Moment-based Markov Equilibrium Estimation of High-Dimension Dynamic Games: An Application to Groundwater Management in California*

Louis Sears C.-Y. Cynthia Lin Lawell Gerald Torres M. Todd Walter

Abstract

Groundwater is a critical natural resource for both irrigated agriculture and for the development of population centers in arid regions of California. As a common pool resource, groundwater suffers from spatial pumping externalities whereby one user's groundwater extraction raises the extraction cost and lowers the total amount available to other nearby users. In addition, groundwater aquifers in California in many cases are located in arid regions with little natural recharge; as a consequence, pricing water to only recover the present costs of extraction may not reflect the full social long-run value of groundwater, and thus may lead to overconsumption. Another source of inefficiency arises because water districts are not pure profit-maximizing organizations, and thus may price water to meet political objectives, rather than promoting long-run social welfare. When empirically modeling groundwater extraction behavior, capturing the dynamic, spatial, and strategic aspects of the decision-making of groundwater users is critical to arrive at unbiased estimators of structural parameters in their decision-making problem. In this paper, we use recent advances in the fields of dynamic game theory and structural estimation to estimate the parameters of the payoff functions of groundwater users under open access, and solve for their full strategies. Our estimation design assumes that observed behavior in the dynamic game is consistent with a moment-based Markov equilibrium, in which knowledge of the state space is limited to the private state and the distribution of the states of all other players. We then analyze how players respond to counterfactual changes in the rules governing extraction, the incentives of players, the hydrology of the system, and the climate and economy of the region. This allows us to measure long-run welfare implications of several of the factors affecting the efficiency of groundwater use in California.

Keywords: structural estimation, dynamic games, moment-based Markov equilibrium, groundwater, California
***JEL* Codes:** Q30, L95, C57
This draft: June 3, 2023

---

*Sears: Cornell University; lss34@cornell.edu. Lin Lawell: Cornell University; clinlawell@cornell.edu. Torres: Yale University; gerald.torres@yale.edu. Walter: Cornell University; mtw5@cornell.edu. David Lim provided excellent research assistance. We thank Todd Gerarden, Shanjun Li, and Ivan Rudik for detailed and helpful comments. We also benefited from comments from seminar participants at Cornell University and conference participants at the Agricultural and Applied Economics Association (AAEA) Annual Meeting. We are grateful to Emmanuel Asinas, Cayle Little, Morrie Orang, and Richard Snyder helping us acquire the data. We received funding for our research from Robert R. Dyson; a Cornell University Ching Endowment Summer Fellowship; a Cornell University Institute for the Social Sciences Small Grant; the U.S. Department of Agriculture (USDA) National Institute of Food and Agriculture (NIFA); a Cornell DEEP-GREEN-RADAR Research Grant; a Cornell TREESPEAR Research Grant; the Khaled H. Kheiravar Memorial Scholarship; the Giannini Foundation of Agricultural Economics; and the 2015-2016 Bacon Public Lectureship and White Paper Competition. Lin Lawell and Walter are Faculty Fellows and Torres is a former Faculty Fellow at the Cornell Atkinson Center for Sustainability. All errors are our own.

1 Introduction

Groundwater in the arid Western United States presents one of the most pressing examples of a "common pool" natural resource problem, with important short- and long-term implications for agriculture, urban development, and the region's environment. California farms produce more than two-thirds of the United States' fruit, nut, and vegetable crops, as well as many of the country's other most profitable specialty crops, on just under 10 million acres of irrigated farmland, bringing in around $50 billion in sales (California Department of Food and Agriculture, 2022; California Department of Water Resources, 2022). Groundwater extraction has generally outpaced recharge in California, leading to long-term declines in groundwater table levels (Famiglietti et al., 2011; Famiglietti, 2014). During droughts, when farmers and other water users have to cope with the absence of surface water supplies, groundwater constitutes close to two-thirds of the water used in California (Stockstad, 2020). This is a long-term concern as projections suggest that extreme weather events like prolonged droughts are expected to occur with greater frequency as global temperatures increase (Hanson et al., 2012; Taylor et al., 2013).

As a common pool resource, groundwater suffers from spatial pumping externalities whereby one user's groundwater extraction raises the extraction cost and lowers the total amount available to other nearby users (Lin Lawell, 2016; Sears and Lin Lawell, 2019). This uninternalized externality can generate social deadweight loss through overextraction (Provencher and Burt, 1993; Brozović et al., 2010; Pfeiffer and Lin, 2012; Lin Lawell, 2016; Sears et al., 2019). In addition, groundwater aquifers in California in many cases are located in arid regions with little natural recharge. As a consequence, groundwater resources should be managed dynamically, and extraction decisions should account for the marginal user cost, or the value to the user of leaving a marginal unit of the resource in the ground for future extraction. Pricing water to only recover the present costs of extraction, as is the case for private well owners, or pricing water to only meet an engineering cost of water supply in the present may not reflect the full social long-run value of groundwater, and thus may lead to overconsumption.

An additional source of inefficiency arises because water districts are not pure profit-maximizing organizations, and thus may price water to meet political objectives, rather than promoting long-run social welfare (Timmins, 2002; Sears et al., 2023). In Sears et al. (2023), we studied the implications of this phenomenon, which we referred to as "consumer surplus weighting", along with the spatial externalities from extraction, using a structural econometric model of a dynamic game played among a mix of cities, farmers, and other well owners in the region around the adjudicated Beaumont Basin in Southern California. We found evidence that both consumer surplus over-weighting and spatial externalities are sources of socially inefficient groundwater extraction, and that the property rights regime instituted to help manage groundwater resources did not correct these problems in the years immediately following their implementation.

