Global Sensitivity Analysis of a Coupled Hydro-Economic Model and Groundwater Restriction Assessment

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Abstract The modeling of coupled food-water systems to represent the effect of water supply variability as well as shocks that may emerge from changes in policies, economic drivers, and productivity requires an understanding of dominant uncertainties. These uncertainties cascade into forecasts of impacts of water management policies, such as groundwater pumping restrictions. This paper assesses how parametric, crop price, crop yields, surface water price, and electricity price uncertainties shape hydro-economic model estimates for agricultural production through a diagnostic global sensitivity analysis (GSA).The diagnostic GSA explores how the uncertainties in combination with a candidate groundwater pumping restriction influence three metrics of concern: total economic revenue, total land use and groundwater depth change. The hydro-economic model integrates a Groundwater Response Function (GRF) by integrating an Artificial Neural Network (ANN) into a calibrated Positive Mathematical Programming (PMP) production model for the Wheeler Ridge-Maricopa Water Storage District located in Kern County, California. Our results show that in addition to groundwater pumping restriction, performance metrics of the system are highly sensitive to prices and yields particularly of profitable crops. These sensitivities become salient during dry years when there is a higher reliance on groundwater.

Keywords Sensitivity Analysis · Hydro-economic model · Groundwater management · California

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1 Introduction

Modeling coupled natural-human systems has high uncertainty, due to the representation of internal dynamics of each system and feed-backs among them (Moallemi et al., 2020) that can yield fundamental changes in their compositions in response to exogenous shocks (Polhill et al., 2016). More specifically for food-water systems, forecasting the effects of socioeconomic and productive changes in addition to water resources management policies involves uncertainty from hydrologic factors as well as farmers' economics-driven decisions (Marques et al., 2005; Loch et al., 2014; Yao et al., 2011; Waldman et al., 2020; Mase et al., 2017). Extreme climate impacts have been observed and studied in agricultural production and the water supply system in California, which mainly affect the variability of rain, temperature and snow-pack (Pathak et al., 2018). These natural drivers affect the variability of surface water supply and changes in crop yields. Highly variable surface water supplies in California have significant impacts on areas highly dependent on groundwater for irrigation, such as the Central Valley as groundwater pumping serves as an important backstop source of water during long dry periods (Hanak et al., 2018). Furthermore, using groundwater as a backstop is the main driver of regional changes in the groundwater storage (Xiao et al., 2017; Yin et al., 2021) and increases in groundwater depths (Vasco et al., 2019).

Other factors such as crop prices particularly for highly profitable crops, produced for trading, such as almonds, pistachios, citrus and deciduous crops, are subject to global markets that are open to price variability. In California policy changes are also a significant source of uncertainty given that groundwater restrictions may be implemented in the face of institutional changes to achieve sustainable groundwater use in over-drafted basins (DWR, 2019). The Sustainable Groundwater Management Act (SGMA) (Senate bills: AB 1739, SB 1168, and SB 1319) outlines the goals and mechanisms to develop plans for achieving groundwater sustainability by mid-century. These restrictions may be implemented by groundwater sustainability agencies, who are responsible for achieving SGMA goals, which aim to maintain a balance between recharge and extraction by 2040. Accounting for future water availability involves factoring the particular characteristics of each groundwater basin and the water conditions of each year (Owen et al., 2019). Recent literature highlights the possible benefits to the aquifer system from implementing pumping constraints and considering the dynamics of water in the aquifer, following the concept of sustainable yield (Miro and Famiglietti, 2019).

Modeling efforts have explored coupling the dynamics of water and agricultural production systems in hydro-economic modeling (HEM) approaches (Harou et al., 2009). Water stakeholders, in this case farmers, make water use and land use decisions driven by expected long term financial benefits, taking into account resources availability, prices, expected yields, irrigation technology, production factor costs, subsidies and policies. These are usually developed for an aggregate of farmers, which enable to analyse regional agricultural adaptations and policies. Furthermore, recent hydro-economic models have shown innovative approaches, coupling hydrologic responses to better represent the co-evolution of the food-water systems including not only their internal dynamics but also their feedbacks. Various approaches in

California and around the world have developed coupling frameworks in HEM. The most common coupling taxonomies are using an iterative process between hydrological and economic models and incorporating response functions, either economic response into hydrological model or a hydrological response into an economic model (Afshar et al., 2020; Forni et al., 2016; Giuliani et al., 2016; MacEwan et al., 2017; Ghadimi and Ketabchi, 2019; Escriva-Bou et al., 2018, 2017).

As food-water systems models grow in their complexity, improved diagnostic tools for better mapping how inputs, assumptions, and uncertainties shape decision relevant insights become increasingly more important. Sensitivity analysis (SA) is a formalized methodology to study how the uncertainty in the output of a model is attributed to uncertainties in the model inputs (Saltelli, 2004). Two general SA methods are used depending on the characteristics of the model: local and global sensitivity analysis (GSA). Local SA is commonly used for linear additive models, where the objective is to map the singular most dominant input a given model output of interest. Global sensitivity analysis is used for non-additive models where there are nonlinear interactions among inputs, the objective of these analysis is to quantify the variability of outputs of interest that result from direct and higher order effects (interactive effects) of uncertain inputs.

Broadly, SA is necessary in any modeling process to identify possible limitations of models due to uncertainty in the input variables and calibration parameters. In complex natural-human systems modeling, when human behavior, natural dynamics and their feedback are diverse sources of uncertainty, diagnostic model evaluations have even more relevance. These coupled systems are usually nonlinear, making GSA more appropriate relative to local SA techniques (Saltelli et al., 2019). Although SA analysis are widely employed in environmental modeling (Pianosi, 2016; Sarrazin et al., 2016), in the HEM literature, sensitivity analyses are seldom performed with only some noticeable exceptions (D'Agostino et al., 2014; Graveline et al., 2012; Maneta et al., 2020; Arribas et al., 2017). SA studies has often been implemented and limited to scenario prediction, to explore impacts on the system from exogenous changes including changes in crop prices, crop costs, crop yields, water availability and salinity (Kahil et al., 2016; Li et al., 2020). D'Agostino et al. (2014) performed a sensitivity analysis for a coupled HEM considering economics and hydrological dynamics, under climate change uncertainty and their effect on the net irrigation requirements of crops due to changes in temperature and precipitation, and their effects on groundwater recharge.

In this work, we contribute a hydro-economic agricultural production and water use developing a HEM and performing a GSA for the Wheeler Ridge-Maricopa Water Storage District in Kern County, California (hereafter Wheeler Ridge-Maricopa). Positive Mathematical Programming (PMP) (Howitt et al., 2012) was used to emulate production decisions. The feedback between the water and food systems is captured by groundwater response function (GRF), which was embedded in the PMP model through an Artificial Neural Network (ANN). The ANN GRF computes the change in groundwater depth at the district level as a function of pumping, surface water deliveries to agriculture, groundwater recharge, and water year type. This allows for discovering promising water conjunctive use operations in an institutionally evolving irrigated agricultural region. Our diagnostic GSA, explores uncertainties in crop

prices, crop yields, the price of surface water, the price of electricity used in groundwater pumping, crop own-price supply elasticities and the potential for groundwater pumping restrictions. The sensitivity analysis results allow for an improved understanding of the most consequential factors shaping the coevolution of the Wheeler Ridge-Maricopa water and food systems.

We compare two different time scales with different water availability conditions: a drought and a wet year, based on the San Joaquin Valley Water Year Hydrologic Classification Index from the Department of Water Resources of California (DWR) (DWR, 2020c). We used 2011 and 2015, to represent a wet year and drought years, respectively. The type of water year serves as a proxy for the amount of surface water available, which affects the use of groundwater pumping to satisfy crop applied water demand.

This paper is organized as follows. In section 2, we lay out the modeling framework used in this paper, including a description of the calibration process for both the agricultural production model and the GRF, as well as the description of the GSA experiments. In section 3, we describe the study area, the spatial and temporal characteristics of the water storage district, evolution of crops and pumping, as well as the description of the two years used in the analysis. Results are summarized in section 4, where we analyze the diagnostic insights from the Sobol to clarify key factors shaping the water and food systems. We close the section by discussing the results and describe limitations and assumptions of this work. Finally, conclusions and areas for future research are described in section 5.

2 Methodological framework

Simulation of food-energy-water systems using hydro-economic models has been done using various coupling approaches that link economic optimization simulation tools with water system models to represent the behavior of water stakeholders under different climatic conditions and the feedback process between human and natural system. This approach was first reported by (Noel and Howitt, 1982), which allows use of spatial and temporal dynamics. Studies that used this coupled modeling framework examine how endogenous and exogenous impacts change the coupled dynamics of agriculture and water, such as climate change and scarcity (D'Agostino et al., 2014; Forni et al., 2016; Torres et al., 2012), impacts of agricultural pumping to groundwater (Medellín-Azuara et al., 2015), water pollution (Peña-Haro et al., 2009), water management policies (Ghadimi and Ketabchi, 2019; MacEwan et al., 2017; Qureshi et al., 2008), and the feasibility of changes in the water governance, economic and financial policies (Gohar and Ward, 2010; Kahil et al., 2016). The approach used in this paper models groundwater depth response modeled using an Artificial Neural Network embedded in the agricultural production model, both were calibrated separately and coupled as explained in the next sections.

2.1 Agricultural production model calibration

We employ PMP calibration as described by Howitt et al. (2012) for the Wheeler Ridge-Maricopa Water Storage District, and two time windows using the average of three years of the historical data, 2010-2012 and 2013-2015. By using the average time window of three years we assume that the response of farmers to economic and resource availability is the same as the average conditions of these years.

