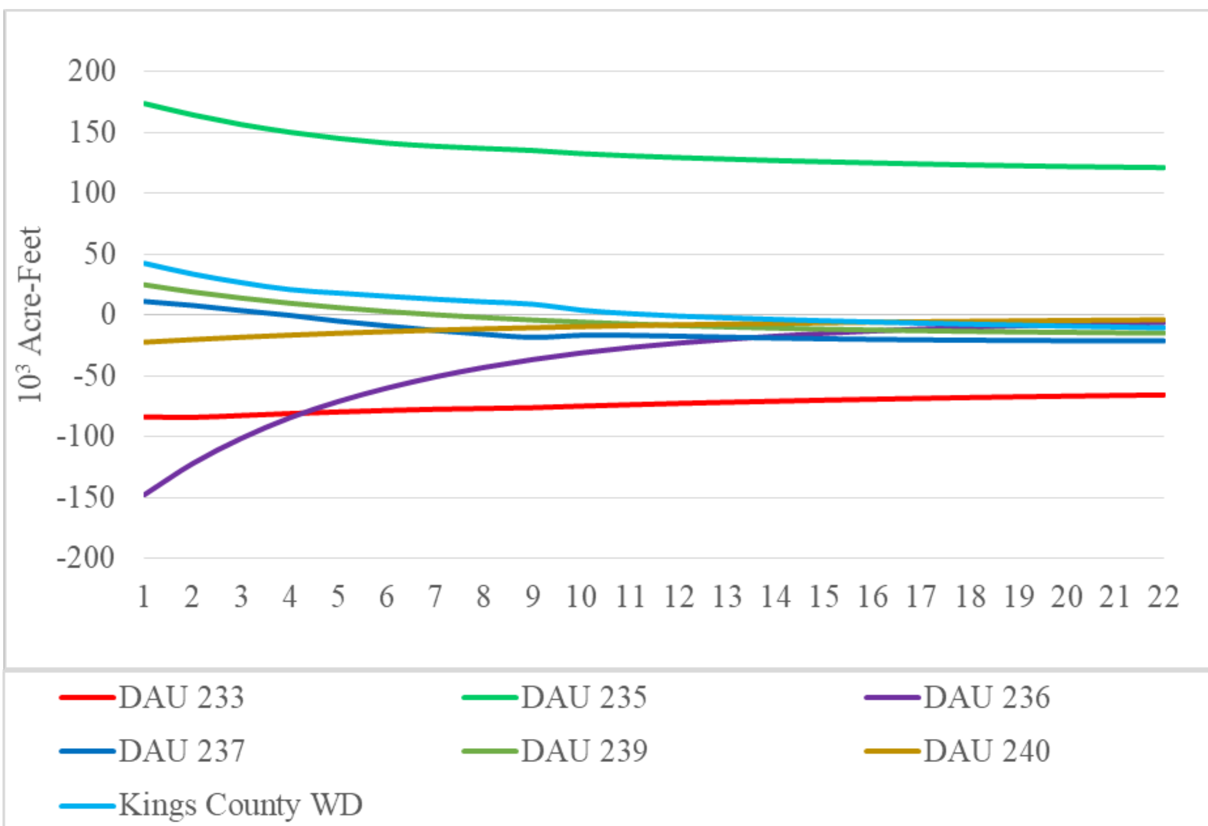


Figure 26. Time path of net groundwater lateral flows by DAU.

As noted earlier, we account for the impact of water salinity on yield, which plays an important role in shaping the optimal plan. Considering the fact that downstream surface diversions have higher salinity levels than upstream diversions, and that groundwater salinity is higher than surface water salinity, the optimal water resources allocation, given existing supply constraints, yields asymmetric outcome in terms of salinity levels in the entire region (see Figure 27). It is evident from the figure that groundwater reliance in DAU 235 and Kings County WD leads to a higher salinity level of applied water.

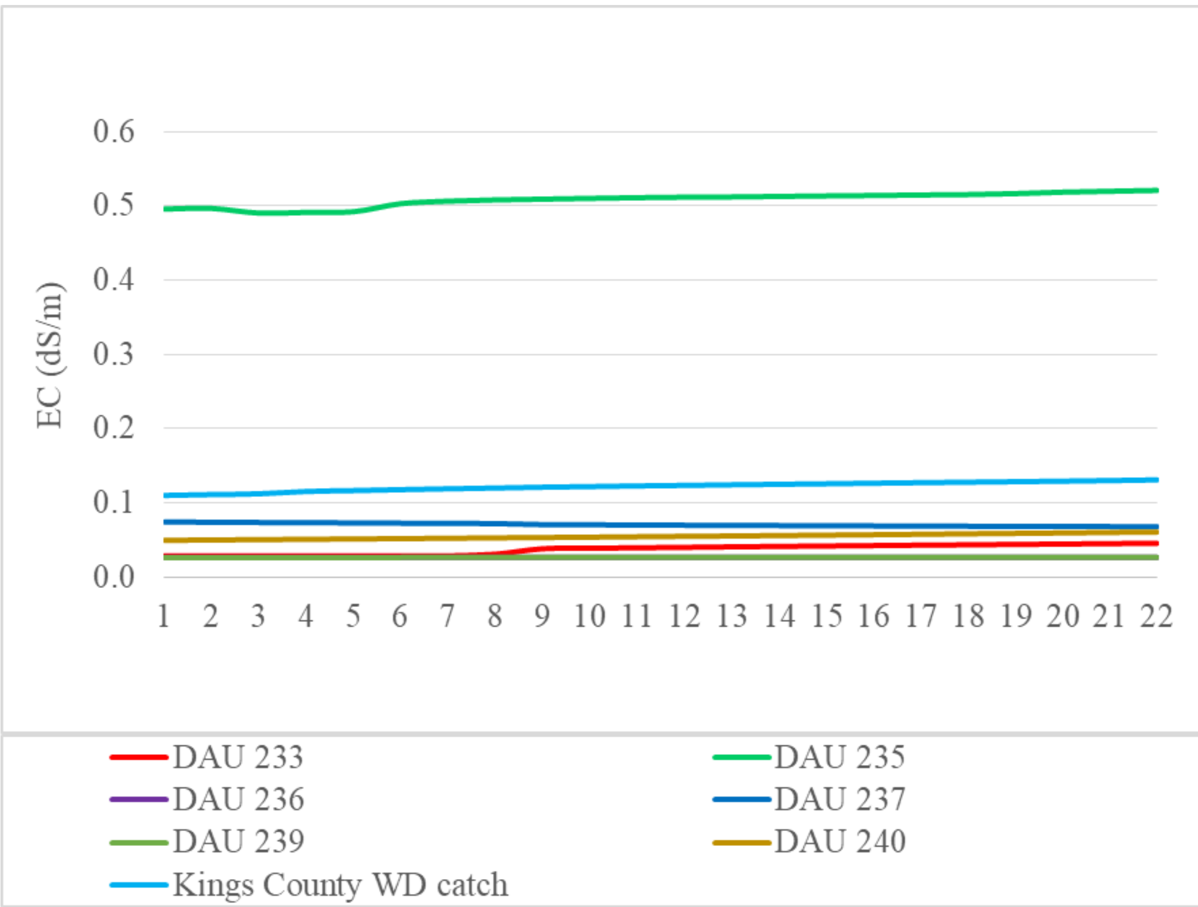


Figure 27. Time path of applied water salinity level by DAU.

The tradeoffs between higher water application level, depletion of groundwater storage (which also increases costs of supply) and yield loss due to poorer water quality, all result in the optimal plan we obtained. The economic implications are presented next. Figure 28 portrays the time path of annual average VMP for each DAU. The value of an additional unit of water in production, represented by VMP also reflects efficient prices according to economic theory—if administered to users those prices would yield the optimal water and land allocation plan. It is evident from Figure 28 that water value in the region is lowest at the northeast, where surface water is most abundant, and increases as surface water availability decreases and reliance on groundwater becomes more prominent. Another prevailing trend that affects water value, which we already mentioned and that fades with time, is the use of excess irrigation at the beginning of the planning horizon in several subregions. The impact of this trend is manifested in the increasing trajectory of water value in DAU 237, Kings County WD, DAU 233 and DAU 235. Interestingly, water value in DAU 235 is lower than for the other DAUs mentioned. This phenomenon is explained by the considerably higher water salinity level in this subregion than in all others.