When empirically modeling groundwater extraction behavior, capturing the dynamic, spatial, and strategic aspects of the decision-making of groundwater users is critical to arrive at unbiased estimators of structural parameters in their decision-making problem. For this reason structural models of dynamic games are an attractive solution. Structural models impose assumptions about the structure of preferences for agents in the model, and about the equilibrium in the dynamic game. Under these assumptions they deliver consistent estimates of parameters in the payoff functions of players, and can be used to conduct counterfactual analysis and quantify welfare for economic actors in the model. Beyond the imposition of assumptions regarding the structure of preferences, these models present two distinct challenges addressed in our paper. First, many impose an assumption of behavior taking place under a Markov Perfect Equilibrium (MPE), in which players maximize the present discounted value of the entire stream of their expected per period profits conditional on their action choice, the state of the game, and the state-space strategies of all other players in the game, which are assumed to be common knowledge (Ericson and Pakes, 1995). Second, in cases like groundwater, with large numbers of players and state variables, the state of the game can have a large dimension, which makes solving for the optimal strategies of players computationally impossible. A solution to this pair of problems is the use of so-called oblivious equilibrium models, in which knowledge of the state space is restricted for players in their decision-making process (Weintraub et al., 2008; Benkard et al., 2015).

In this paper we build on our approach in Sears et al. (2023) by using recent advances in the modeling of dynamic games to develop a maximum likelihood estimator for the structural parameters in the payoff functions of groundwater extractors in Beaumont. Our estimation design assumes that observed behavior in the dynamic game is consistent with a moment-based Markov equilibrium, in which knowledge of the state space is limited to the private state and the distribution of the states of all other players (Ifrach and Weintraub, 2017). We then solve for the full optimal strategies of players under different assumptions about the hydrology of the basin, the rules governing players, and the state of the regional climate and economy. This allows us to interpret differences in payoffs as the long-run effect of these counterfactual assumptions. We can also decompose the social welfare losses observed under open access in Sears et al. (2023) to determine the relative social costs of the distortions we identified in our analysis.

Our paper proceeds as follows. Section 2 discusses how our paper fits in the literature surrounding structural models of dynamic games. Section 3 presents our model of moment-based Markov equilibrium in our dynamic extraction game, and explains our estimation procedure. Sectionsec:data discusses our data sources and empirical setting. Section 5 presents our preliminary results. In Section 6, we run counterfactual simulations to analyze the sources of inefficiency in groundwater management in California. Section 7 discusses the implications of our results, our planned next steps, and conclude.

2 Literature Review

Our paper contributes to a growing literature dealing with adapting full solution-based structural econometric models to high dimension dynamic games. Full solution-based methods nest the solution to a dynamic optimization problem in the estimation procedure, ensuring that observed behavior is consistent with the player's value function under the estimated structural parameters and a single equilibrium. This approach was developed in the single agent context by Rust (1987) through a nested fixed point maximum likelihood estimation procedure. It has been extended to dynamic games in applications including Igami (2017); Goettler and Gordon (2011); Seim (2006). This motivates our paper's estimation procedure which nests a solution to a dynamic game within a maximum likelihood estimation procedure. Using this approach gives us a solution to the players' policy functions over the full state space, allowing us to analyze how players would behave over the long term. We can also re-solve for policy functions under counterfactual assumptions and determine the long-term welfare consequences.

One alternative to full solution methods that was introduced by Hotz and Miller (1993) is to use a mapping of observed choice probabilities to differences in the action dependent value function to avoid embedding solutions to the full dynamic optimization problem in the estimation procedure. This approach has been adapted to dynamic games (Bajari et al., 2007; Pakes et al., 2007). Another alternative to full solution methods, the forward simulation-based approach of Bajari et al. (2007), which we used in Sears et al. (2023), has been used widely in empirical research to study a wide range of industries and issues (Ryan, 2012; Fowlie et al., 2016; Gerarden, 2023; Yi et al., 2023; Leyden, 2019; Rojas Valdés et al., 2023; Sears et al., 2023). This approach involves approximating the action dependent value function through simulating the game using estimates of the observed policy function and state transition density. The key disadvantage to using forward simulation under observed equilibrium strategies is in how counterfactual analysis can be interpreted. By using policy functions based on the observed data to approximate behavior under counterfactual assumptions, the analysis must be interpreted as short run, meaning that players cannot adjust their strategies in the immediate term. For the purposes of this paper, it is important to understand how players would adapt to significant changes in the fundamental rules and conditions governing behavior. Thus our paper harnesses the advantages of full solution methods, and may be a useful example for future research using these techniques.

Our paper also contributes to the literature surrounding the so-called "curse of dimensionality". Many of the structural econometric models of dynamic games in the literature rely on an assumption of behavior being consistent with a Markov Perfect Equilibrium (MPE) (Ericson and Pakes, 1995; Maskin and Tirole, 1988a,b). Under a MPE, the full state of the game is common knowledge, as are strategies for each of the players and the transition dynamics for the state variables. Then players dynamically optimize by maximizing the present discounted value of the stream of expected payoffs conditional on the current state of the game. Players' actions may or may not affect the payoffs of other players and the transition of the state over time; nevertheless, since strategies are common knowledge, each player's equilibrium action choice can be viewed as a best response to the choices of all other players. As dynamic games expand in the number of players in the market, or the number of states for a given player, the state space grows exponentially. This is referred to as the curse of dimensionality. Thus, even if each player possesses only a single binary state, representing being an active participant in the game, if there are 20 players involved, there will be 2^{20}, or over one million, different possible values for the state of the game. This becomes infeasible rapidly when the number of states for the player grows, or the states become more complex variables.