The first step of the calibration process solves a linear optimization problem (equations 1 to 4), which maximizes a linear net profit objective function (equation 1) on land use for crop group i. Crop groups represent single crops or group of crops for which cost, prices and yield are selected based on a proxy crop within each group subindex, in our case the set i includes almonds and pistachios, alfalfa, cotton, cucurbits, other deciduous, other truck, grain, other field, fresh tomatoes, processing tomatoes, onions and garlic, sugar beets, dry beans, pasture, subtropical, vine, potatoes, safflower and corn. The PMP follows a two-step calibration process for which a constrained linear program is solved by restricting the model to the baseline (observed) land use in each time window, this is referred to as the calibration constraint set. A second set is conformed by the resources constraints, in these cases land and water. Lagrange multipliers obtained from the first optimization step on the calibration constraint set are used to parameterize an exponential cost function. A sub index to represent the two time windows was omitted since the mathematical representation is the same for both calibrations.

The linear optimization problem is formulated as:

$$Max_{x_{i,land}} \prod = \sum_i (p_i \cdot y_i - \sum_j \omega_{i,j} \cdot a_{i,j}) \cdot x_{i,land} \tag{1}$$

Subject to:

$$\sum_i x_{i,land} \leq b_{land} \tag{2}$$

$$\sum_i a_{i,water} \cdot x_{i,land} \leq b_{water} \tag{3}$$

$$\sum_i x_{i,land} \leq \bar{x}_{i,land} + \varepsilon \tag{4}$$

Where p is the average price and y the average yield by crop group i. $\omega_{i,j}$ is the average cost by input j = water,land,labor,other supplies. For the case of $\omega_{i,water}$ we used a weighted price by volume since we are aggregating groundwater and surface water. Equations 2 and 3 represent the resources' constraints. The variables b_{land} and b_{water} represent the available land and water in the base case respectively, and $\alpha_{i,water}$ represents the Leontieff coefficient of the use of water by crop group i. Lastly, equation 4 represents the calibration constraint, where $\bar{x}_{land,t}$ is the base historical land use. The linear program solves $x_{land,i}$ for and the Lagrange multipliers of the constraints λ_{land} and λ_{water} for the land and water availability constraints respectively, and $\lambda_{land,i}$ for the crop specific calibration constraint (equation 4) which is used later in the calibration of the exponential cost function described below.

The parametrization of a crop production function (equation 5) is given by a Constant Elasticity of Substitution (CES) production function (Beattie et al., 1985) with constant returns to scale. CES production function allows substitution between production inputs defined as:

$$y_i = \tau_i \cdot [\sum_j \beta_{i,j} \cdot x_{i,j}^{\rho_i}]^{\upsilon/\rho_i} \tag{5}$$

Where y_i represents the output in tonnes per acre using the inputs j. The scale parameter is τ_i given by $\frac{y_i \cdot \bar{x}_i}{[\sum_j \beta_{i,j} \cdot x_{i,j}^{\rho_i}]^{\upsilon/\rho_i}}$. The parameter $\beta_{i,j}$ represents the relative use of inputs j. In order to obtain returns to scale, the scale coefficient requires to be equal to one. The parameter ρ is equal to (σ-1)/σ where σ is the elasticity of substitution. Due to limited data to estimate the elasticity of substitution we fixed this value at 0.17 for all the crops.

The calibrated model maximizes the economic profit of the producers of the irrigation district by taking decisions on the use of inputs j by crop i, with emphasis on land and water, expressed by equations 6 to 11. The second term in the objective function (equation 6) is the crop specific exponential cost function (Howitt et al., 2012), where we calibration parameters, γ_i and δ_i, are parametrized using dual values obtained from the first phase. $\delta_{i,t}$ equals $(\omega i, land, t + \lambda land, i)/(\gamma_{i,t} \cdot \exp(\gamma \cdot \bar{x}_{land,i}))$ where γ_i equals $1/\theta_i \cdot \bar{x}_i$ and θ_i is the own-price supply elasticity by crop group i.

$$\begin{aligned} Max_{x_{i,j},wat_w} \prod = \sum_i (p_i \cdot yld_i \cdot y_i) - \sum_i (\delta_i \cdot \exp(\gamma_i \cdot x_{i,land})) - \\ \sum_i \sum_{j \neq land} (\omega_{i,j} \cdot x_{i,j}) - \sum_w (\hat{\omega}_w \cdot wat_w) \end{aligned} \tag{6}$$

Where p_i is the price for crop i, y_i is the production function (equation 5) and $yld_{i,y}$ is the yield change coefficient for the sensitivity analysis (see section 3). In the third term there is a linear cost $\omega_{i,j}$ of the use of other inputs j than water and land by acre produced for each crop. Lastly $\widehat{\omega}_w$ is the cost per acre foot of water used from every source w = surface water (SW) and groundwater (GW).

Additionally the unit (1 acre-foot) pumping cost $\widehat{\omega}_{GW}$ is given by the equation 7, where ω_{pump} is the capital cost of the well pump, $A_{service}$ is the assumed pumping service area (in acres), $\widetilde{x}_{water}$ is the average irrigation demand per unit area (acre-feet/acre), i is the discount rate, n is the pump lifetime (in years), ζ is the operation and maintenance costs for the pump $\frac{\$}{AF \cdot m}$,$\omega_{electricity}$ is the average price of electricity (\$/kWh), η_{pump} is the average pump efficiency, h is the Average Potentiometric Depth (APD) per water district (in feet), Q is the assumed pumping rate (m^3/s), C is the Hazen-Williams coefficient, and d is the pipe diameter (m). Pipe material is assumed to be cast-iron or steel (C = 120). The characteristic well is assumed to be a large production irrigation well (Q = 2000 gpm, d = 16 inches).

$$\widehat{\omega}_{GW} = \left(\frac{\omega_{pump}}{A_{service} \cdot \widetilde{x}_{water}} \cdot \frac{i(1+i)^n}{(1+i)^n - 1}\right) + \left(\zeta + \frac{3.354 \cdot \omega_{electricity}}{\eta_{pump}}\right) \cdot \left(\frac{h}{3.28084} \cdot \left(1 + 10.64 \cdot \frac{h \cdot Q^{1.852}}{3.28084 \cdot C^{1.852} d^{4.8704}}\right)\right) \tag{7}$$

The calibrated optimization model has a set of resource constraints: land availability (equation 8), surface water availability (equation 9), and groundwater availability (equation 10). Surface water and groundwater availability are the observed water uses from that source during the years of analysis. **GWR** represents the groundwater management restriction policy limited to the observed groundwater pumping values.

$$\sum_i x_{i,land} \leq b_{land} \tag{8}$$

$$\sum_i x_{i,water} \leq \sum_w wat_w \tag{9}$$

$$wat_{SW} \leq b_{SW} \tag{10}$$

$$wat_{GW} \leq (1 - GWR) \cdot b_{GW} \tag{11}$$

2.2 Groundwater depth change response

In order to estimate the groundwater pumping cost, a first-order regressive model was formulated to estimate the groundwater depth level or average potentiometric depth (APD). The regressive model is described by the following equation :

$$d_{g,t} = d_{g,t-1} + \Delta d_{g,t} \tag{12}$$

Where, $d_{g,t}$ is the APD for water district g, and year t. $d_{g,t-1}$ is similar to $d_{g,t}$ but calculated for the previous year t-1. $\Delta d_{g,t}$ is the change in APD between the years t and t-1. We used water years, which runs from October 1 to September 30, so that the variable t refers to the end of the water year. For instance, d2,2004 refers to the APD for water district 2 (Wheeler Ridge-Maricopa) at midnight of September 30, 2004.

To estimate $\Delta d_{g,t}$ a regional rather than a Wheeler Ridge-Maricopa specific ANN was trained to increase the data points and performance. The regional ANN employs data from twenty-four water districts within the Kern county region, the districts are listed in Table S1 (Supplementary 1). The regional ANN has nine input variables, one output variable, and two hidden layers, each one with nine neurons, as shown in Figure 1. The nine input variables can be grouped into categorical and continuous variables, yet the model only has one categorical variable, namely the water district identification number (g). The continuous variables for the times t and t-1 are: (i)

San Joaquin Valley Water Year Hydrologic Classification Index (WYI), (ii) the annual volume of surface water used in agriculture (VSW), (iii) the annual volume of groundwater used in agriculture (VGW), and (iv) the annual volume of intentional groundwater recharge (VIR). Data sources for the calibration process are explained in section 3.1. For the regional ANN, 80% of the records were randomly selected and used for its training and the 20% rest for its validation. Details about the ANN calibration results for Wheeler Ridge-Maricopa can be found in the Supplementary Information (Figure S1).

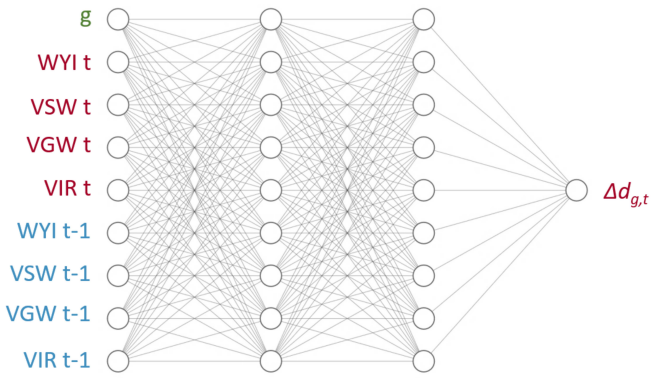

Fig. 1 Regional Artificial Neural Network (ANN) which estimates the change in the average potentiometric depth ($\Delta d_{g,t}$) by water district

2.3 Global sensitivity analysis

The economic production model and groundwater depth response neural network were calibrated and coupled in a single model in Python. We developed the experimental design of the GSA in three phases. First, we selected the model input variables with the highest uncertainty: crop prices, crop yields, surface water price, price of electricity used for the groundwater pumping cost, crops own-price supply elasticities used for the calibration of the exponential cost function. A groundwater restriction was included in the GSA analysis, which enabled us to incorporate a possible pumping regulation policy and evaluate the performance of the policy when other input variables are uncertain. Figure 2 shows the flow of inputs for the calibration of the model and GSA. The three output analyzed were groundwater depth change at the end of the agricultural year, total net revenue, which is the sum of produced land times the net profit $P_i = \sum_i (p_i \cdot y_i - \omega_{i,j} \cdot x_{i,j}) \cdot x_{land,i}$ and total land use $\sum_i x_{land,i}$.