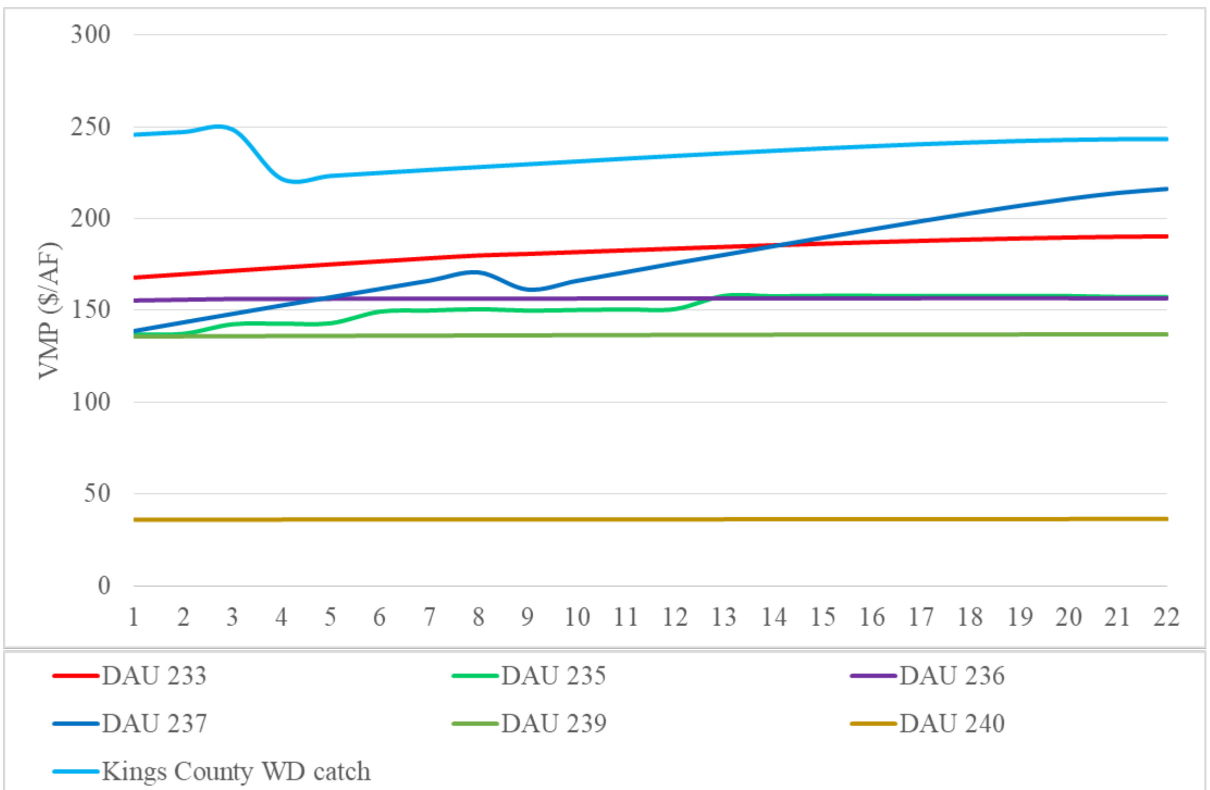


Figure 28. Time path of VMP of applied water by DAU.

To summarize, the optimal plan under *Average* conditions suggests a very similar land allocation to crops in the region as observed in the baseline year of 2014. The northeastern part of the region specializes mainly in citrus and deciduous trees, the central northern part mostly in almonds and vines, and the southwest outskirts predominantly grow field crops and almonds. However, regional groundwater extraction is decreased dramatically with respect to historical quantities in the region, leading to deficit irrigation and an increase in average groundwater level. While intentional recharge through infiltration basins is not recommended according to the model results, two other forms of MAR are warranted to support production of high-value crops in groundwater-reliant areas. The first is through excess irrigation of field crops and flooding of fallowed land, which is practiced at the beginning of the planning horizon in several subregions. The second is percolation of increased quantities of discharged treated wastewater from urban centers. Overall, the optimal plan suggested by the model results predicts an annual regional profit of about $2.2 billion USD, shared roughly according to DAU size (Figure 29).

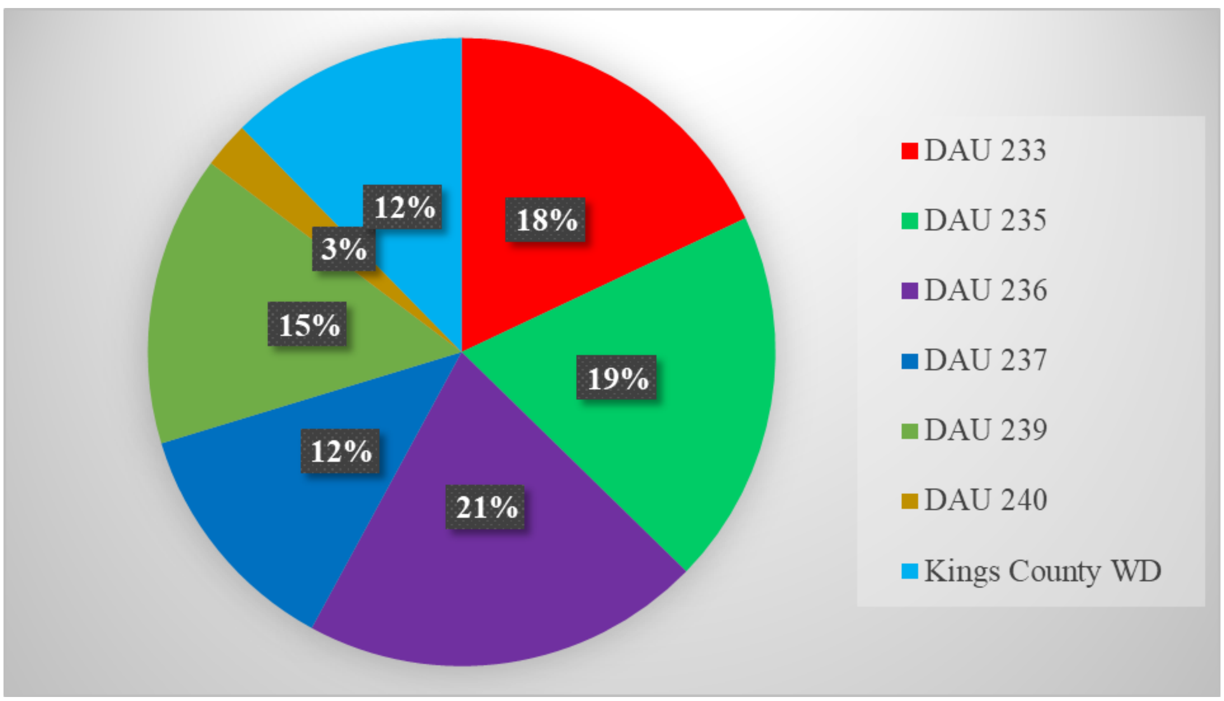


Figure 29. Share of each DAU in annual average regional profit.

5.2 Policy and climate scenarios

We now describe the impact of policy and climate scenarios on the optimal paths of decision and state variables in the model, and the hydrological and economic implications to the region. We first compare land allocation results from the three policy scenarios under *Average* conditions. Values of annual average acreage devoted to each general crop category are reported in Table 8 as percentage of observed regional levels. As we already described, the results of the *Sustainable* scenario are similar to the results we presented earlier for the *Social* scenario. That is, land fallowing decreases and field crops share of land increases for most subregions, but DAU 235 is the exception. However, it is evident that the institutional arrangement simulated under the *Credit* scenario causes significant changes that are different from the ones induced by the other policy scenarios. According to Table 8, the results of the *Credit* scenario suggest a dramatic increase in land fallowing in DAU 235, mostly on the expense of tree crops, and to a smaller extent on field crops. For the rest of the region, land allocation differences with respect to the other policy scenarios are far less significant.