One solution to address the curse of dimensionality and provide a full solution to the game is to weaken the assumption that players condition their strategy on the full state of the game. Under an oblivious equilibrium, proposed by (Weintraub et al., 2008), players track their own individual state, which is a component of the full state of the game, while assuming that the full state remains at a long-term average level. One particular disadvantage of this assumption comes when players' payoffs, or the evolution of their payoff-relevant state variables, depend on the states or action choices of other players. In this case, when the private states of other players diverge from the long-term average, the player's own expectations about thier future payoffs will also diverge from the true value. In the case of groundwater, this could clearly be the case, since the stock of groundwater in a water stressed region could be falling over time, making the long-term average a poor proxy for the state of other players. Benkard et al. (2015) deal with this problem by allowing firms to track the private states of a small subset of so-called "dominant" firms while treating all other firms as part of a"fringe" group who are assumed to remain at the long-term average state. Ifrach and Weintraub (2017) allows firms to track moments of the distribution of the fringe group's private states. The equilibrium proposed by Ifrach and Weintraub (2017) is called a moment-based Markov equilibrium (MME), and is the equilibrium assumption we make in this paper. Our paper is one of a number of recent papers to make use of this methodological development, including Jeon (2022); Corbae and D'Erasmo (2021); Gowrisankaran et al. (2023); Gerarden (2023).

MME reduces the full state of all fringe firms to a set of moments of its distribution. While this allows for the player to build in more information about the state of other players, the moments are not sufficient to fully characterize the expected transition dynamics. Several different distributions consistent with the same set of moments may produce different expected transition dynamics, meaning that the econometrician must make assumptions regarding how players form their beliefs about a "perceived transition density" at a given moment state. Our paper contributes to this literature by interpreting this assumption as a realistic limitation on the information publicly available to players. In other words, players were likely to only have access to summary statistics, or a subset of monitoring data regarding the state variable in the game (depth to groundwater), rather than measured levels at each well when making their decisions. We can solve for the additional value any player can gain by having access to the full state vector when making their action choice. We interpret this as the value of information to players. This contributes to the literature around the value of information in dynamic games, and the value of groundwater monitoring data.

3 Model and Estimation Procedure

3.1 Model Setup

We model a dynamic extraction game played in open access by a fixed number of players I in a single market. In each period t, each player i chooses their action $a_{it} \in A_i$, where the action a_{it} represents player i's extraction at his wells during period t and A_i represents the set of action choices for player i. The full state of the game s_t in each period t is comprised of a vector of depth to groundwater x_{it} at the wells for each player i; as well as a vector z_t of public states representing weather, the hydrology of soil around each of the wells, and the state of the economy. Let $\eta_{it} \equiv \eta(a_{it} \| a_{it} \in A_i$ represents a vector of action-specific private information payoff shocks assumed to be known only to the player, and are therefore not observed by either other players or the econometrician. For each player i, payoffs are determined by the player's own extraction a_{it}, the player's own depth to groundwater x_{it}, the public state z_t, and the private information shocks η_{it}. We assume that payoffs for each player are linear in parameters θ, where the vector $W(\cdot)$ of terms in the deterministic component of payoffs is a function of the state and action choice:

$$\pi_i(a_{it}, x_{it}, z_t, \eta_{it}) = \theta' W(a_{it}, x_{it}, z_t) + \eta_{it}(a_{it}). \tag{1}$$

Here it is important to note that the actions of other players do not directly affect the player's period payoffs, but instead affect the expected future payoffs of the player through their expected impact on the future value of the player's private state, depth to groundwater x_{it}. Let $x_t \equiv (x_{1t}, ..., x_{It}) = (x_{it}, x_{-it})$ denote the vector of depth to groundwater x_{it} of all players i. The true state transition density for the vector x_t of depth to groundwater is a stochastic function of the depth to groundwater of all players x_t, the action choices of all players $a_t \equiv (a_{1t}, ..., a_{It}) = (a_{it}, a_{-it})$, and the public state z_t:

$$x_{t+1} = T(x_t, a_t, z_t) + \epsilon_t, \tag{2}$$

where $T(\cdot)$ is the deterministic component of the transition dynamics for the depth to groundwater for all players x_t, and $\epsilon_t \equiv (\epsilon_{1t}, ..., \epsilon_{It})$ is a vector of i.i.d. random draws from a distribution g.

We treat behavior as part of a moment-based Markov equilibrium (MME), wherein players do not have full knowledge of the private states x_{it} of other players, but instead only track moments of the distribution of others' private states (Ifrach and Weintraub, 2017). We therefore restrict each player i's knowledge of the state space to player i's own private depth to groundwater state x_{it}, player i's own extraction action a_{it}, the public state z_t, and $\hat{x}_t$, where $\hat{x}_t$ equals the mean depth to groundwater x_t over all players at time t. Making this assumption restricts each player's knowledge of the expected transition dynamics, meaning that instead of having access to the true state transition density $T(x_t, a_t, z_t)$, player i only has access to his "perceived transition density" $\hat{T}_i(x_{it}, a_{it}, z_t, \hat{x}_t)$.

An important component of how we structure the MME is the assumptions we make about players' beliefs at a given value of mean depth to groundwater $\hat{x}_t$. Ifrach and Weintraub (2017) suggests using simulation to sample the state space and produce expected transitions from these simulated data. We discuss our assumptions regarding how we determine beliefs in our estimation section. From their beliefs $\bar{x}_{-it}$ about the distribution of others' private states x_{-it}, as well as their knowledge of the public state z_t, the distribution f_{-i} of private information for other players, and the payoff functions $\pi_{-it}(\cdot)$ of other players, each player i can form beliefs about the expected action choices of other players $\bar{a}_{-it}$, and about the expected transition density (or "perceived transition density") $\hat{T}_i$ of the moment state. Then we can define $\hat{T}_i$ as:

$$\hat{T}_i(x_{it}, a_{it}, z_t, \hat{x}_t) = T_i((x_{it}, \bar{x}_{-it}(\hat{x}_t)), (a_{it}, \bar{a}_{-it}(\bar{x}_{-it}(\hat{x}_t), z_t, f_{-i})), z_t), \tag{3}$$

where $\hat{T}_i(\cdot)$ is the deterministic component of player i's perceived transition dynamics for the depth to groundwater for all players x_t, from which player i can then generate their expectation for the mean depth to groundwater $\hat{x}_{t+1}$ next period. Thus we can define the value function for each period t of the finite-horizon dynamic game using the Bellman operator as:

$$V_{it}(x_{it}, \hat{x}_t, z_t, \eta_{it}) = \max_{a_{it} \in A_i} \pi(a_{it}, x_{it}, z_t, \eta_{it}) + \beta E_i[V_{it}(x_{i,t+1}, \hat{x}_{t+1}, z_{t+1}, \eta_{i,t+1}) | a_{it}, x_{it}, \hat{x}_t, z_t, \eta_{it}, \hat{T}_i]. \tag{4}$$

Then each player's strategy can be interpreted as a best response given the value of their own private state x_{it}, their private information shocks η_{it}, their beliefs $\bar{a}_{-it}(\cdot)$ about other players' state space strategies (as formed from the mean depth to groundwater $\hat{x}_t$, the public state z_t, the distribution f_{-i} of private information for other players, and the payoff functions $\pi_{-it}(\cdot)$ of other players), the public state z_t, and their assumed beliefs $\hat{T}_i$ about the distribution of next period's moment state.

3.2 Estimation Strategy

To estimate our model we make use a maximum likelihood estimator with a nested solution to our dynamic game. This provides us with parameter estimates for θ that generate equilibrium behavior that is consistent with with the observed behavior and our modeling assumptions. Here we explain both steps of our estimation procedure, as well as the assumptions used to identify the model.

3.2.1 Maximium Likelihood Procedure

Our estimation procedure uses maximum likelihood to identify parameters in the payoff functions of players. This differs from our approach in Sears et al. (2023), where we minimized profitable deviations from observed strategies to identify parameters. Our estimation strategy follows a simple algorithm summarized in Table 1.

In our estimation procedure we use an unconstrained nonlinear function minimization algorithm

Table 1: Maximum Likelihood Algorithm

1. Propose initial parameter vector guess $\hat{\theta}$ and arbitrary value for the log likelihood $\hat{l}$
2. Solve for the action-dependent value function $v_{it}(a_{it}, x_{it}, \hat{x}_t, z_t, \hat{\theta})$ for each period t using backwards induction solution algorithm for finite horizon game
3. Determine the conditional choice probabilities for each period t at each observed state in the dataset for each player using $f_i(\eta_{it})$, the probability density for each player's private information
4. Set $\hat{l}$ equal to the sum of the log of the conditional choice probabilities in the observed states
5. Check for convergence of $\hat{l}$
    5a. If converged, return the current parameter vector guess $\hat{\theta}$
    5b. If not converged, perturb the current parameter vector guess $\hat{\theta}$ and return to Step 2

to solve for the parameter vector that minimizes the negative value of $\hat{l}$, and estimate our model using MATLAB Version R2021b. We used several candidate initial guesses for the parameter vector and chose our ultimate guess based on the overall fit with the actual data.

We make several assumptions. The first identifying assumption relates to equilibrium in our dynamic game.

Assumption 1. While multiple equilibria may exist, all observed behavior is part of a single equilibrium.

Assumption 1 is a common assumption in identifying structural models of dynamic games. While we cannot provide an empirical test of this assumption, we argue that the rules governing groundwater extraction did not vary during our sample period. Our sample is from only one game and the sample period is relatively short, meaning that while key features like the level of the stock, weather, and the regional economy varied during our short time period, we are unlikely to see changes in longer term features of these variables that might arise from structural changes such as climate change, structural changes in the economy, or changes in irrigation and groundwater recharge technology. In particular, managed artifical recharge was not practiced during this time as the region was not interconnected with aqueduct systems that allowed for water imports. We shorten the timeframe of our model to avoid shifts in each of these variables which occurred in later years. Thus, we think it is reasonable to assume that behavior is generated from a single equilibrium.

The choice conditional value function represents the expected value in period t of each action choice excluding the effect of private information. Our second assumption is in regards to f_i, the distribution of the private information shocks η_{it}.

Assumption 2. $f_i(\eta_{it})$ is distributed i.i.d. type 1 extreme value.

Assumption 2 allows us to compute a closed form solution for the conditional choice probabilities using the values of the payoff function for each action choice. This is a common modeling choice in discrete choice models like ours, and allows us to avoid computationally expensive alternative like numeric integration over the distribution of the private information shocks η_{it}.

3.2.2 Backwards Induction Solution

The major step in our estimation procedure is to solve our finite-horizon dynamic game. To do this we make use of backwards induction to solve the game by interating backwards from the terminal period T. We discretize the action space A_i, the private state space, and the moment state space for the average depth to groundwater. Thus the modified state space observed by the econometrician can then be summarized using the vector $(x_{it}, \hat{x}_t, z_t)$. Solving for the strategy of each player in the final period involves a simple profit maximization problem over A_i for each tuple $(x_{iT}, \hat{x}_T, z_T, \eta_{iT})$. For appropriators we determine payoffs as a function of profits from water sales, consumer surplus, and the effects of other state variables on other volume related costs and benefits. To determine profits from water sales and consumer surplus we use a model of residential water demand estimated in Sears et al. (2023).[1] Results for this model can be found in Table B.1.

The public state z_t is assumed evolve according to the players' rational expectations, and thus does not add to the dimension of the modified state space in any year. After solving for the period profit as a function of the action choice, excluding the additive effects of private information, we can determine conditional choice probabilities, and integrate over the action choices and their values to determine estimate of the optimized value in the final period T of reaching each discretized value in the state space, $\hat{V}_{iT}$. We can then move one step backwards to period $T-1$.