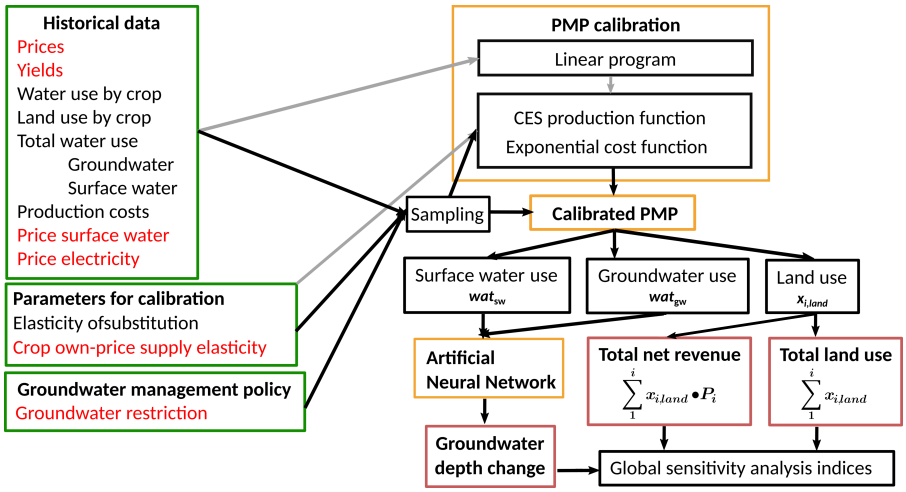

Fig. 2 Global Sensitivity Analysis experiment, in red are the inputs selected for the GSA experiment from all the inputs used (green boxes). The gray arrows represent the flow of inputs and outputs for the calibration of the PMP model. The flow of inputs and outputs for the GSA experiment is depicted with black arrows. The yellow boxes represent the two models (PMP and ANN) and the red boxes represent the outputs of analysis.

The GSA method selected for this study was Sobol (Sobol', 2001), a variance-based method. Variance based methods such as Sobol, are characterized for being computationally efficient, easy to interpret, and mathematically reliable (Saltelli, 2004). Moreover, it allows modelers to use the principle of variance decomposition, to estimate the single interaction, higher order and total effects of each input variable to the output. Since the distribution of the selected input variables is unknown we used the Saltelli sampling scheme (Saltelli, 2002) extension of the Sobol sequence (Sobol', 2001) sampling, using minimum and maximum boundaries for each input. This method is among the most commonly used by modelers to estimate sensitivity indices particularly for nonlinear models.

The use of variance of the conditional expectation can be considered as a summary measure of sensitivity (Saltelli, 2002). Following Saltelli et al. (2010) the first order sensitivity index represents the contribution of a parameter X_i to the variance of the output Y given by equation 13. Where $V(Y)$ is the total variance of the output and $X_{\sim i}$ is a matrix of all parameters but X_i. The mean of Y is taken over all the possible values of $X_{\sim i}$ while keeping X_i constant, finally $S1_i$ is normalized so the first order index have values between zero and $V(Y)$.

$$S1_i = \frac{V_{X_i}(E_{X_{\sim i}}(Y|X_i))}{V(Y)} \tag{13}$$

Using the Sobol variance decomposition, we are able to capture interactions among parameters (high order effects) that are present due to nonlinearities in the model. The second order sensitivity is given by the joint effect of two parameters (X_i, X_j) on the variance of the output Y. This index is the result of the difference between the joint effect of the two parameters minus their first order effects.

$$S2_{ij} = V(f_{ij}(X_i, X_j) = V(E_{X_{\sim ij}}(Y|X_i, X_j)) - V(E_{X_{\sim i}}(Y|X_i)) - V(E_{X_{\sim j}}(Y|X_j)) \quad (14)$$

Finally the total order index for an input X_i is given by equation 15. This represents the total effect of any input parameter X_i to the output Y, accounting for the first order effect and higher order effects. The difference of $V(Y)$ and the first order effect (additive effect) is the residual or the contribution of all terms in the variance decomposition that include X_i, $V(Y) - V_{X_i}(E_{X_{\sim i}}(Y \mid X_i)) = E_{X_i}(V_{X_{\sim i}}(Y \mid X_i)$.

$$ST_i = \frac{E_{X_{\sim i}}(V_{X_i}(Y|X_{\sim i}))}{V(Y)} = 1 - \frac{V_{X_{\sim i}}(E_{X_i}(Y|X_{\sim i}))}{V(Y)} \quad (15)$$

To perform this experiment we used the SALib (Herman and Usher, 2017) python library, this library has different global sensitivity analysis supported methods. The number of simulations for a high confidence on the sensitivity indexes depend on the number of parameters sampled in the GSA (Saltelli et al., 2010). The need of a large number of samples to achieve convergence is usually high, hence computationally expensive. For this study, we performed simulations from 1,000 to 20,000 samples (n) for each parameter. The convergence of the total order sensitivity indexes happened after n=2,000, however first order sensitivity indexes converged after n=15,000. For the final simulations we chose n=20,000 samples for each input parameter for a total of 2,080,000 state of the world scenarios for the wet year conditions and 1,960,000 for the dry year conditions. First order Sobol indices were compared to Delta Moment-Independent Measure (Plischke et al., 2013) available in the SALib library. Parallel computing was used to run the simulations in The Cube computer cluster in the Cornell University Center for Advanced Computing (CAC).

For the GSA experiment, we use lower and upper boundaries for each input parameter. For uncertainty on crop prices we assume a relative price uncertainty of 20% and changes in yields of 10% as assessed by Medellín-Azuara et al. (2011) and Pathak et al. (2018), both from the observed values for each of the base years. It is important to distinguish the source of uncertainty of prices and yield, meanwhile crop prices show constant volatility, yield change can be the result of farm-scale decisions (e.g. water stress, technology and fertilization) and climate events.

Since the agricultural production model is developed for a regional scale, we assume yield and crop price uncertainty for the region. We assumed subsidies for low profitable crop groups: field, corn, safflower, pasture, grain and alfalfa. These crops exhibit potentially negative marginal profitability under observed conditions based on available data. For low-value crops, it is likely that water is received at lower rates than data may suggest or that other inputs are similarly subsidized in some way to reach some profitability point. Price of surface water is charged by water districts using different tariff schemes, there is no historical data available, hence we use a base price and plus and minus 20% bounds from a reported value in 2015. Electricity charged by PG&E has different rates for agricultural users; we used the minimum and maximum values reported in 2015. For own price supply elasticities, some values were found in the literature for the state of California (Maneta et al., 2020; Russo et al., 2008; Volpe et al., 2010), we used the minimum and maximum values reported

as boundaries, and for the crops which we relied only on our approximations, we used plus and minus 20% boundaries from the calculated values. Finally, we modeled a groundwater pumping restriction policy, which can restrict up to 50% from the observed groundwater pumped for each year. Base values used for the calibration of the model and the GSA experimental are reported in Tables S2-S4 (Supplementary 2)

Table 1 Boundaries of input variables for Global Sensitivity Analysis Experiment

Input parameter	Name	Lower bound	Upper bound
p_i	Price by crop	80%	120%
yld_i	Yield change by crop	90%	110%
$\hat{\omega}_{SW}$	Price of surface water	80%	120%
$\omega_{electricity}$	Price of electricity	\$0.1/kWh	\$0.25/kWh
θ_i	Own price supply elasticity by crop	Lowest value in literature or 20% less than approximation	Highest value in literature or 20% more than approximation
GWR	Groundwater pumping restriction	0	50%

3 Study area description

Kern County is located in the Central Valley of California, one of the most productive agricultural counties in the USA. The county often ranks as the county with the most total gross value of production, and it is the production leader in grapes, almonds, citrus, milk and pistachios (USDA, 2017). Agriculture and related sectors occupy the largest share of employment, gross returns and value added in the region. However, irrigated agriculture is also the largest driver of groundwater depletion, despite the sizable water imports and diversions into California's Central Valley. Our case study within Kern County is the Wheeler Ridge-Maricopa Water Storage District (Figure 3), which is the third-largest district in crop acreage in the county.

California has a Mediterranean climate, with winter precipitation and largely dry summers. This rather stable seasonal climate has enabled a thriving agricultural sector, particularly for perennial trees. However the interannual variability of precipitation and snowpack make irrigated agriculture reliant on groundwater to satisfy water demand during dry years. The district spans two groundwater basins Kern County and White Wolf, the first is critically overdrafted according to DWR Bulletin 118 DWR (2014). These groundwater basins, particularly Kern County, are facing regulatory pressure to achieve groundwater sustainability by 2040 following SGMA requirements. The recently filed groundwater sustainability plans for Kern County basin (available at: `http://www.kerngwa.com/gsp.html`) indicate that based on their historical and future water budgets, different regulations and strategies should

be implemented to fulfill the sustainability goals. These include aquifer recharge and policies to reduce groundwater pumping. In this study, we focus on groundwater demand management policy by modeling pumping restrictions.