Table 8. Regional land allocation to crops as percentage of observed levels

	Fallow	Almonds and Pistachios	Field Crops	Fruit	Vegetables	Vine
<u>*Sustainable*</u>						
DAU 233	79	99	115	99	110	100
DAU 235	161	96	118	89	97	93
DAU 236	68	98	156	96	110	99
DAU 237	66	98	105	97	100	98
DAU 239	73	100	109	100	105	99
DAU 240	58	98	793	93	113	95
Kings County WD	79	98	102	98	104	99
<u>*Credit*</u>						
DAU 233	86	100	106	100	110	100
DAU 235	2636	32	66	16	98	26

DAU 236	77	99	128	99	110	100
DAU 237	74	99	103	99	103	100
DAU 239	73	100	108	100	106	100
DAU 240	58	99	631	96	113	97
Kings County WD	94	99	101	99	105	99

Figure 30 shows optimal water management strategies corresponding to the land allocation decisions presented in Table 8. Except for recharged quantities, which are measured in TAF per year on the primary vertical axis of Figures 30(b), 30(d) and 30(f), all other indices are normalized values, such that for each index the first year value of the *Social* scenario is normalized to one. As we already presented, the *Social* scenario suggests recharging groundwater, using mainly excess irrigation in certain subregions at the beginning of the planning horizon. For that scenario, total water use in agriculture decreases with time (Figure 30(a)) and recharged quantities from wastewater treatment plants only slightly increase (Figure 30(f)). Consequently treated wastewater reuse in agriculture increases according to population growth. This latter finding is in congruence to the one in Reznik et al. (2017). These trends result in an increase of average groundwater levels in the region of about 10% (Figure 30(f)).

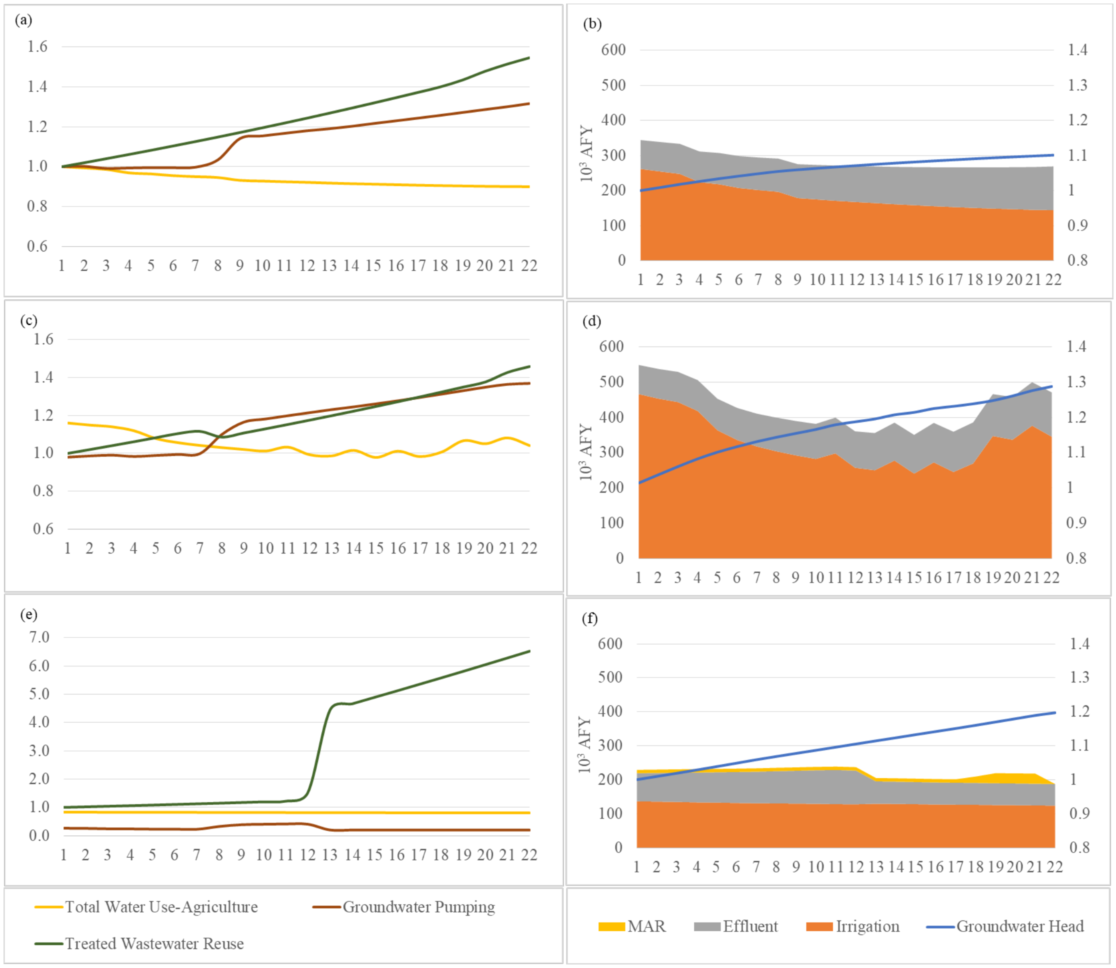


Figure 30. Panels (a), (c), (e): Time paths of total water use for agriculture, regional groundwater extractions, and treated wastewater reuse in agriculture under the *Social*, *Sustainable*, and *Credit* scenarios, respectively. Panels (b), (d), (f): Time paths of annual recharged quantities by source and groundwater head trend under the *Social*, *Sustainable*, and *Credit* scenarios, respectively.

Under the *Sustainable* scenario, total water use in agriculture is higher than in the *Social* scenario. Similar to the *Social* scenario, a decreasing trend in water use is also suggested according to results of the *Sustainable* scenario; however, towards the end of the planning horizon water use increases again (Figure 30(c)). This translates to excess irrigation, mainly at the beginning and the end of the planning horizon, which is manifested in significantly higher recharged quantities to groundwater than under the *Social* scenario (compare Figure 30(d) with 30(b)). Obviously, given the end condition requiring that groundwater head will not fall below baseline conditions at the subdistrict level, this recharge strategy results in higher regional groundwater levels, on average, with respect to the *Social* scenario (compare Figure 30(d) with 30(b)). As in the *Social* scenario, intentional recharge through infiltration basins is not found to be an optimal strategy under the *Sustainable* scenario. Trends in groundwater pumping and treated wastewater reuse in agriculture demonstrate minute differences with respect to the *Social* scenario.

As already mentioned, the third policy scenario demonstrates significantly different trends. Results of the *Credit* scenario suggest substantially lower use of water in agriculture, compared to the *Social* scenario. Groundwater pumping is profoundly lower, and reused quantities of treated wastewater are higher under this scenario compared to the optimal plan under the *Social* scenario (Figure 30(e)). Due to lower water use in agriculture, recharged quantities are also smaller for this scenario compared to the others. However, as mentioned, pumping is also considerably smaller, therefore regional groundwater level increases on average over time, more than in the *Social* scenario. This is the only scenario in which intentional recharge through infiltration basins is found optimal. This is because some subdistricts in DAU 235 and Kings County WD rely solely on groundwater, which forces recharge as a means to accumulate credit to enable groundwater extraction in these subdistricts throughout the planning horizon.

Examining the results of the different climate simulations, two noteworthy phenomena arise. In Figure 31, we present time trends in the total surface water supply to the region, total water use in agriculture, groundwater pumping, and treated wastewater reuse in agriculture for the *Hist1* and *Hist2* simulations under the *Social* scenario. As can be seen, treated wastewater and groundwater storage are used as sources for stabilizing supply and smoothing consumption. This is when significant reductions in surface water supply occur under these simulations. This result presents further evidence for previously developed contributions in the literature concerning benefits of conjunctive use (Tsur and Graham-Tomassi 1991), and of treated wastewater reuse in agriculture (Feinerman and Tsur 2014). Additionally, land allocated to field crops is fallowed intermittently to offset reductions in surface water supply (see Figure 32).