In each of the periods t leading up to T, our solution for the optimized value $\hat{V}_{it}$ of the state from that period t onwards differs from the terminal period through its dependence on the continuation value, or the expected value of the state in the next period.

As explained in our model setup, players must judge the impact of their own action on the stock x_{it} at their own well, and the average level of the stock $\hat{x}_t$ at each well in the game. To do this players must form expectations over the set of full state variables they believe they could be at, that are consistent with the private state and average state which they observe. They also must form expectations over the strategy they believe the other players would play at each of these states. To do this we make three additional assumptions:

Assumption 3. For any value of $\hat{x}_t$, the perceived value of the state for other players is given by $\bar{x}_{-it}(\hat{x}_t) = \hat{x}_t + C_{-i}$, where C_{-i} is a vector of constants representing differences in the long-term average of depth to groundwater at each of the wells.

In particular, for each of the other players, the corresponding component of the vector of constants C_{-i} is the period 1 difference between that player's actual state x_{it} and the actual average state $\hat{x}_t$. This would treat the groundwater table for other players as a perceived bathtub with different elevation levels for player wells that are known and vary over space. Assumption 3 simplifies our task of forming expectations over all possible distributions of the state that are consistent with the

[1] Our residential water demand function is not a new contribution from this paper, and so our discussion of our modeling choices and results are limited in the main text. In Appendix Section B.1 we include our description of this model from Sears et al. (2023).

observed average, a computationally intensive task. It also has a useful interpretation, as differences in the long-term average depth to groundwater across wells correlate closely with differences in elevation at the wells. Treating the beliefs about differences in depth to groundwater across space as wholly dependent on these differences in elevation, is equivalent to assuming that players use a "bathtub" model to form their expectations about the level of the groundwater stock across space. In future versions of this paper we will solve for the implications of providing more information to players about spatial heterogeneity in the water table level.

> **Assumption 4.** The strategy $\bar{a}_{-it}(\bar{x}_{-it}(\hat{x}_t), z_t, f_{-i})$ of other players $-i$ is the average static profit maximizing action for each other player $-i$.

Assumption 4 allows us to form an expectation of the strategy of other players that only depends on the beliefs $\bar{x}_{-it}(\hat{x}_t)$ about their current depth to groundwater, the public state z_t, the distribution f_{-i} of the private information shock, and the structural parameter vector θ. Crucially it does not depend on beliefs about the beliefs of other players regarding the player's own strategy, and thus allows us to form expectations for each player independently in each period. We believe this is a realistic and reasonable assumption to make given the open access environment in which players operated during this period. Open access common pool resource extraction is often modeled using static profit maximization given the strong incentives for players to free-ride on the conservation efforts of others. In future extensions of this paper we plan to test the robustness of our results to different assumptions about the strategies of other players. In our algorithm we take a set of random draws to iterate over the distributions of the transition shocks ϵ, and simulate the expected transition for each action choice in the current player's action set to form the player's perceived transition function $\hat{T}_i$.

> **Assumption 5.** The true state transition density's form is known by players for a given full state x_t and full set of action choices a_t.

Assumption 5 allows us to determine perceived transitions that are consistent with the true state transition density and the player's beliefs about the full state, and the strategies of all other players. Note though that while the player knows how the state would transition with full knowledge of the state vector and the strategies of all other players, that they do not have access to this full information set, and thus, in practice they make use of the perceived transition density to form their payoff expectations. In our estimation procedure we use the estimated state transition densities from Sears et al. (2023). These functions can be found in Table 4.

With these assumptions about the beliefs of the player, and our knowledge of the value function over the moment states in the next period, we can form the choice-dependent expected value function for each action choice in each moment state in the current period. We determine the period profits and add the discounted value of the expected value of the next period's moment state conditional on the current moment state, the action choice, and the perceived transition function. Here we make the following further assumption:

Assumption 6. The discount factor β is constant and known across players and equals 0.9.

Assuming a value of β helps to identify our model, since our likelihoods will depend on differences in expected payoffs which vary with the level of the discount factor. We use the same discount factor used in Sears et al. (2023) to make our results comparable.

Once the choice-dependent value function is formed for period t we can again use the distribution of private information to solve for conditional choice probabilities for period t and integrate over the action choices and their values to assign a value for the moment state. After conducting this step for each player we can move to the previous period $t-1$ and repeat all the way until we have solved for the value function in the first period $t = 1$. Our backwards induction algorithm is summarized in Table 2.