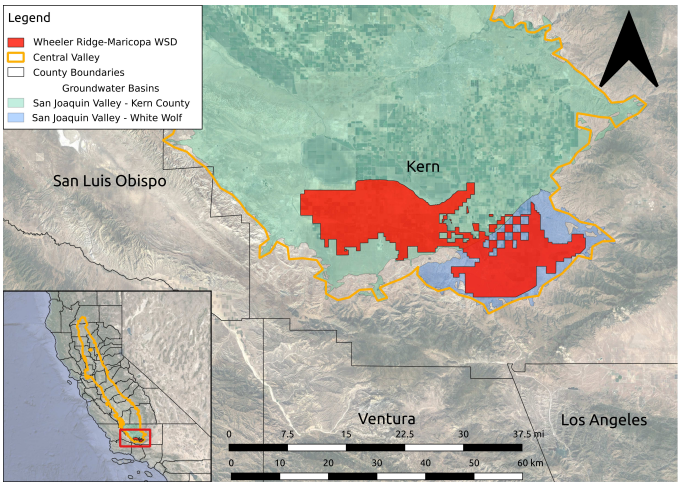

Fig. 3 Wheeler Ridge-Maricopa Storage Water District

3.1 Data sources

Model calibration of PMP and the GRF requires a variety of historical data sets of inputs including land use, water use and crop production economics. Land use (Figure S2) was obtained from digitized spatial crop boundary data provided by the Kern County Department of Agriculture and Measurement Standards, KCDAMS (available at: `http://www.kernag.com/gis/gis-data.asp`). Crop applied water requirements were obtained from the Department of Water Resources using the unit water use estimates (DWR, 2020a). Price and yield information were obtained from the US Department of Agriculture (USDA) National Agricultural Statistics Service using county-level data for Kern (USDA, 2019). Costs of production were obtained from UC Davis Cost and Return Study estimates, using proxy crop costs per group (Davis, 2015). Agricultural surface water cost was estimated from rates published in the water district Agricultural Water Management Plans DWR (2020b).

Surface water delivery (VSW), groundwater pumping (VGW) and groundwater recharge (VIR) amounts were obtained from simulations of the California Food-Energy-Water Systems (CALFEWS) model (Zeff et al., 2021) for historical conditions. Groundwater pumping was calculated by subtracting the total water demand from surface water deliveries shown in Figure S2 (Supplementary 3). Potentiometric depths and pumping rates were obtained from C2VSim-FG outputs (Brush and Dogrul, 2013) using the average grid cell depth within the district area. Average potentiometric depths per water district were calculated through weighted-averaged

regarding agricultural pumping rates. C2VSim-FG is supported by the physically-based Integrated Water Flow Model (IWFM) to California's Central Valley. WYI was obtained from the California Data Exchange Center (CDEC) (DWR, 2020c). Additionally, for the electricity costs for groundwater extraction we used Pacific Gas and Electric Company (PG&E) published rates for the agricultural customers rate plans AG-4B, AG-4C, AG-5B, AG-5C (available at: `https://www.pge.com/tariffs/index.page`).

For this study we focus on two extreme water scenarios (wet and critical dry year) to compare how the results and conclusions change under two different water supply conditions, for this reason the year 2011 was chosen to represent a wet year conditions and 2015 a dry year. For the wet year the surface water supply was 73.9% of the demand, while for the critical dry year, surface water supplied 31.5% of the demand. The total land use was 99,200 acres and 107,500 acres during the year 2011 and 2015, respectively. The approximate total net revenue for these years, calculated as price times yield minus water costs, land cost and cost of labor and other supplies given the historical cropland use was 248 million USD in 2011 and 459 million USD in 2015. The large difference of total net revenue between the two years is result of a higher price of almonds in 2015. The use of two extreme types of water year gives us the ability to compare how the sensitivities of the system vary in different water conditions and inform the best strategies to improve the forecast and quality of the coupled model.

4 Results and discussion

The results allow us to compare the sensitivity of groundwater depth change, total net revenue and total land use at the irrigation district level to different input variables uncertainties. Different water availability, economic, productive and groundwater policy conditions are explored by the diverse state of the worlds captured using the Saltelli sampling. Figures 4 and 5 show the Sobol indices for the three outputs for the years 2011 (wet year) and 2015 (critical dry year) respectively. The Sobol sensitivity indices are depicted in a chord-diagram and heat-map, where second order indices (S2), the interaction effect of two input variables, are depicted by the ribbons in the diagrams. First order indices (S1) are the next outer circle, where the color of the circle represents the first order effect or direct effect that each input variable has on each output. Total order sensitivity indices (ST) depicted in the outermost color circle represent the total effect (direct effect plus higher order effects) of each input variable. Finally, the last circle shows the name of the crop group, variables related to the water system (surface water price, price of electricity and groundwater restriction) are labeled as "water" group. Visualization of the results were filtered in the visualization to show the ten inputs with the highest total order sensitivity for each output. The Python library used for the experiment, SALib, computes confidence intervals for the three indices, which for the results for all the outputs satisfied a significance level of 0.05. First order effects from Sobol were compared to Delta Moment-Independent Measure indexes which can be found in Tables S5-S10 (Supplementary 4).

For wet year conditions, the results show (Figure 4) that highest ranked input variables in the coupled system are the groundwater restriction and variables related to the most produced crops: Vine, Almonds and Pistachios, Other Truck, Subtropical and Cotton. Changing conditions in water availability and profitability in crops cause substitutions among crops, that may be replace a lower profitable crop for a higher profitable crops like almonds and pistachios. The allocation of land shows being highly sensitive to a reduction in groundwater pumping, which has a 68.3% total effect to total land allocation. Additionally, the price of almonds and pistachios, price of other truck, and yield of cotton are among the most important inputs that affect land allocation based on their ST, however their effect is related more to joint effects than direct effect. On the other hand total net revenue is highly sensitive to price and yield of vine and price of other truck crops. Price of vine has a ST of 60% and a S1 of 59.6%, i.e. no other interactions are important (joint effects) to explain the effect this variable has on the total net revenue output.

For the base wet year of analysis (2011), 74% of the water demand was supplied from surface water sources. Inputs related to the water system showed a large effect on groundwater depth change, mainly the groundwater restriction parameter with a total order sensitivity index of 73.08%, followed by price of almonds and surface water price. Furthermore, depth change showed high sensitivity to inputs related to crop groups, such as yield and of almonds and pistachios, yield of cotton and subtropical crops, and price of vine. Price of surface water and price of electricity show larger total order indices than first order indices, highlighting how these inputs affect the system mainly from the multiple joint effects, given by the trade-offs between groundwater and surface water and the effect that they have on allocation of water given surface water and groundwater cost. This output also shows the two largest joint effects in the wet year conditions, first between price of almonds and pistachios with groundwater restriction (2.6% S2) which is also the largest joint effect of the study, and second between the yield and price of almonds and pistachios.

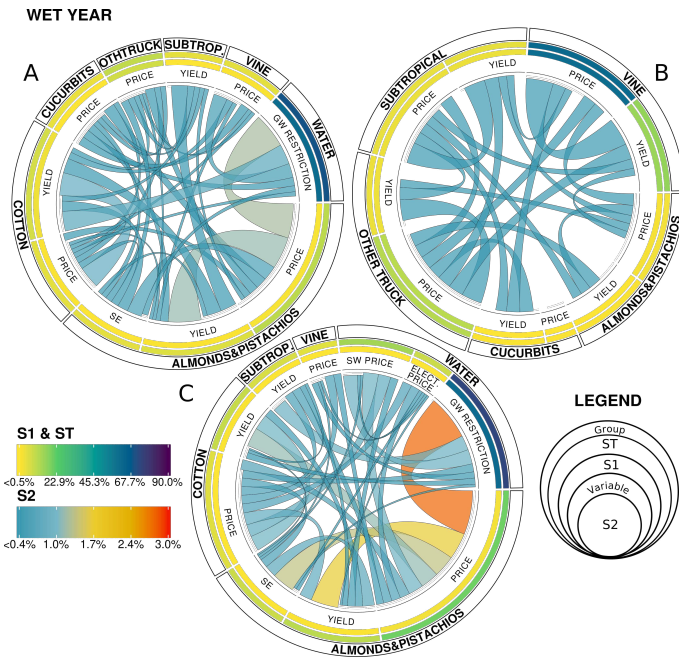

Fig. 4 Results GSA for wet year conditions for Total Land Use (A), Total Net Revenue (B), and Groundwater Depth Change (C)

Cropland choice for almonds and pistachios has increased in the last ten years as shown in Figure S2 (Supplementary 3). This has been driven by higher profits, however this group also has a large water demand, 4 feet per acre on average, which impacts the total demand of water of the district and as shown in the results to the groundwater depth change. The supply elasticity of almonds and pistachios used in the PMP calibration process has a total effect on the total land and groundwater depth change of 4.% and 7.6%, respectively. An expansion or reduction of cropland is incentivized by changes in their marginal profitability, in the PMP formulation the calibrated exponential cost function shapes the objective function, which conditions the allocation of inputs from the calibration point. These results show the effect that an uncertainty in the calibration parameters can have on our model results.

Sobol second order indices show the joint effect of two variables to the outputs due to the nonlinearities present in the model. For the wet year conditions interaction among input variables are less important than first order effects by comparing the ratio of the sum of first order indices and sum of second order indices to the sum of total order indices. First order effects are more important than joint effects for the three outputs, which improve our understanding of the uncertainty propagation from model inputs to outputs.

Results for a dry year are shown in Figure 5, and compared to the wet year conditions a lower number of inputs have a large total effect on the outputs. In a dry year, given a higher dependence on groundwater pumping (68.4% of the total water de-

mand), the groundwater restriction is the variable with the largest first order and total order effects, particularly to the total land allocation and groundwater depth change.