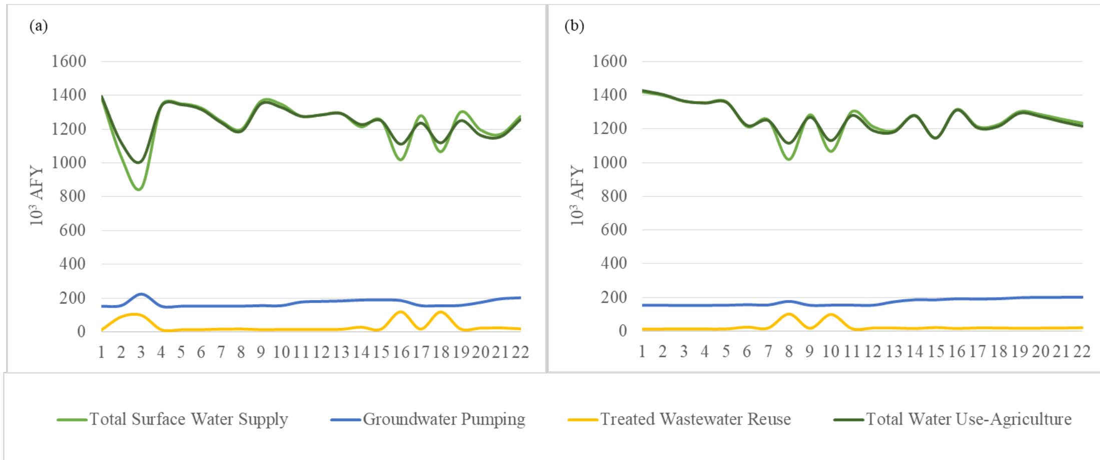


Figure 31. Time trends of regional surface water supply, total water use in agriculture, groundwater pumping and treated wastewater reuse, under the *Hist1* (panel a), and *Hist2* (panel b) simulations.

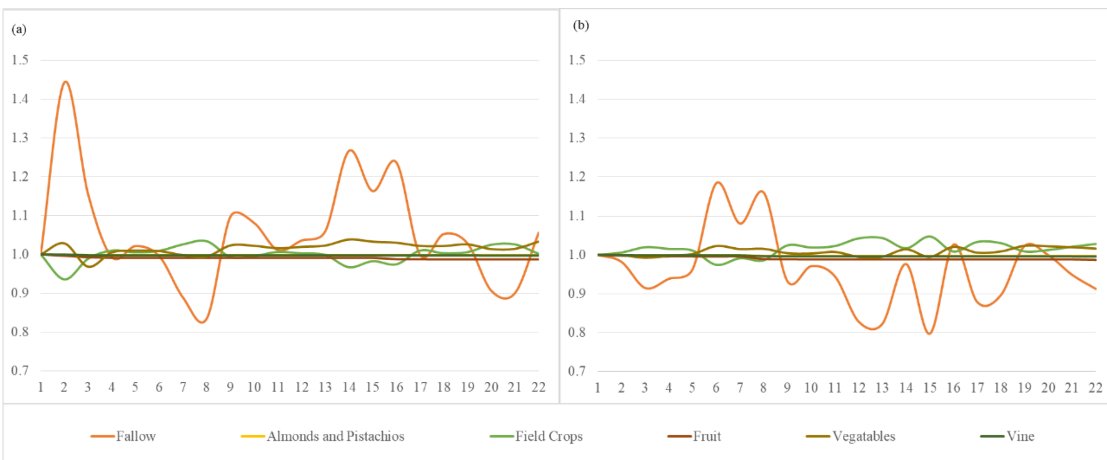


Figure 32. Time trends of annual percent change in regional land allocation by crop category, under the *Hist1* (panel a), and *Hist2* (panel b) simulations.

The second interesting result from the analysis of climate simulations emerges when we compare land allocation across all scenarios. For the most part, as we already mentioned, land allocation to crops in the region remains similar regardless of the assumed policy scenario or climate simulation imposed. The exception to this rule is the *Credit* scenario, in which we find land allocation results sensitive to the assumed climate conditions. Table 9 presents land allocation results for the *Credit* scenario under the *Hist1* simulation. Values reported in the table are percentages of observed levels according to general crop categories and by DAU. It is evident from the table that under this simulation profound changes in land allocation occur with respect to both the *Credit* scenario under *Average* conditions (Table 8), as well as with respect to results from all other scenarios (Table 7).

Table 9. Regional land allocation to crops as percentage of observed levels

	Fallow	Almonds and Pistachios	Field Crops	Fruit	Vegetables	Vine
DAU 233	142	100	76	100	97	100
DAU 235	2833	34	23	29	53	34
DAU 236	113	100	107	100	53	100
DAU 237	244	108	83	111	50	109
DAU 239	49	106	68	116	96	107
DAU 240	63	100	370	100	13	100
Kings County WD	244	100	91	100	169	100

It is evident from Table 9 that under the *Hist1* simulation land fallowing increases for most subregions, where DAU 239 and DAU 240 are the exception. For DAU 237 and DAU 239 permanent crops' land share increases with respect to their observed levels, and differently than all other scenarios. Land share for field crops is also reduced for most DAUs, and again in contrast to results of other scenarios reported earlier. We focus on the differences in land allocation results of the *Credit* scenario in Tables 8 and 9. The impact of the institutional arrangement is almost isolated to DAU 235 under the *Average* simulation; however, it is much wider and affects almost the entire region under the *Hist1* simulation. This leads to the conclusion that the regional optimal plan of water resources management and farm practices under climate uncertainty is highly sensitive to the institutional arrangement that prevails.

We note that intentional recharge through infiltration basins was found optimal only according to results of the *Credit* scenario. Given that the results of this scenario are probably sensitive to initial credit endowment, the asymmetry of water resources availability in the region, and the fact that the institutional arrangement imposed limits groundwater extractions, we decided to run a fourth scenario as a sensitivity analysis. We term this scenario *Mandatory-Recharge*, in which we impose minimal MAR quantities at the subdistrict level according to results from the *Credit* scenario. Additionally, we adopt the end conditions imposed under the *Sustainable* scenario. Thus, in this *Mandatory-Recharge* scenario no constraint is placed on groundwater pumping; however, intentional recharge through infiltration basins must be practiced. We find results from the *Mandatory-Recharge* scenario almost indistinguishable from the *Sustainable* scenario, and therefore skip the detailed presentation of its results. Instead, we go on to describe the economic implications resulting from the different policy scenarios and climate simulations.

Figure 33 shows changes in profits at the subregion level across all scenarios and climate simulations with respect to their *Social* scenario counterparts.[15] As was mentioned earlier, given the relative robustness of the land allocation results, for most scenarios and climate simulations profits at the subregion level also remain similar. The impact of climate uncertainty and institutional arrangement is highlighted in Figure 33. It is clear that significant economic impact is observed only for the *Credit* scenario, and that this impact is wider under the *Hist1* simulation.

[15] Changes in profits for *Average* and *Hist2* are similar. Therefore, we present the outcomes under the *Average* simulation as representative for both.