Table 2: Backwards Induction Algorithm

1. Set t=T
   - 1a. Set $v_{iT}(a_{iT}, x_{iT}, \hat{x}_T, z_T) = \pi_i(a_{iT}, x_{iT}, z_T, \theta)$
   - 1b. Determine $Pr_{iT}(a_{iT}|x_{iT}, \hat{x}_T, z_T, v_{iT}, f_i(\eta_{iT}))$
   - 1c. Set $\hat{V}_{iT}(x_{iT}, \hat{x}_T, z_T) = \sum_{a_{iT}\in A_i} Pr_{iT}(a_{iT}|x_{iT}, \hat{x}_T, z_T, v_{iT}, f_i(\eta_{iT})) \cdot v_{iT}(a_{iT}, x_{iT}, \hat{x}_T, z_T)$
   - 1d. Set t=T-1
2. While $t \geq 1$
   - 2a. Set $\bar{x}_{-it}(\hat{x}_t) = \hat{x}_t + C_{-i}$
   - 2b. Set $a_{-it}(\bar{x}_t, z_t, \eta_{-it}) = E_{\eta_{-it}}\left[\arg\max_{a_{-it}\in A_{-i}} \pi(a_{-it}, \bar{x}_t, z_t, \eta_{-it})\right]$ for each of the other players $-i$.
   - 2c. Form $Pr_{-it}(a_{-it}|\bar{x}_t, z_t, f_{-i})$. Set $\bar{a}_{-it} = \sum_{a_{-it}\in A_{-i}} Pr_{-it}(a_{-it}|\bar{x}_t, z_t, f_{-i}) \cdot a_{-it}$
   - 2d. Take K draws of ϵ_t. Simulate forward K times for each tuple (a_{it}, x_{it}, z_t), using $T((x_{it}, \bar{x}_{-it}(\hat{x}_t)), a_t, z_t)$. Using K values of x_{t+1}, form $\hat{T}_i(x_{it}, a_{it}, z_t, (x_{it}, \bar{x}_{-it}(\hat{x}_t)))$, player i's perceived expected transition density for $x_{i,t+1}$ and $\hat{x}_{t+1}$.
   - 2e. Set $v_{it}(a_{it}, x_{it}, \hat{x}_t, z_t) = \pi_i(a_{it}, x_{it}, z_t, \theta) + E_i[\hat{V}_{i,t+1}(x_{i,t+1}, \hat{x}_{t+1}, z_{t+1})|a_{it}, x_{it}, \hat{x}_t, z_t, \hat{T}_i]$.
   - 2f. Determine $Pr_{it}(a_{it}|x_{it}, \hat{x}_t, z_t, v_i, f_i(\eta_{it}))$
   - 2g. Set $\hat{V}_{it}(x_{it}, \hat{x}_t, z_t) = \sum_{a_{it}\in A_i} Pr_{it}(a_{it}|x_{it}, \hat{x}_t, z_t, v_i, f_i(\eta_{it})) \cdot v_{it}(a_{it}, x_{it}, \hat{x}_t, z_t)$
   - 2h. Set $t = t - 1$

3.3 Standard Errors

We compute standard errors by bootstrapping our estimation procedure. In each bootstrap, we draw a sample of players from our dataset that is balanced across locations and types of players to be consistent with our original dataset. We then re-run our estimation procedure, and track the parameter estimates. We run this process for 100 bootstrapped parameter estimates, and take sample standard deviations of the parameter estimates to determine standard errors. We then use a student's t-distribution to determine statistical significance for our structural parameters, and our welfare quantity differences.

In Sears et al. (2023) we used a slightly different procedure to compute our bootstrap. In that paper we drew an alternate set of years from the dataset and used the variation in the exogenous state variables in these alternate datasets to produce variation. This was possible because we assumed that our parametric policy functions captured the players' strategies and could predict action choices correctly in these counterfactual datasets. In contrast, in our maximum likelihood estimation we can only use data from our observed dataset to estimate the model. Since differences in the continuation value help to explain action choices, altering the path of payoff relevant state variables will generate variation in payoffs. This variation can not be used to explain actual behavior in our dataset, since the observed behavior represents the strategy under the expectation that the states will evolve as they do in the actual dataset. Thus we need an alternative source of variation.

4 Data and Empirical Application

We make use of the same dataset used in (Sears et al., 2023). We rely on a number of sources. Summary statistics for data we have incorporated into our estimation can be found in Tables A.1-A.3 in the Appendix.

Our data covers extraction at the player-basin-year observation level. For our extraction data we use a mix of data from the San Timoteo Watershed Management Authority, the San Gorgonio Pass Water Agency, and the Beaumont Basin Watermaster. For appropriators in the judgment we have two extraction observations each year (i.e., extraction inside Beaumont Basin and extraction outside Beaumont Basin), while for other extractors we have one observation per year (i.e., extraction either inside or outside Beaumont Basin).

We make use of detailed well construction reports from administrative records kept by the State of California to determine well characteristics and location for each owner in each year. These records come from the California State Water Resources Control Board's Groundwater Recordation Program (California State Water Resources Control Board, 2021). We merge the handwritten hard-copy historical records wells location data from the Groundwater Recordation Program and a well completion report dataset from the California Department of Water Resources with the well's state well identification number to determine the location of each the wells, and then merge the resulting well characteristics and location data with reported data from the Beaumont Basin Watermaster and the San Timoteo Watershed Management Authority. Crucially, these data allow us to observe when any new wells are brought online, and thus provide variation within a single owner's data in the characteristics of well ownership. We map our well locations data to data from the USDA Web Soil Survey and calculate an average saturated hydraulic conductivity value for each owner's wells inside and outside the Beaumont Basin; these data are fixed over time.

We use observations from the US Geological Survey (USGS) Historical observations dataset to determine elevation of the water table and depth to groundwater. We determine an annual depth to groundwater value near each owner's wells inside or outside the boundaries of the Beaumont Basin. We use the well location, and the location of the monitoring sites to average over the nearest neighbor monitoring observations for each well owned by an owner either inside or outside the basin.

We interpolate for missing years in our depth to groundwater data by using the inverse-distance weighted annual change in depth to groundwater at other nearby wells with available data.

We obtain prices for relevant agricultural crops (apples, cherries, grapes, alfalfa, olives, and strawberries) from the USDA NASS Monthly Agricultural Prices survey. We use end-of-March surveys in each year to map a price. We choose this month to correspond to the price data available at the time of the planting decision for farmers. For our policy function and state transition estimation involving electricity prices, we use data from the Southern California Edison on annual end-use price by sector. For real GDP per capita, we use statewide annual data from the US BEA, with chained 1997 prices. For data on unemployment rate and CPI, we use state-level data from the Federal Reserve Economic Data supplied by the St. Louis Federal Reserve Bank. For county-level personal income, we use data from the State of California Franchise Tax Board. We take prices for untreated water from the Metropolitan Water District, a large State Water Project Contractor in Southern California.