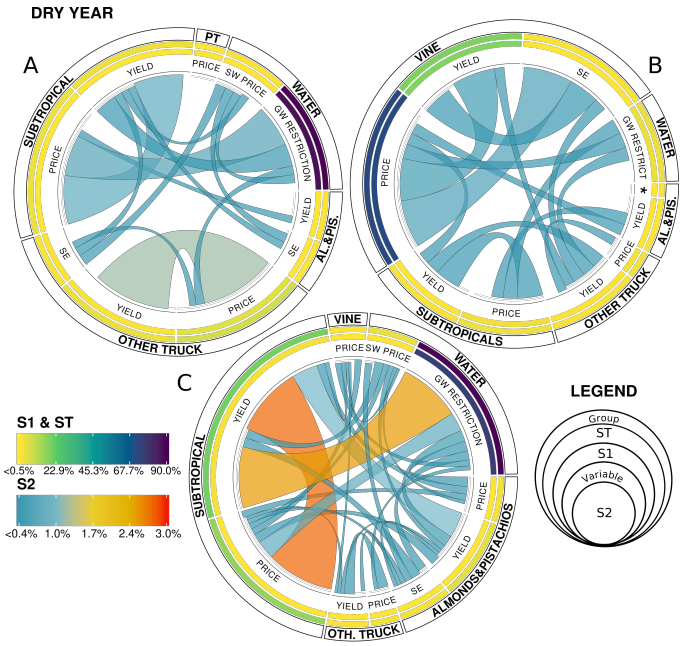

Fig. 5 Results GSA for dry year conditions for Total Land Use (A), Total Net Revenue (B), and Groundwater Depth Change (C). *Price, PT=Processing tomatoes

The total land use was found to be highly sensitive to the groundwater restriction, which explained 89.8% of the variance, the highest direct and total effect indices of the experiment. Next, the price of other truck crops was the input with highest total effect with 7.0% ST, direct and joint effects from other inputs show low effect. Total net revenue as in the wet year shows these are highly sensitive to price and yield of vine, however, no other inputs were found to be important. As in total land use, the groundwater restriction is the most important input variable that affects the variance of groundwater depth change (73.1% ST). Additionally, the yield and price of subtropical crops have high total order effects, which are highly contributed from the high joint effect of these two inputs (2.6% S2), being this the highest joint effect in dry year conditions, followed by the joint effect between yield of subtropical and the groundwater restriction (2.5% S2).

We also compared both wet and dry water conditions and we conclude that during a critical year first order and higher order effects of variables related to the most important crop groups on average are the most significant along with a groundwater restriction. This highlights the importance of groundwater during dry years which offsets the shortage of surface water, and that with a groundwater restriction the allocation of total land would likely be substantially reduced. The sum of first order

effects in a critical year are higher than in the wet year for all the outputs, meaning that direct effects of the inputs are explaining more of the variance of the outputs than joint effects. This effect is driven mainly by groundwater restriction and variables related to perennial crop trees: vineyards, subtropical and almonds and pistachios. Additionally we can observe that the adaptation of farmers to water shortage may be more flexible during wet years, offsetting the loss of revenue from a groundwater restriction.

Calibrated economic models such as PMP have been used to predict impacts of endogenous and exogenous changes to the food-water system. However, given the uncertainties of the system that increase when incorporating dynamics from natural systems, like hydrologic dynamics, it is of interest to explore how the system sensitivities change under different water variability conditions. The results demonstrate which input variables have the greatest impact on model outputs and highlight the need for a refined understanding of the coupled system to make reliable forecasts. Our study also highlights the difference in model sensitivity between dry and wet conditions.

One of the largest uncertainties that PMP modelers face are the values of exogenous supply elasticities, used for the calibration of nonlinear cost function parameters. These values are usually obtained from econometric studies, however the literature for own-price elasticities for specific crops and specific agricultural regions in the world is limited and values for the same region can differ largely. Our analysis suggests that the variability of supply elasticities do not rank highly among other input variables for most model outputs. However, those with the highest profits have an effect on the outputs due to the PMP formulation as explained above. It is also possible to pre-calibrate these elasticities following a Monte-Carlo or other sampling process to examine the combination of values that gives the best fit to the calibration base year or average of years target, using an error coefficient.

Other objectives beyond factor ranking can be achieved using the results of a GSA experiment. Factor fixing is a common practice that can improve the quality of the model once we obtain higher order sensitivity results. Using the total order index, we know if an input is influential by its direct effect and joint effects, hence an input with total order equals to zero can be fixed. In other words, this means that inputs with zero (or ~ 0) total order sensitivity indices can be fixed at any value in the range space of the variation boundaries and will not affect any output. Since we are focusing on three outputs of the coupled model and two base conditions, we have six sets of total order indices. Even though there are no inputs that satisfy this condition for all the outputs, some inputs show consistently low total order sensitivity, these include supply elasticity for safflower, cucurbits, other field, onions and garlic, other deciduous, yield of fresh tomatoes, safflower, other field, and price of other deciduous, cotton, alfalfa, grain, among others. We expect that fixing their values will not have an impact to the results and we can reduce the number of inputs that we have uncertainty. Further research can explore fixing the values for these inputs to a value within the boundaries used in the experiment.

Figure 6 shows the three output metrics analyzed in the sensitivity analysis and the groundwater use from the PMP model. These results give us insights into the possible effects of a groundwater management restriction policy. Considering other

sources of uncertainty informed by the sensitivity analysis, we know the most important inputs that drive these changes. The results from the experiment can also be used to explore the space of scenarios that can be used to identify particular combinations of inputs or outputs of interest and understand trade-offs between objectives. The analysis shows that in both water conditions, having as a goal the reduction of groundwater use or maintaining the groundwater depth in a defined sustainable level, have direct effects to the total net revenue and total land use; however, the sensitivity analysis supports the robustness in the forecast and policy recommendation. Additionally, as observed in the wet year scenario, limitations to groundwater pumping can enhance the groundwater recharge in the district (negative groundwater depth change). This also can be improved by increasing intentional groundwater recharge, which was maintained constant using the observed value in this analysis.

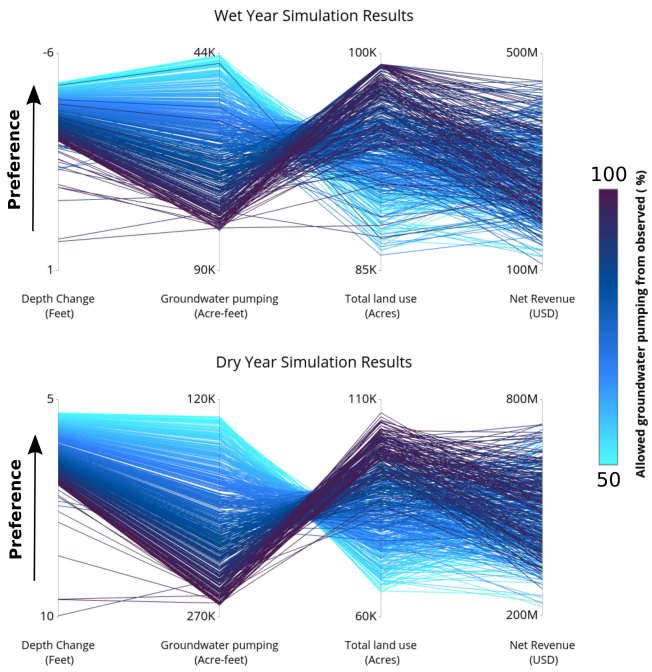

Fig. 6 Random sample of five hundred scenarios from for each year from the sensitivity analysis experiment

Furthermore, in a dry year the relation of a groundwater restriction (groundwater pumping) with depth change and total land use is higher correlated than in a wet year. From the GSA results we know that the groundwater restriction explains largely the variance of depth change and total land use. However, during a wet year there are other variables that are affecting the outputs of analysis, given the adaptation of farmers in a more flexible system (more surface water), such as price of almonds and pistachios. For the case of total net revenue in both water year types, the groundwater

restriction is shown to have very low total order effect, which is evident in the scenario exploration. The net revenue results can explain adaptation behavior of farmers by allocating inputs to offset the loss in net revenue due to a groundwater restriction, in a wet year given a larger supply of surface water the agricultural production system is more flexible to allocate land to other crops and reduce the economic loss. On the other hand, this restriction reduces the capacity of farmers to offset loss of cropland and revenue during a dry year, as observed from the scenarios results.

5 Conclusions

Results from this study show how sensitivities in the coupled food production - groundwater system change under different water availability conditions to groundwater depth change, economic profit and land use. Results inform of the relative importance of a candidate groundwater pumping restriction for the Wheeler Ridge - Maricopa Water Storage District located in Kern County, California. Our findings also highlight the importance of designing diagnostic GSA studies to capture differences in water year type extremes. Significant differences emerge for the effects of the model inputs to wet and dry year extremes. This practice should be more widely employed when evaluating the effects of coupling natural and socioeconomic dynamics human-natural system modeling.

Although this analysis focused on the Wheeler Ridge-Maricopa Water Storage District, the results are expected to be relevant to the other districts in the region. Similar rankings could be expected for other irrigation districts in the same region, where groundwater restriction and input variables associated with important crops in revenue and land use are the most important. Moreover, as observed in the results, during dry periods the individual dominant effects of these variables increases. This means that during dry years crop prices changes, crop productivity changes and limitations to groundwater access have a magnified effect on the system relative to wet years, when the farmers have more flexibility to adapt. Future work will compare how these sensitivities change not only in time but in space, under different agricultural production contexts. Additionally although individual second order interactive effects were relatively small compared to first order effects, their total influence in key periods of stress should not be neglected.

The inclusion of a groundwater restriction allowed us to explore the impacts of this policy on the production system and groundwater levels considering different sources of uncertainty. In both years, the restriction parameter showed the largest effect on groundwater depth change, while other uncertainties also had substantial impacts on the other economic performance metrics. Other water policies can be evaluated in this Wheeler Ridge Mariposa, such as surface water pricing and an increase of price of electricity; however, these inputs showed to have a low total effect on the outputs, hence these policies would have little impact in the short-term decisions of farmers on water use.