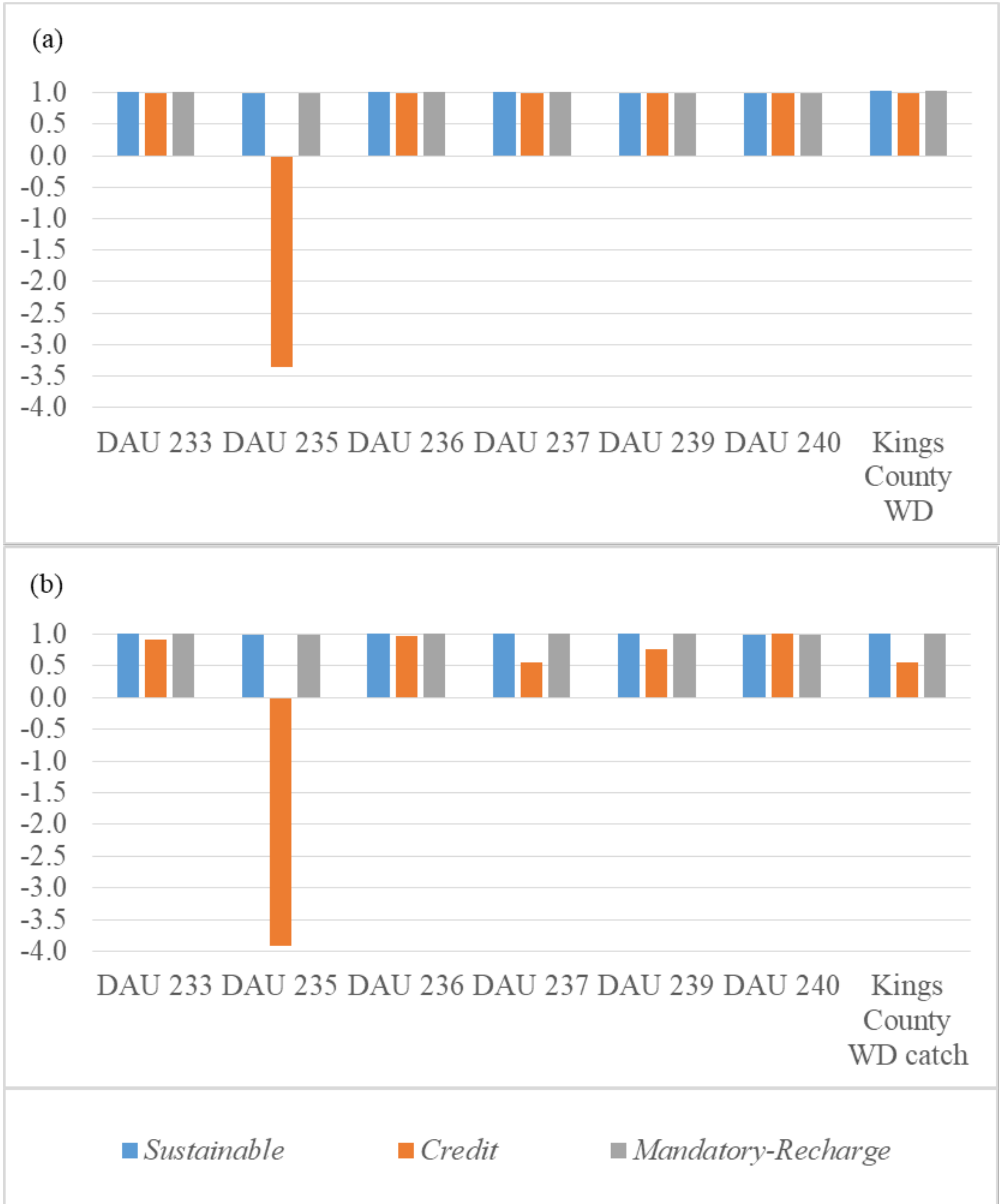


Figure 33. Changes in profit at the subregion level for the different policy scenarios, under the *Average* (panel a), and *Hist1* (panel b) simulations.

Table 10 presents total regional economic welfare differences with respect to the *Social* scenario in annual terms, across scenarios and simulations.[16] As already demonstrated, the institutional arrangement under the *Credit* scenario promotes significant implications on the region, and specifically on subregion DAU 235, which according to Table 10, results in a detrimental welfare impact amounting to about \$2 billion USD annually. As earlier noted, for this scenario, the differences in the optimal plan across climate simulations are substantial, resulting in a significant difference in the economic welfare of about \$500 million USD annually. The economic cost of the *Sustainable* scenario is in the range of \$8 to \$10 million USD annually, which is relatively inexpensive for the region. Imposing intentional recharge through designated infrastructure raises regional economic costs by roughly 30 to 40%, with respect to the *Sustainable* scenario.

Table 10. Differences in economic welfare with respect to the *Social* scenario (10^3 USD)

	Average	*Hist1*	*Hist2*
Social	–	–	–
Sustainable	7,893	9,921	9,879
Credit	1,756,849	2,283,592	1,732,795
Mandatory-Recharge	10,275	14,406	13,195

Finally, we use the differences in economic welfare between scenarios and simulations to compute an estimate of the dollar value for recharged quantities in the region. In principle, the costs and benefits of a unit of water recharged differ according to the method of recharge used. For example, the contribution of an acre-foot of water used in irrigated agriculture can be measured by its marginal value in production, in addition to the value generated by the portion of the acre-foot that percolates to the ground. An acre-foot diverted away from production to an infiltration basin generates only the latter, yet bears the opportunity cost from not irrigating crops. Direct costs and benefits associated with all forms of recharge, such as the VMP in agriculture, costs of conveyance, reduced pumping costs, and others are easy to measure. However, even though

[16] The regional economic welfare achieved under the *Social* scenario is the highest. Therefore, differences presented in Table 10 are all negative, meaning that the other policy scenarios have a lower value of economic welfare.

common pool resource externalities (in the form of groundwater lateral flows) are endogenized in our analysis, tracking and computing the indirect regional costs and benefits associated with an additional unit of water that percolated in a specific area and migrated underground is a much harder task. Instead, we use the difference in regional economic welfare divided by total recharged quantities as an upper limit for this value,exploiting the differences in the optimal plans across scenarios, generated by the fluctuations in water availability under each historical climate simulation, compared to the *Average* simulation. Under the *Average* climate simulation, the total quantity recharged in the region over the entire time-horizon ranges between 4.88 MAF (under the *Credit* scenario) to 9.54 MAF (under the *Mandatory-Recharge* scenario). Table 11 presents the differences with respect to the *Average* climate simulation of total recharged quantities in the region over the entire planning horizon, as well as the differences in economic welfare per unit of water recharged, across policy scenarios for the climate simulation *Hist1* and *Hist2*.

Table 11. Differences in total recharged quantity and economic welfare per unit of water recharged with respect to the *Average* climate simulation and across policy scenario

	Differences in total quantity recharged (TAF)	Differences in economic welfare per unit of water recharged ($/AF)
Hist1		
Social	667	1556
Sustainable	447	421
Credit	713	38
Mandatory-Recharge	509	471
Average	584	622
Hist2		
Social	316	682
Sustainable	323	294
Credit	116	332
Mandatory-Recharge	361	324
Average	279	408

The results presented in Table 11 indicate that total quantities recharged over the entire planning horizon in the region are lower on average by 584 TAF, and 279 TAF, for the *Hist1* and *Hist2* simulations, respectively. The value of an acre-foot recharged to the region is in the range of $38 to $1,556 USD per AF with an average of $622 USD per AF, and $294 to $682 USD per AF with an average of $408 USD per AF, according to the *Hist1* and *Hist2* simulations, respectively. As we presented earlier the value of water in production (under the *Average* climate simulation) is in the range of $50 to $250 USD per AF (see Figure 28). As presented in Table 11, for most policy scenarios, the value of unit of water recharged exceeds the value of water in production. This suggests that the indirect benefits associated with recharged water quantities are substantial and overwhelm their direct benefits in most cases. Thus, the results suggest that recharging groundwater in order to support the optimal plan under different institutional arrangements is of high value to the region of interest.

6. Discussion, conclusions and policy implications

The main objective of this study was to understand the potential role of institutional arrangements on the feasibility and economic efficiency of MAR. Specifically, when this practice is adopted as a strategy to mitigate drought effects on agricultural productivity, and within a regional water resources management context. For that purpose, we used an integrated approach that combines detailed regional hydro-economic and agricultural optimization partial equilibrium models with a larger-scale hydrological simulation model of California's Central Valley. The benefit of this approach is that it enables an economic-driven modeling of high-resolution decision-making processes at the regional scale (e.g., land allocation to crops, water application level, and water resources management strategies). It also guarantees that the optimal regional strategy suggested is feasible on a broader scale, accounting for all hydrological and physical water infrastructure linkages inside and outside the region of interest.