We make use of precipitation and daily maximum temperature data from the PRISM Climate Group (PRISM Climate Group and Oregon State University, 2018). We use 4 km resolution data from the PRISM's historical dataset, and map it to the extraction wells in our dataset based on location. We then collapse our data into annual and growing season (April-October) averages across wells inside or outside the Beaumont Basin for each owner.

In our demand estimation, we use data on per household monthly residential water demand, fixed charge, variable price, and connection fee from the California/Nevada Water Rate Survey conducted by the American Water Works Association. This survey is conducted once every two years and covers a large sample of municipal water districts in California. We use data on household size and population by city and county from the California Department of Finance; data on median adjusted gross income by county from the California Franchise Tax Board; and data on the industrial average electricity price for California from the US EIA.

5 Results

5.1 Parameter Estimates

Using our empirical strategy and dataset from the Beaumont Basin region, we estimate our MME structural model for the years 1991-1996. The parameter point estimates can be found in Table 5. Looking first at appropriator payoffs we see that all parameters are significant. We find that consumer surplus weighting is still present and on a similar scale as we found in Sears et al. (2023), despite our use of a more flexible payoff function for these players. This suggests that the payoff functions of these players were not well aligned with those of a social planner seeking to maximize the sum of consumer and producer surplus. We find important differences for players payoffs based around the location of extraction, suggesting differences in the perceived costs and benefits of extracting from the different regional basins.

Moving next to farmers, we do not see strong effects from crop prices, as each of the terms associated with a price weighted variable is insignificant. However we do see significant effects from weather, the number of wells owned, and the location of the wells. We do not see a significant cost to ramping up extraction, which we model through a quadratic per well extraction term. These results suggest that farmers may have had access to different agricultural markets based on their relative locations, but were not price sensitive in their decision-making. This may have to do with the small scale of some of these farms, and the relatively smaller extensive margins they may have had to make adjustments to their planting decision. In addition, if these farmers were growing perennial crops, they may have had less flexibility to adjust their irrigation to changes in crop prices through planting/removal each year. In this case weather conditions, which impact the intensive margin of irrigation decisions, through the level of irrigation supplied to each acre, would make up a greater share of the extraction decision.

Finally examining the parameters for our third group of players, golf courses and housing developments, we see that parameter estimates are significant in each case. We see that there was significant variation across different types of players in this group, with golf courses and retirement homes relatively less profitable all else equal. We see that ramping up did create a significant cost for these players, however so did operating a large stock of groundwater wells. We find that when demand for these players services was greatest (periods of housing construction growth, periods of greater economic growth), revenues were unsurprisingly higher.

We can interpret each of these parameters in dollar terms through our identification of extraction lift costs. By including a term that captures this cost in dollars, or the product of the price of electricity, depth to groundwater, extraction, and a conversion factor constant representing the electricity requirement to lift groundwater each additional foot, we can normalize the value of this payoff term to one. This fixes the parameter values for all other terms to dollars.

5.2 Model Fit

We examine the performance of the MME model by simulating behavior under our baseline conditions and comparing it with our observed data. To do this we solve the model backwards using our structural parameter estimates. We then forward simulate 25 trajectories using random draws for the structural error terms ϵ and η. We take means from our simulations for extraction, and depth to groundwater across players and player groups. We produce standard errors by repeating this process using the bootstrapped parameter estimates and taking standard deviations of the simulated quantities.

In Table 6 we show the player group means for depth to groundwater for the period 1991-1996. We differentiate between wells inside and outside the Beaumont Basin for appropriators. We see that the simulated means are generally quite close to the actual data's means. We tend to underestimate depth to groundwater outside of the Beaumont Basin, and slightly overestimate depth inside the Beaumont Basin, though differences are small in magnitude.

In Table 7 we show similar model simulated and actual means for extraction by the different groups of players in our game. Again we find that differences are small generally. We find that slight differences in extraction by appropriators help to explain the differences we observed in depth to groundwater across basins. We find in each case that model simulated bias is around one standard error or less in absolute size.

We then show player group trajectories for depth to groundwater and extraction in Figures 4-6. We find that for appropriators extraction and depth to groundwater generally follow the patterns observed in the data over time. We see that the mean differences we found in tabular form are largely explained by differences in one year of our dataset, but that our model rebounds to values closer to the actual data in the years following this. For farmers we see some variation in depth to groundwater, with our model slightly underestimating depth inside the Beaumont Basin, and over estimating depth outside of the Beaumont Basin. For golf courses and housing developments our model tracks closely with the actual data. The large spike in the final year is due to one player with significantly higher elevation and thus, depth to groundwater, exiting the game in the final period and thus being removed from the sample average. We show individual player trajectories in Figures A.2-A.15.

5.3 Welfare Results

We next turn our analysis to the welfare of players and the welfare of society as a whole. To quantify welfare we solve and simulate our dynamic game. We conduct 25 simulations of the dynamic game and take means of the present discounted payoffs for each player. To produce standard errors we solve and simulate the model 25 times using each of the 100 bootstrapped estimates of the parameter vector and take means for the simulated quantities in each bootstrap. We first compare the simulated welfare with what we observe in the actual data. To determine actual player welfare quantities we compute payoffs using the observed actions, states, and the estimated structural parameters. We then take the present discounted value of the payoffs across the sample period.