In this study, we used the CES production function - exponential cost function formulation for the economic calibrated model, however in the PMP literature other formulations have been developed (Garnache et al., 2017; Mérel and Howitt, 2014).

Further work will consider the sensitivity of land and water allocation to changes in input variables using various formulations. This will give insight to all researchers that use calibrated economic models, particularly PMP models about how formulations can estimate different sensitivities to inputs uncertainties while considering structural uncertainty. The results provide insight about what input variables would need the best uncertainty characterization or approximation to have an informed forecast of impacts on the outputs given the wide range of socioeconomic and hydrological factors in food production systems. In this regard, future work will evaluate the feasibility of values in the inputs space to occur from crop yield change models and price projections forecasts. Likewise, own-price crop supply elasticities known to be highly uncertain parameters in literature, highlight the need for more focused efforts in refining these parameters and asses the effect of their uncertainty in PMP model applications as showed in this study.

With this study we developed a coupled Hydro-economic model incorporating a groundwater depth response into an agricultural production model, that enabled us to model the feedback of farmers decisions and the aquifer. Coupling frameworks are needed to evaluate the evolution of food-water systems to water, economic and policy shocks. The results show the most important factors that affect the dynamics of the system and what inputs need a better characterization when forecasting a water policy. Without the knowledge of the system given the results of the sensitivity analysis the conclusions of the impacts of a groundwater management policy would be incomplete.

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Supplemental Information

The online version contains supplementary material referenced in the article.

Data and code availability

Readers can refer to the repository (`https://doi.org/10.5281/zenodo.4784301`) to access the inputs and results from the global sensitivity analysis experiment and scripts to generate the plots of this study.

Authors' Contributions

Conceptualization: J.M. Rodriguez-Flores, J.A. Valero-Fandiño, S.A. Cole, K. Malek, T. Karimi, H.B. Zeff, J. Medellin-Azuara. Methodology and Validation: K. Malek, T. Karimi, P.M. Reed, A. Escriva-Bou, J. Medellin-Azuara. Model performance and analysis of the results: J.M. Rodríguez-Flores, S.A. Cole, K. Malek, T. Karimi, H.B. Zeff, P.M. Reed, J. Medellin-Azuara. Writing-Review and Editing: K. Malek, T. Karimi, P.M. Reed, A. Escriva-Bou, J. Medellin-Azuara. All authors discussed the results and contributed to the final manuscript.

Conflict of interests

The authors declare that they have no conflict of interest.

Ethical Approval

Not applicable.

Consent to Participate

All authors gave explicit consent to participate in this study.

Consent to Publish

All authors gave explicit consent to publish this manuscript.

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Supplementary 3

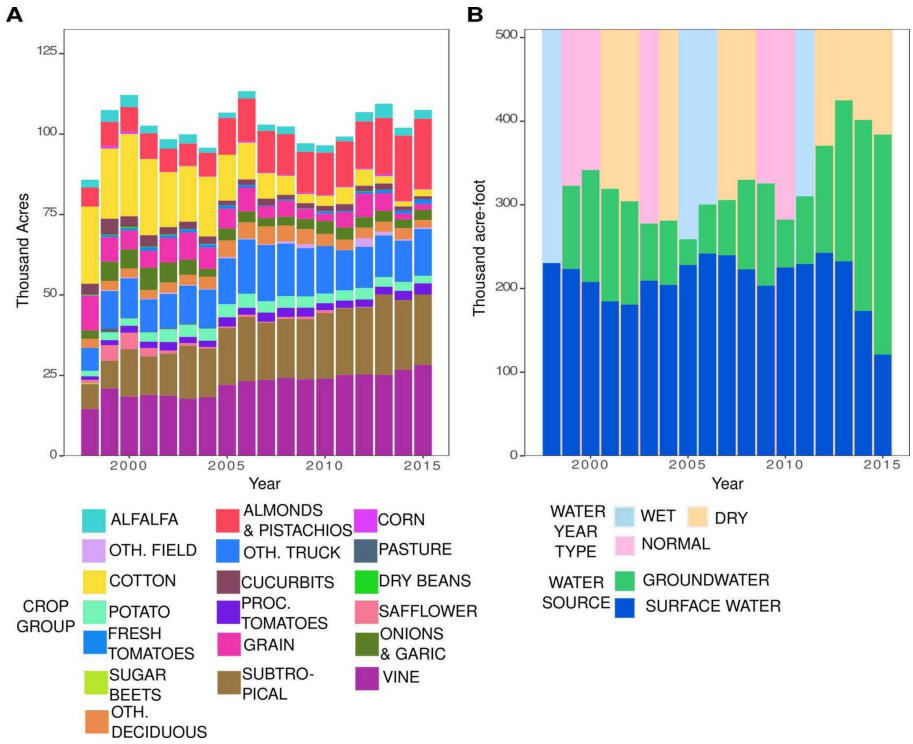

Figure S2: Historical cropland use (KCDAMS) and water use (Zeff et al., 2021) for Wheeler Ridge-Maricopa, from 1998 to 2015.

The historical water use shows an increasing demand for water, of which the proportion supplied from groundwater pumping has increased in the last years. During dry periods, groundwater offsets the lack of surface water to meet the demand, as observed in the 2012-2015 drought. On the other hand, the land devoted to perennial crops such as vine, subtropical and almonds and pistachios has increased in the last years. This land configuration has several implications on the adaptation of farmers to water and economic shocks, since these crops have high establishment costs, any shock to the production system represents a risk to the investment and capability to irrigate tree crops. Transitions to perennial crops represent a hardening of water demand as they cannot be readily deficit irrigated or fallowed without long-term consequences. Other representative crops for the years of analysis include other truck crops, processing tomatoes and onions and garlic.

Supplementary 4

The next tables show the first order Delta Moment-Independent and Sobol Indices and significance levels for the three output metrics and two water conditions. Notice that there are negative values in Sobol indixes these are direct outputs form SALib when an index already converged to zero this might get negative values, hence these can be considered zero.

Input Variable	**Delta**		**Sobol**	
	S1	S1_conf	S1	S1_conf
Alfalfa Price	0.0007	0.0001	0.0004	0.0017
Almonds and Pistachios Price	0.0189	0.0005	0.0207	0.0130
Corn Price	0.0005	0.0001	0.0002	0.0007

Cotton Price	0.0025	0.0001	-0.0008	0.0045
Cucurbits Price	0.0028	0.0002	-0.0012	0.0019
Fresh Tomatoes Price	0.0005	0.0001	0.0004	0.0006
Grain Price	0.0003	0.0001	0.0006	0.0010
Onions and Garlic Price	0.0005	0.0001	0.0000	0.0011
Other Deciduous Price	0.0005	0.0001	0.0003	0.0008
Other Truck Price	0.0014	0.0001	0.0005	0.0020
Potatoes Price	0.0006	0.0001	-0.0005	0.0007
Processing Tomatoes Price	0.0007	0.0001	0.0000	0.0011
Safflower Price	0.0006	0.0001	0.0003	0.0006
Subtropical Price	0.0016	0.0001	0.0021	0.0031
Vine Price	0.0027	0.0001	0.0029	0.0044
Other Field Price	0.0002	0.0000	0.0002	0.0005
Alfalfa Yield	0.0011	0.0001	0.0008	0.0016
Almonds and Pistachios Yield	0.0062	0.0002	0.0071	0.0073
Corn Yield	0.0005	0.0001	0.0002	0.0007
Cotton Yield	0.0080	0.0003	0.0071	0.0063
Cucurbits Yield	0.0013	0.0001	0.0002	0.0016
Fresh Tomatoes Yield	0.0003	0.0001	-0.0001	0.0006
Grain Yield	0.0006	0.0001	-0.0002	0.0009
Onions and Garlic Yield	0.0010	0.0001	0.0006	0.0018
Other Deciduous Yield	0.0003	0.0001	0.0004	0.0010
Other Truck Yield	0.0004	0.0001	0.0004	0.0013
Potatoes Yield	0.0004	0.0001	0.0001	0.0008
Processing Tomatoes Yield	0.0003	0.0001	0.0000	0.0008
Safflower Yield	0.0004	0.0001	0.0001	0.0005
Subtropical Yield	0.0038	0.0002	0.0038	0.0044
Vine Yield	0.0009	0.0001	0.0011	0.0023
Other Field Yield	0.0006	0.0001	0.0000	0.0005
Surface Water Price	0.0075	0.0002	0.0043	0.0083
Supply Elasticity Alfalfa	0.0003	0.0001	0.0000	0.0009
Supply Elasticity Almonds and Pistachios	0.0041	0.0002	0.0036	0.0064
Supply Elasticity Corn	0.0003	0.0001	0.0003	0.0007
Supply Elasticity Cotton	0.0003	0.0001	-0.0002	0.0007
Supply Elasticity Cucurbits	0.0003	0.0001	0.0003	0.0007
Supply Elasticity Fresh Tomatoes	0.0004	0.0001	-0.0003	0.0006
Supply Elasticity Grain	0.0004	0.0001	0.0000	0.0006
Supply Elasticity Onions and Garlic	0.0004	0.0001	-0.0002	0.0009
Supply Elasticity Other Deciduous	0.0017	0.0002	-0.0001	0.0006
Supply Elasticity Other Truck	0.0003	0.0001	-0.0003	0.0008
Supply Elasticity Potatoes	0.0011	0.0001	0.0003	0.0008
Supply Elasticity Processing Tomatoes	0.0005	0.0001	-0.0001	0.0008
Supply Elasticity Safflower	0.0005	0.0001	0.0001	0.0007
Supply Elasticity Subtropical	0.0007	0.0001	0.0008	0.0020
Supply Elasticity Vine	0.0017	0.0001	0.0014	0.0025
Supply Elasticity Other Field	0.0006	0.0001	-0.0005	0.0005
Groundwater Restriction	0.6019	0.0019	0.6138	0.0252
Electricity Price	0.0023	0.0002	0.0017	0.0044