The analysis concentrated on the Kings Groundwater Basin in the Central Valley of California, a highly productive region, in which revenues from agricultural commodities are estimated at $6 to $8 billion USD annually. Similar to many other parts of the Central Valley aquifer system, the Kings Groundwater Basin is characterized by severe groundwater depletion. Considering this state of groundwater depletion and future uncertainty regarding climate conditions and the availability of surface water supply, the sustainability of groundwater resources in these severely over-drafted basins is threatened. As such, the introduction of SGMA in California was designed by state agencies to ensure the sustainable use of the resource. A concern has been raised that management practices derived from SGMA could impose significant losses in terms of agricultural revenues. According to water experts in California, MAR, whether through on-field flooding or using existing and newly developed infiltration basins, could have an important role in mitigating some of these tradeoffs (Hanak et al. 2019).

The results of our analysis, according to the first-best scenario, suggest a significant reduction in groundwater use, which is complemented by deficit irrigation, and without inflicting significant changes with respect to observed crop-yield levels and land-use decisions. This outcome is partially attributed to the inclusion of crop-yield sensitivity to water salinity and the tradeoffs between water quantity and quality in production. Groundwater is generally more saline than surface water in the region. Hence, the model outcomes suggest irrigating crops with less water at higher quality to produce a similar yield. MAR is warranted mainly through on-field flooding, however ignoring potential damages to crop yield. Another substantial source for recharge of groundwater in the region is unused quantities of treated wastewater, which, in this region, usually percolate to the ground through evaporation ponds or spread fields. Volume of treated wastewater reuse in irrigated agriculture is not substantial on a regional scale (similar to observed levels) but does become substantial when surface water supply instability is accounted for. This latter result supports previous work indicating that the value of treated wastewater reuse in agriculture is partly associated with stabilizing water supply (Feinerman and Tsur 2014).

Examining the impact of institutional arrangements on the optimal plan for the region suggests several interesting outcomes and conclusions. First, with respect to MAR, we find that both recharged quantities and methods of recharge applied are sensitive to the type of institutions in place for groundwater management. For the most part, according to the model results, excess irrigation of field crops and some flooding of fallowed land at the beginning of the planning horizon is the preferred method for recharging groundwater stocks, regardless of the assumed climate conditions. This strategy is amplified when minimal threshold levels with respect to groundwater head at the end of the planning horizon are imposed, as part of our *Sustainable* scenario, suggesting this institution incentivizes intentional recharge and increases its value to the region. This result is congruent with previous findings by Haruo and Lund (2008) in their study of the Tulare Basin in the Central Valley. They indicated that under similar end conditions (in their

"No overdraft" scenario), the value of intentional recharge capacity increases substantially. Diverting water to infiltration basins and away from irrigation of crops is only warranted under the *Credit* scenario, and at a high economic cost, suggesting there are substantial tradeoffs associated with this recharge method for the region, as it is represented in our model. These tradeoffs are partially driven by the assumption that no yield damage is suffered when excess irrigation is adopted, an assumption that is supported by recent evidence (Dahlke et al. 2018).

We also find that a more rigid institution, represented in our analysis by the *Credit* scenario, imposing limitations on groundwater extractions, promotes significant changes in regional land allocation under the optimal strategy and, consequently, detrimental economic implications. This result also supports previous findings regarding the impact of constrained groundwater pumping in this region (MacEwan et al. 2017). However, it also emphasizes the importance of high-resolution representation of the regional problem by demonstrating that changes in land use and water allocation decisions, as well as their economic implications, are not homogenous across the region. Furthermore, it is demonstrated that the regional scale of these implications is dependent on assumed climate conditions. Thus, the analysis suggests that the impact of future climate uncertainty on the region is highly dependent on the prevailing institutions, and provides an estimate of about $500 million USD annually as an upper limit for the regional economic costs associated with uncertainty in water availability. Total recharged quantities in the region over the entire planning horizon across policy scenarios and climate simulations are substantial, ranging between 4.88 MAF to 9.54 MAF. In most cases, the calculated value of unit of water recharged is high with respect to the direct value of water in production. This suggests that recharging groundwater intentionally can benefit the region and help mitigate some of the economic implications associated with future climate uncertainty.

Comparing the different policy scenarios analyzed and their hydrologic and economic implications, we find that the *Sustainable* scenario presents a good compromise for the region between the ideal benchmark (the *Social* scenario) and the more stringent institutional arrangement (the *Credit* scenario). In the *Sustainable* scenario, groundwater levels increase the most, economic losses are small, and the simulated climate conditions appear to have a small impact on the optimal strategy. As mentioned, this scenario is constructed according to objectives specified under long-term plans (GSPs) derived from SGMA of the stakeholders (GSAs) in the region of interest. This in turn implies that this institution is likely feasible and relatively easy to implement, monitor and enforce, which supports our conclusion.

Our analysis, as well as the SGMA framework assumes a high level of cooperation and coordination between stakeholders in the region. Such cooperation is essential, according to Hanak et al. (2019), for a sustainable water future in this region. Our analysis supports this claim by demonstrating the importance of regional cooperation, and its ability to mitigate the asymmetric economic implications associated with different institutional arrangements, which result from regional heterogeneity in terms of exogenous conditions. Such a high level of cooperation is obviously hard to achieve and can be very fragile. Again, as highlighted by the results of our analysis, the regional heterogeneity in terms of access to water resources, available water quantities, and agricultural-growing conditions imply, for example, that some subregions specializing in field crop agriculture will act as a buffer for the entire region—decreasing their surface water diversions and increasing land fallowing when water supply fluctuates. Another example is the intentional recharge through excess irrigation, recommended according to the model results in subregions that do not rely on groundwater, for the sole purpose of affecting groundwater flow direction. These behaviors are a direct outcome of the assumption that subregions fully cooperate, and are highly unlikely to sustain under less lenient institutions or more extreme changes in climate and other exogenous conditions. Thus, exploring a wider set of institutional arrangements under different coalitional structures, different strategic behavior assumptions and under equilibrium solutions is a promising endeavor for effective policy recommendation purposes, and where we should aim our future research.

7. References

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8. Annexes

Annex A

Table A.1 Values of Evapotranspiration Functions for Fruit Crops

	$\bar{e}_{udj}$	α_{1udj}	α_{2udj}	α_{3udj}	α_{4udj}	α_{5udj}
Almond						
Function A	5.204	0.122	1.000	8.434	-1.192	1.972
Function B	5.404	0.126	1.000	8.694	-1.175	1.932
Function C	5.146	0.117	1.000	8.681	-1.177	1.924
Function D	4.802	0.105	1.000	8.663	-1.180	1.914
Peach & Nectarine						
Function A	5.234	0.115	1.000	8.157	-1.163	2.032
Function B	5.495	0.125	1.000	8.670	-1.175	1.971
Function C	5.357	0.122	1.000	8.672	-1.173	1.951
Function D	5.174	0.117	1.000	8.676	-1.171	1.925
Plum						
Function A	5.241	0.102	1.000	8.561	-1.164	2.044
Function B	5.519	0.115	1.000	9.214	-1.190	1.973
Function C	5.433	0.115	1.000	9.249	-1.192	1.943
Function D	5.318	0.116	1.000	9.294	-1.194	1.904
Cherries/Pomegranate/Apples						
Function A	5.247	0.286	1.000	4.719	-1.089	2.262
Function B	5.545	0.309	1.000	4.913	-1.097	2.195
Function C	5.535	0.302	1.000	4.947	-1.087	2.180
Function D	5.522	0.292	1.000	4.992	-1.074	2.160
Oranges						
Function A	5.245	0.081	1.000	9.953	-1.191	2.033
Function B	5.535	0.092	1.000	10.481	-1.204	1.963
Function C	5.491	0.095	1.000	10.562	-1.209	1.926

Function D	5.432	0.099	1.000	10.671	-1.215	1.877
Olives						
Function A	5.247	0.007	1.000	29.274	-1.180	2.152
Function B	5.545	0.009	1.000	31.393	-1.194	2.072
Function C	5.535	0.011	1.000	32.331	-1.217	2.006
Function D	5.522	0.013	1.000	33.583	-1.248	1.917
Grapes						
Function A	5.067	0.061	1.000	14.924	-1.297	1.794
Function B	5.083	0.062	1.000	15.821	-1.319	1.749
Function C	4.646	0.054	1.000	15.925	-1.345	1.749
Function D	4.063	0.044	1.000	16.062	-1.380	1.749