Table S5: First Order Delta Moment-Independent and Sobol Indices for Ground Water Depth Change-Wet Year

Input Variable	Delta		Sobol	
	S1	S1_conf	S1	S1_conf
Groundwater Restriction	0.5952	0.0013	0.6010	0.0139
Electricity Price	0.0012	0.0001	0.0012	0.0022
Surface Water Price	0.0002	0.0000	-0.0019	0.0027
Alfalfa Price	0.0004	0.0001	-0.0026	0.0019
Almonds and Pistachios Price	0.0146	0.0004	0.0133	0.0069
Corn Price	0.0005	0.0001	-0.0008	0.0021
Cotton Price	0.0082	0.0003	0.0094	0.0043
Cucurbits Price	0.0037	0.0002	0.0025	0.0041
Fresh Tomatoes Price	0.0006	0.0001	0.0009	0.0020
Grain Price	0.0083	0.0002	0.0103	0.0027
Onions and Garlic Price	0.0019	0.0001	0.0011	0.0021
Other Deciduous Price	0.0003	0.0001	0.0008	0.0018
Other Field Price	0.0003	0.0001	-0.0007	0.0019
Other Truck Price	0.0730	0.0006	0.0724	0.0068
Potatoes Price	0.0027	0.0001	0.0006	0.0021
Processing Tomatoes Price	0.0047	0.0002	0.0025	0.0029
Safflower Price	0.0004	0.0001	-0.0004	0.0018
Subtropical Price	0.0009	0.0001	0.0001	0.0032
Vine Price	0.0076	0.0002	0.0066	0.0041
Supply Elasticity Alfalfa	0.0002	0.0000	-0.0015	0.0021
Supply Elasticity Almonds and Pistachios	0.0030	0.0002	0.0060	0.0039
Supply Elasticity Corn	0.0003	0.0001	-0.0001	0.0021
Supply Elasticity Cotton	0.0003	0.0001	0.0018	0.0021
Supply Elasticity Cucurbits	0.0002	0.0000	-0.0021	0.0018
Supply Elasticity Fresh Tomatoes	0.0003	0.0001	-0.0010	0.0020
Supply Elasticity Grain	0.0010	0.0001	0.0009	0.0019
Supply Elasticity Onions and Garlic	0.0011	0.0001	0.0001	0.0022
Supply Elasticity Other Deciduous	0.0015	0.0001	0.0000	0.0019
Supply Elasticity Other Field	0.0005	0.0001	-0.0014	0.0023
Supply Elasticity Other Truck	0.0009	0.0001	-0.0008	0.0027
Supply Elasticity Potatoes	0.0009	0.0001	0.0011	0.0024
Supply Elasticity Processing Tomatoes	0.0004	0.0001	-0.0004	0.0022
Supply Elasticity Safflower	0.0005	0.0001	-0.0007	0.0018
Supply Elasticity Subtropical	0.0008	0.0001	-0.0006	0.0028
Supply Elasticity Vine	0.0025	0.0002	0.0034	0.0036
Alfalfa Yield	0.0007	0.0001	-0.0009	0.0017
Almonds and Pistachios Yield	0.0036	0.0002	0.0073	0.0046
Corn Yield	0.0005	0.0001	-0.0004	0.0018
Cotton Yield	0.0242	0.0004	0.0257	0.0050
Cucurbits Yield	0.0009	0.0001	0.0029	0.0040
Fresh Tomatoes Yield	0.0003	0.0001	-0.0013	0.0023
Grain Yield	0.0080	0.0002	0.0072	0.0028
Onions and Garlic Yield	0.0054	0.0002	0.0046	0.0026

Other Deciduous Yield	0.0003	0.0001	0.0012	0.0021
Other Field Yield	0.0003	0.0000	0.0000	0.0019
Other Truck Yield	0.0173	0.0003	0.0173	0.0035
Potatoes Yield	0.0008	0.0001	0.0015	0.0024
Processing Tomatoes Yield	0.0014	0.0001	0.0000	0.0021
Safflower Yield	0.0002	0.0001	0.0001	0.0016
Subtropical Yield	0.0057	0.0002	0.0063	0.0038
Vine Yield	0.0022	0.0001	0.0023	0.0021

Table S6: First Order Delta Moment-Independent and Sobol Indices for Total Land Use -Wet Year

Input Variable	Delta		Sobol	
	S1	S1_conf	S1	S1_conf
Groundwater Restriction	0.0034	0.0002	0.0031	0.0014
Electricity Price	0.0004	0.0001	-0.0002	0.0010
Surface Water Price	0.0013	0.0001	0.0007	0.0013
Alfalfa Price	0.0001	0.0000	0.0000	0.0008
Almonds and Pistachios Price	0.0169	0.0004	0.0157	0.0026
Corn Price	0.0002	0.0001	-0.0005	0.0008
Cotton Price	0.0006	0.0001	-0.0004	0.0009
Cucurbits Price	0.0037	0.0002	0.0032	0.0018
Fresh Tomatoes Price	0.0001	0.0000	-0.0007	0.0010
Grain Price	0.0001	0.0000	-0.0003	0.0007
Onions and Garlic Price	0.0003	0.0001	-0.0002	0.0007
Other Deciduous Price	0.0005	0.0001	0.0000	0.0009
Other Deciduous Price	0.0002	0.0000	-0.0009	0.0008
Other Truck Price	0.1061	0.0008	0.1055	0.0065
Potatoes Price	0.0017	0.0001	0.0008	0.0014
Processing Tomatoes Price	0.0004	0.0001	-0.0012	0.0009
Safflower Price	0.0001	0.0000	-0.0008	0.0007
Subtropical Price	0.0306	0.0005	0.0312	0.0039
Vine Price	0.5970	0.0007	0.5962	0.0149
Other Field Price	0.0003	0.0001	-0.0006	0.0010
Other Field Price	0.0003	0.0001	-0.0005	0.0010
Other Field Price	0.0002	0.0001	-0.0003	0.0009
Other Field Price	0.0002	0.0001	0.0000	0.0008
Other Field Price	0.0003	0.0001	-0.0004	0.0008
Other Field Price	0.0003	0.0001	0.0000	0.0010
Other Field Price	0.0005	0.0001	-0.0007	0.0008
Other Field Price	0.0005	0.0001	-0.0001	0.0008
Other Field Price	0.0002	0.0001	0.0001	0.0008
Other Field Price	0.0001	0.0000	-0.0010	0.0008
Other Field Price	0.0016	0.0001	-0.0003	0.0011
Other Field Price	0.0003	0.0001	-0.0012	0.0009
Other Field Price	0.0001	0.0000	-0.0003	0.0010
Other Field Price	0.0001	0.0000	-0.0007	0.0007
Other Field Price	0.0002	0.0000	-0.0012	0.0009
Other Field Price	0.0002	0.0001	-0.0013	0.0011

Alfalfa Yield	0.0001	0.0000	-0.0006	0.0009
Almonds and Pistachios Yield	0.0045	0.0002	0.0043	0.0017
Corn Yield	0.0001	0.0000	-0.0007	0.0009
Cotton Yield	0.0004	0.0001	-0.0003	0.0009
Cucurbits Yield	0.0011	0.0001	0.0013	0.0018
Fresh Tomatoes Yield	0.0001	0.0000	-0.0005	0.0009
Grain Yield	0.0004	0.0002	-0.0010	0.0011
Onions and Garlic Yield	0.0003	0.0001	-0.0003	0.0007
Other Deciduous Yield	0.0012	0.0001	-0.0008	0.0011
Other Deciduous Yield	0.0001	0.0000	-0.0007	0.0009
Other Truck Yield	0.0266	0.0004	0.0262	0.0037
Potatoes Yield	0.0004	0.0001	-0.0008	0.0011
Processing Tomatoes Yield	0.0002	0.0000	-0.0006	0.0010
Safflower Yield	0.0001	0.0000	-0.0009	0.0010
Subtropical Yield	0.0320	0.0005	0.0313	0.0043
Vine Yield	0.1503	0.0009	0.1485	0.0072

Table S7: First Order Delta Moment-Independent and Sobol Indices for Total Net Revenue-Wet Year

Input Variable	Delta		Sobol	
	S1	S1_conf	S1	S1_conf
Grain Price	0.0001	0.0003	0.0001	0.0004
Alfalfa Price	-0.0007	0.0008	-0.0008	0.0009
Almonds and Pistachios Price	-0.0010	0.0023	-0.0008	0.0028
Corn Price	-0.0001	0.0002	-0.0001	0.0003
Cotton Price	-0.0004	0.0007	-0.0004	0.0009
Cucurbits Price	-0.0002	0.0005	-0.0004	0.0008
Fresh Tomatoes Price	-0.0001	0.0006	-0.0002	0.0011
Onions and Garlic Price	-0.0007	0.0006	-0.0010	0.0009
Other Deciduous Price	-0.0001	0.0006	-0.0002	0.0008
Other Deciduous Price	0.0000	0.0000	0.0000	0.0000
Other Truck Price	-0.0005	0.0021	0.0004	0.0035
Potatoes Price	-0.0004	0.0006	-0.0006	0.0009
Processing Tomatoes Price	-0.0004	0.0007	-0.0004	0.0009
Subtropical Price	0.0039	0.0074	0.0042	0.0082
Vine Price	-0.0001	0.0018	-0.0001	0.0018
Grain Yield	-0.0001	0.0005	-0.0002	0.0007
Alfalfa Yield	-0.0003	0.0014	-0.0004	0.0014
Almonds and Pistachios Yield	0.0005	0.0038	0.0008	0.0037
Corn Yield	0.0000	0.0002	-0.0001	0.0003
Cotton Yield	-0.0008	0.0010	-0.0010	0.0012
Cucurbits Yield	-0.0004	0.0005	-0.0006	0.0007
Fresh Tomatoes Yield	0.0001	0.0003	0.0002	0.0005
Onions and Garlic Yield	-0.0003	0.0003	-0.0005	0.0005
Other Deciduous Yield	0.0000	0.0001	0.0001	0.0003
Other Deciduous Yield	0.0002	0.0003	0.0004	0.0005
Other Truck Yield	0.0000	0.0011	0.0002	0.0027
Potatoes Yield	0.0001	0.0003	0.0002	0.0005

Processing Tomatoes Yield	-0.0001	0.0004	-0.0001	0.0006
Subtropical Yield	0.0148	0.0106	0.0148	0.0110
Vine Yield	-0.0001	0.0011	-0.0003	0.0012
Price Surface Water	0.0003	0.0037	0.0006	0.0038
Other Field Price	-0.0001	0.0001	-0.0002	0.0002
Other Field Price	-0.0004	0.0006	-0.0002	0.0009
Other Field Price	-0.0016	0.0023	-0.0019	0.0022
Other Field Price	-0.0001	0.0001	-0.0002	0.0002
Other Field Price	-0.0001	0.0001	-0.0002	0.0003
Other Field Price	-0.0003	0.0005	-0.0005	0.0007
Other Field Price	0.0000	0.0002	-0.0002	0.0008
Other Field Price	-0.0002	0.0002	-0.0003	0.0003
Other Field Price	-0.0002	0.0005	-0.0004	0.0007
Other Field Price	-0.0001	0.0003	-0.0002	0.0005
Other Field Price	-0.0002	0.0007	-0.0005	0.0008
Other Field Price	-0.0001	0.0002	-0.0001	0.0003
Other Field Price	0.0000	0.0003	0.0001	0.0005
Other Field Price	0.0003	0.0018	0.0003	0.0017
Other Field Price	0.0003	0.0008	0.0001	0.0011
Groundwater Restriction	0.7527	0.0239	0.7377	0.0230
Price Electricity	0.0000	0.0002	0.0000	0.0003

Table S8: First Order Delta Moment-Independent and Sobol Indices for Ground Water Depth Change-Dry Year

Input Variable	Delta		Sobol	
	S1	S1_conf	S1	S1_conf
Grain Price	0.0001	0.0004	0.0001	0.0000
Alfalfa Price	0.0003	0.0005	0.0002	0.0001
Almonds and Pistachios Price	0.0018	0.0011	0.0012	0.0001
Corn Price	0.0002	0.0004	0.0001	0.0000
Cotton Price	0.0001	0.0008	0.0004	0.0001
Cucurbits Price	0.0005	0.0006	0.0003	0.0001
Fresh Tomatoes Price	0.0007	0.0008	0.0008	0.0001
Onions and Garlic Price	0.0006	0.0005	0.0005	0.0001
Other Deciduous Price	0.0004	0.0005	0.0003	0.0000
Other Deciduous Price	0.0000	0.0000	0.0012	0.0002
Other Truck Price	0.0476	0.0052	0.0471	0.0006
Potatoes Price	0.0005	0.0005	0.0003	0.0001
Processing Tomatoes Price	0.0017	0.0011	0.0021	0.0001
Subtropical Price	0.0013	0.0036	0.0010	0.0001
Vine Price	0.0000	0.0007	0.0005	0.0001
Grain Yield	0.0004	0.0004	0.0002	0.0000
Alfalfa Yield	0.0005	0.0008	0.0001	0.0000
Almonds and Pistachios Yield	0.0022	0.0016	0.0022	0.0001
Corn Yield	0.0002	0.0003	0.0015	0.0001
Cotton Yield	0.0006	0.0006	0.0002	0.0000
Cucurbits Yield	0.0004	0.0005	0.0001	0.0000
Fresh Tomatoes Yield	0.0001	0.0003	0.0001	0.0001

Onions and Garlic Yield	0.0004	0.0006	0.0003	0.0001
Other Deciduous Yield	-0.0004	0.0007	0.0007	0.0001
Other Deciduous Yield	-0.0003	0.0005	0.0002	0.0001
Other Truck Yield	0.0091	0.0029	0.0095	0.0003
Potatoes Yield	-0.0002	0.0008	0.0002	0.0000
Processing Tomatoes Yield	0.0008	0.0008	0.0014	0.0001
Subtropical Yield	0.0031	0.0028	0.0016	0.0001
Vine Yield	0.0002	0.0007	0.0001	0.0000
Price Surface Water	0.0020	0.0019	0.0003	0.0001
Other Field Price	0.0001	0.0004	0.0002	0.0001
Other Field Price	-0.0002	0.0004	0.0001	0.0000
Other Field Price	0.0004	0.0012	0.0001	0.0000
Other Field Price	0.0002	0.0002	0.0001	0.0000
Other Field Price	0.0003	0.0005	0.0003	0.0000
Other Field Price	0.0005	0.0006	0.0006	0.0001
Other Field Price	-0.0002	0.0005	0.0003	0.0001
Other Field Price	0.0003	0.0003	0.0001	0.0000
Other Field Price	0.0006	0.0005	0.0005	0.0001
Other Field Price	0.0004	0.0004	0.0002	0.0001
Other Field Price	0.0088	0.0020	0.0076	0.0002
Other Field Price	-0.0001	0.0004	0.0001	0.0000
Other Field Price	-0.0001	0.0005	0.0001	0.0000
Other Field Price	0.0003	0.0009	0.0001	0.0000
Other Field Price	0.0006	0.0011	0.0002	0.0000
Groundwater Restriction	0.8685	0.0139	0.8690	0.0007
Price Electricity	0.0000	0.0004	0.0001	0.0000

Table S9: First Order Delta Moment-Independent and Sobol Indices for Total Land Use-Dry Year

Input Variable	Delta		Sobol	
	S1	S1_conf	S1	S1_conf
Groundwater Restriction	0.0316	0.0005	0.0315	0.0038
Price Electricity	0.0011	0.0001	0.0010	0.0006
Price Surface Water	0.0003	0.0001	0.0003	0.0007
Alfalfa Price	0.0001	0.0001	-0.0001	0.0002
Almonds and Pistachios Price	0.0019	0.0001	0.0024	0.0011
Corn Price	0.0002	0.0001	0.0000	0.0001
Cotton Price	0.0001	0.0000	-0.0001	0.0002
Cucurbits Price	0.0003	0.0001	0.0001	0.0003
Fresh Tomatoes Price	0.0008	0.0001	0.0007	0.0006
Grain Price	0.0012	0.0001	0.0000	0.0001
Onions and Garlic Price	0.0019	0.0002	0.0010	0.0006
Other Deciduous Price	0.0013	0.0001	0.0003	0.0004
Other Deciduous Price	0.0001	0.0000	0.0000	0.0000
Other Truck Price	0.0184	0.0004	0.0182	0.0030
Potatoes Price	0.0004	0.0001	0.0005	0.0004
Processing Tomatoes Price	0.0001	0.0000	0.0000	0.0003
Subtropical Price	0.0237	0.0004	0.0234	0.0032

Vine Price	0.7077	0.0006	0.7077	0.0142
Other Field Price	0.0002	0.0000	0.0000	0.0001
Other Field Price	0.0001	0.0000	0.0001	0.0004
Other Field Price	0.0035	0.0002	0.0001	0.0001
Other Field Price	0.0004	0.0001	0.0000	0.0000
Other Field Price	0.0002	0.0001	-0.0001	0.0002
Other Field Price	0.0001	0.0000	0.0000	0.0002
Other Field Price	0.0002	0.0000	0.0000	0.0002
Other Field Price	0.0004	0.0001	0.0000	0.0001
Other Field Price	0.0001	0.0000	0.0001	0.0001
Other Field Price	0.0001	0.0000	-0.0001	0.0001
Other Field Price	0.0009	0.0001	0.0007	0.0005
Other Field Price	0.0016	0.0001	0.0000	0.0001
Other Field Price	0.0002	0.0001	0.0000	0.0001
Other Field Price	0.0001	0.0000	0.0002	0.0003
Other Field Price	0.0007	0.0001	0.0006	0.0015
Alfalfa Yield	0.0001	0.0000	0.0000	0.0002
Almonds and Pistachios Yield	0.0032	0.0002	0.0033	0.0014
Corn Yield	0.0002	0.0000	0.0000	0.0001
Cotton Yield	0.0001	0.0000	0.0000	0.0001
Cucurbits Yield	0.0002	0.0001	0.0001	0.0001
Fresh Tomatoes Yield	0.0003	0.0001	0.0003	0.0004
Grain Yield	0.0001	0.0000	0.0000	0.0001
Onions and Garlic Yield	0.0003	0.0000	0.0001	0.0003
Other Deciduous Yield	0.0003	0.0001	0.0000	0.0004
Other Deciduous Yield	0.0002	0.0001	0.0000	0.0001
Other Truck Yield	0.0047	0.0002	0.0051	0.0017
Potatoes Yield	0.0002	0.0000	0.0000	0.0004
Processing Tomatoes Yield	0.0001	0.0000	0.0000	0.0002
Subtropical Yield	0.0061	0.0002	0.0060	0.0020
Vine Yield	0.1783	0.0009	0.1786	0.0080

Table S10: First Order Delta Moment-Independent and Sobol Indices for Total Net Revenue-Dry Year

References

Zeff HB, Hamilton AL, Malek K, Herman JD, Cohen JS, Medellin-Azuara J, Reed PM, Characklis GW (2021) California's food-energy-water system: An open source simulation model of adaptive surface and groundwater management in the Central Valley. Environmental Modelling & Software 141:105052, DOI 10.1016/j.envsoft.2021.105052

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