Table A.2 Values of Evapotranspiration Functions for Field Crops

	$\bar{e}_{udj}$	α_{1udj}	α_{2udj}	α_{3udj}	α_{4udj}	α_{5udj}
Alfalfa						
Function A	1.915	0.024	1.000	5.066	-1.209	2.157
Function B	2.139	0.030	1.000	5.657	-1.237	2.044
Function C	2.132	0.037	1.000	5.708	-1.278	1.949
Function D	2.124	0.046	1.000	5.777	-1.332	1.821
Corn						
Function A	1.821	0.051	1.000	4.253	-1.233	1.836
Function B	1.823	0.042	1.000	4.530	-1.141	1.896
Function C	1.823	0.043	1.000	4.503	-1.166	1.883
Function D	1.824	0.045	1.000	4.467	-1.199	1.865
Cotton						
Function A	2.775	0.001	1.000	28.131	-1.074	2.199
Function B	2.785	2.4E-10	1.000	81.257	-0.366	5.245
Function C	2.788	2.7E-04	1.000	66.343	-0.569	4.347
Function D	2.792	0.001	1.000	46.459	-0.839	3.149
Wheat						

Function A	1.485	0.003	1.000	8.242	-1.215	2.344
Function B	1.733	0.004	1.000	9.660	-1.174	2.298
Function C	1.735	0.005	1.000	9.918	-1.182	2.212
Function D	1.737	0.006	1.000	10.262	-1.194	2.097
Onion						
Function A	5.249	0.073	1.000	8.388	-1.123	2.287
Function B	5.559	0.076	1.000	8.741	-1.111	2.258
Function C	5.635	0.080	1.000	8.932	-1.119	2.225
Function D	5.736	0.085	1.000	9.186	-1.130	2.181
Sorghum						
Function A	1.485	0.001	1.000	14.219	-1.132	2.508
Function B	1.733	0.001	1.000	15.390	-1.103	2.499
Function C	1.665	0.001	0.820	44.930	-0.898	2.685
Function D	1.576	2.3E-04	0.580	84.318	-0.625	2.934
Pasture						
Function A	1.915	0.024	1.000	5.066	-1.209	2.157
Function B	2.139	0.030	1.000	5.657	-1.237	2.044
Function C	2.132	0.037	1.000	5.708	-1.278	1.949
Function D	2.124	0.046	1.000	5.777	-1.332	1.821

Table A.3 Values of Evapotranspiration Functions for Vegetable Crops

	$\bar{e}_{udj}$	α_{1udj}	α_{2udj}	α_{3udj}	α_{4udj}	α_{5udj}
Melon						
Function A	1.433	0.054	1.000	3.178	-1.278	1.769
Function B	1.454	0.051	1.000	3.338	-1.253	1.781
Function C	1.457	0.052	1.000	3.324	-1.265	1.774
Function D	1.460	0.053	1.000	3.306	-1.281	1.765
Broccoli						
Function A	0.979	0.005	1.000	4.158	-0.971	2.526
Function B	1.041	0.007	1.000	3.467	-1.127	2.450

Function C	1.051	0.007	1.000	3.513	-1.132	2.432
Function D	1.063	0.007	1.000	3.575	-1.137	2.409
Tomatoes						
Function A	5.249	0.005	1.000	11.965	-0.719	2.765
Function B	5.559	0.001	1.000	13.128	-0.501	3.338
Function C	5.635	0.007	1.000	14.276	-0.691	3.012
Function D	5.736	0.015	1.000	15.806	-0.945	2.578

Table A.4

DWR/KRB land category	Land Category EOM	DWR: Statewide Crop Mapping 2014
Fallow	Fallowed	Idle
Almonds and Pistachios	Almond	Almonds, Pistachios and Walnuts
Alfalfa	Alfalfa	Alfalfa and Alfalfa Mixtures
Corn	Corn	Corn, Sorghum and Sudan
Cotton	Cotton	Cotton
Cucurbits	Melon	Melons, Squash and Cucumbers
Dry Bean	Garbanzo Beans	Beans (Dry)
Tomatoes for Market	Tomatoes	
Grain	Wheat	Wheat
MultiCrop	Other Field crops	
Onions and Garlic	Onion	Onions and Garlic
Other Deciduous	Peach & Nectarine	Peaches/Nectarines
	Plum	Plums, Prunes and Apricots
	Cherries	Cherries
	Pomegranate	Pomegranates
	Apples	Apples, Pears, Young Perennials and Miscellaneous Deciduous,

Other field	Sorghum	Miscellaneous Field Crops and Miscellaneous Grain and Hay
Other truck	Broccoli	Peppers, Carrots, Strawberries, Bush Berries, Lettuce/Leafy Greens, Miscellaneous Truck Crops, Cole Crops, Flowers, Nursery and Christmas Tree Farms
Pasture	Pasture	Mixed Pasture and Miscellaneous Grasses
Potato	Potatoes	Potatoes and Sweet Potatoes
Processing Tomatoes	Tomatoes	Tomatoes
Rice	Rice	
Safflower	Safflower	Safflower
Sugar Beets	Sugar Beet	
Subtropical	Oranges	Citrus
	Olives	Olives, Kiwis and Miscellaneous Subtropical Fruits
Vine	Grapes	Grapes

Note: DWR crop categories are widely defined over the entire Central Valley. Hence, some categories are irrelevant for the case of the Kings Groundwater Basin and therefore are not included in our model. These are: Dry Bean, Tomatoes for Market, Multi Crop, Potato, Rice, Safflower and Sugar Beets.

Annex B

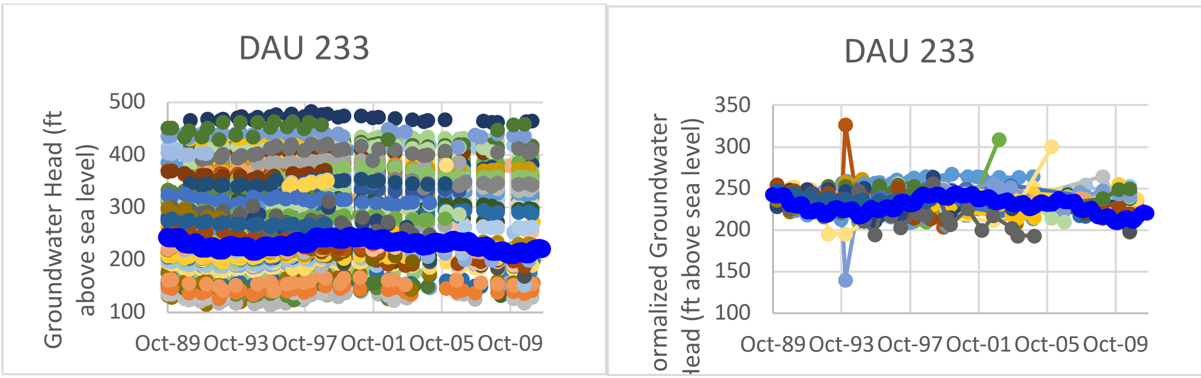

Figure B.1. Simulated groundwater head (bright blue), compared to observed groundwater head from various wells, one color per well record (left), and the same observed values, normalized to WEAP's initial head (right).

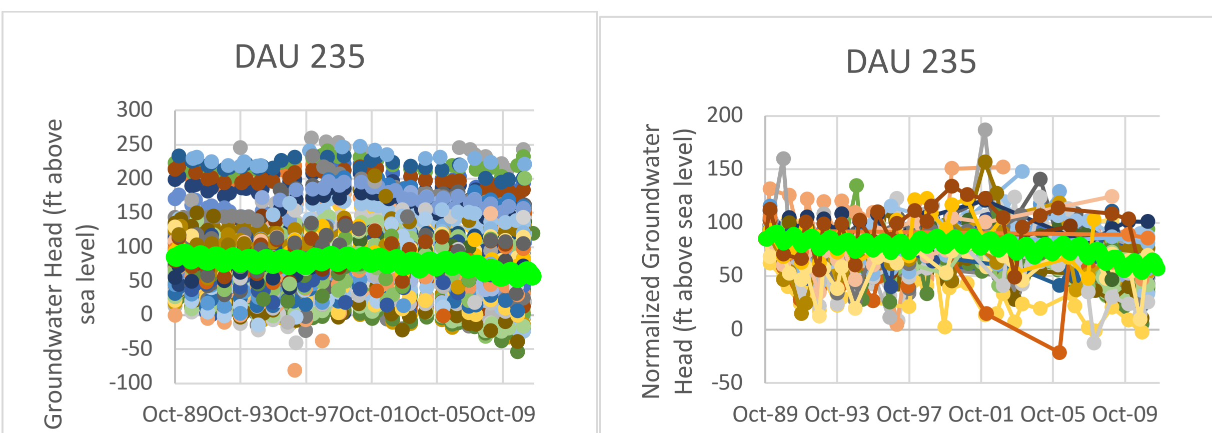

Figure B.2. Simulated groundwater head (bright green), compared to observed groundwater head from various wells, one color per well record (left), and the same observed values, normalized to WEAP's initial head (right).

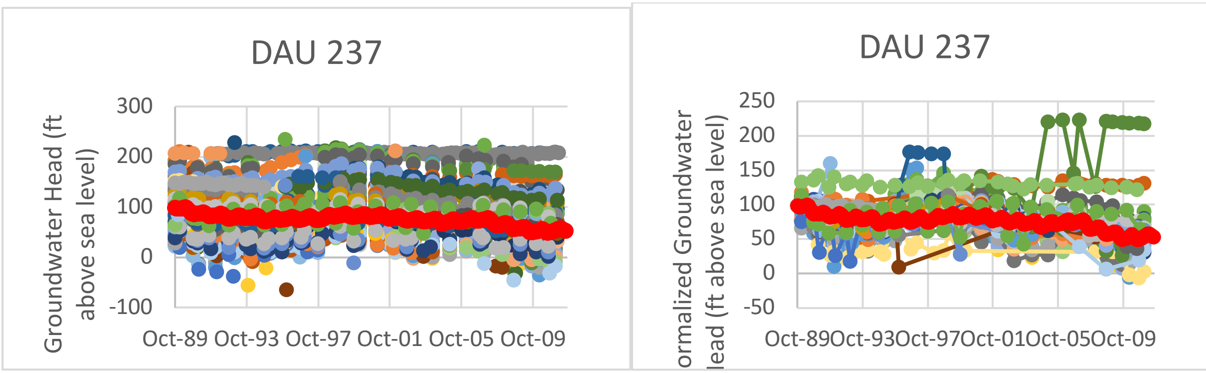

Figure B.3. Simulated groundwater head (red), compared to observed groundwater head from various wells, one color per well record (left), and the same observed values, normalized to WEAP's initial head (right).

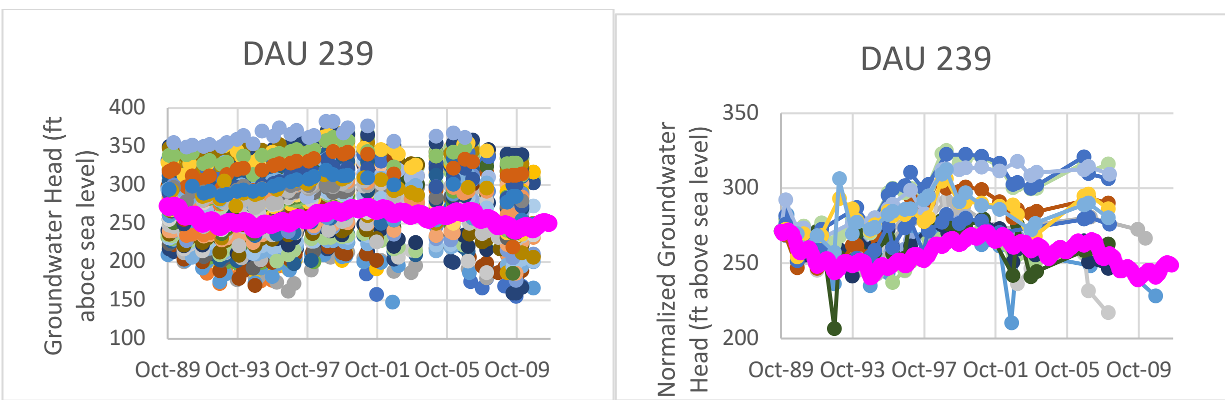

Figure B.4. Simulated groundwater head (pink), compared to observed groundwater head from various wells, one color per well record (left), and the same observed values, normalized to WEAP's initial head (right).

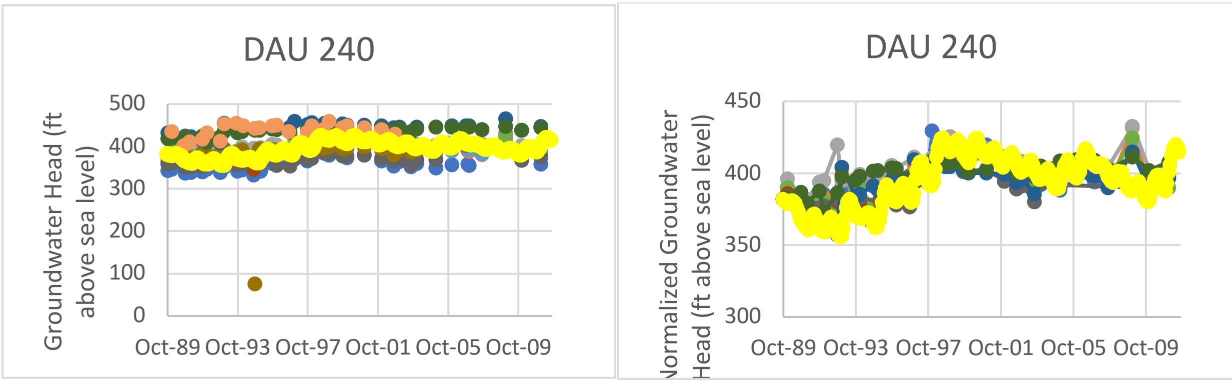

Figure B.5. Simulated groundwater head (yellow), compared to observed groundwater head from various wells, one color per well record (left), and the same observed values, normalized to WEAP's initial head (right).

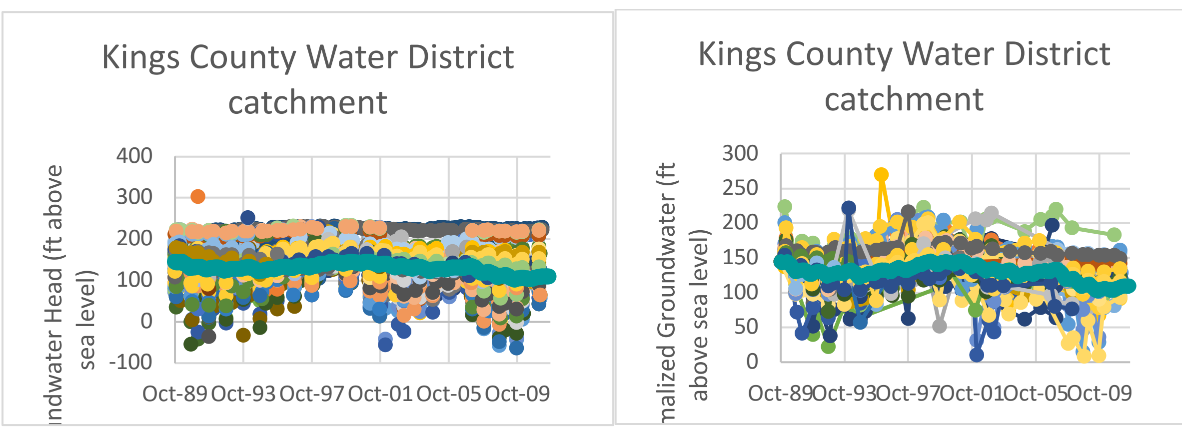

Figure B.6. Simulated groundwater head (teal), compared to observed groundwater head from various wells, one color per well record (left), and the same observed values, normalized to WEAP's initial head (right).