We show the model simulated player welfare, actual welfare, and their difference in Table 8. We find that payoffs were large, around $42.7 million dollars per year on average, with the vast majority coming from payoffs to appropriators who extracted the majority of the water in the dynamic game. This is strikingly close to our result from Sears et al. (2023), where we found actual welfare of $42.5 million per year. We find a significant but relatively small upward bias in the model simulated welfare for these players. However, this is not uniformly positive across players, nor is it positive across player groups. We find that farmers generally made smaller profits, likely reflecting the fact that these are relatively small scale farmers. We found significant variation in the final group of players with larger players including the golf course and larger housing development, making significant returns from groundwater extraction, while the retirmenent homes in our model made much smaller returns. Coscan Stewart Partnership, the player that exited our game in the final period was found to not clear any profit. Since we don't model exit, but instead assume it to be known at the start of the game by the players, this suggests that our model does a strong job of capturing payoffs, as this player would have good reason to exit the game if they were indeed earning negative payoffs by staying in it.

We next quantify social welfare generated from groundwater extraction in the dynamic game. To differentiate between social welfare and player welfare we assume that a social planner would weigh consumer surplus equally with water sale revenues and costs in their payoff function. We assume that producer profits enter directly into social welfare and are determined by the structural parameters in the player payoff functions. In Table 9, we show consumer surplus, producer profits and total social welfare as determined by our model simulated data, our actual data, and the differences in these quantitites. We see that social welfare generated from groundwater extraction owes largely to the consumer surplus generated by appropriators for their customers. Of the \$23.4 million per year generated in social welfare, around \$23.0 comes from consumer surplus. We find a slight bias upwards in our social welfare quantities, primarily due to appropriators, however it is not economically significant, and does not alter our primary findings. Our results here are in line with both our findings in Sears et al. (2023) and make sense given our parameter estimates. Clearly over weighting consumer surplus caused appropriators to generate high quantities of it, while producing barely any producer profits. By weighing this at a lower rate, clearly social welfare will be lower than the sum of player welfares or payoffs. Our results here should be in line with our previous findings if both methods produce valid estimates. Since our prior results rely on a methodology with a longer history of use in the empirical literature, this helps to bolster our case that our current method is valid.

5.4 Valuation of Groundwater Stock

A key factor undermining the social efficiency of groundwater extraction under open access is the degree to which players privately value groundwater stock in the ground vs. the value that society places upon this. In our model groundwater acts according to a so-called "egg-carton" model rather than a "bathtub" model. In other words, the effects of extraction by other players on stock at a groundwater extractor's well depends on proximity to one another and decays as distance increases. This enables players to at least partially manage their groundwater stock and means that they should value stock on their land based on the private benefits it will deliver to them in future periods if they are not fully myopic.

To measure variation in welfare over different levels of groundwater stock for players at their own well and the average of depth to groundwater for all players in the game, we solve for and examine the value function for each player over the full discretized state and moment state space. For each player, the value function in year t is the present discounted value of the entire stream of expected per-period payoffs expected to be earned by the player from year t onwards. The value of the value function at a particular state and moment state is the present discounted value of the entire stream of expected per-period payoffs expected to be earned by the player from year t onwards upon reaching the state and moment state in year t. Value functions and policy functions are solved for by solving the dynamic game using backwards induction over the years 1991-1996 using the estimated structural parameters and state transition densities.

We then examine the value function for each year t as a function of own depth to groundwater and average depth to groundwater in the dynamic game. Since we model our dynamic game as having a finite number of periods, the value function varies for each year t. For appropriators, we differentiate between own depth to groundwater at wells inside the Beaumont Basin and wells outside the Beaumont Basin, while for overlyer players we only include a single value. Since greater levels of depth to groundwater increase costs in the present and in future years, we should expect depth to groundwater at one's own wells to have a negative coefficient. The predicted effect of depth to groundwater at other wells is ambiguous. While greater depth at other wells nearby may be expected to lead to greater flows of groundwater away from one's own wells, and greater costs in the future, it also should lead to less extraction by other players in the present which would decrease present period drawdown effects. Moreover, some players payoffs and behavior may not be strongly impacted by the state of the stock outside of their own wells.

To visualize the relationship between stock and value, we plot the individual player-year value functions for overlying players separately for each player and each year in Figures A.16-A.25 in Appendix A.

To examine the effects of stock on the value function, we run fixed effects regressions for each player group of the value function for players in that player group in that year on the discretized state and moment state for players in that player group in that year. Each row in Table 10 reports the results of a separate regression of the value function for the respective player group in the respective year on the discretized state and moment state for that player group in that year. Regressions by year include player fixed effects. Regressions that pool over all years for a player group include player-year fixed effects. For each player, the value function in that year is the present discounted value of the entire stream of expected per-period payoffs expected to be earned by the player from that year onwards. The value of the value function at a particular state and moment state is the present discounted value of the entire stream of expected per-period payoffs expected to be earned by the player from that year onwards upon reaching the state and moment state in that year. Value functions and policy functions are solved for by solving the dynamic game using backwards induction using the estimated structural parameters and state transition densities.

Looking first at appropriators, we find that the sign for own depth to groundwater is negative and significant across basins. The effect decreases over time in each case and is significantly larger at wells outside the Beaumont Basin, averaging around \$12.6 thousand per foot at wells outside Beaumont and \$1.6 thousand per foot at wells inside Beaumont. Individual year results suggest a positive but insignificant sign for average depth. Pooling all observations produces a significant results of around \$205 per foot. For farmers we find that own depth has a negative and significant sign, and produces an average of only \$63 dollars. average depth again has no effect as results show a precisely estimated 0 value. For golf courses and housing developments we find an own well depth effect that is consistently negative and averages just under \$200 per foot. For average depth we find generally positive results that diminish over time before reaching a value of 0 in the final year of the model. This suggests that for these players the primary effect on welfare for this variable comes through its effect on expected future payoffs.

To examine heterogeneity in our sample across different players and different types of players, we run ordinary least squares (OLS) regressions for each player of the value function for that player in each year on the discretized state and moment state for that player in that year. Each row in each of Tables A.4-A.9 reports the results of a separate regression of the value function for the respective player (or players in the respective player group) in the respective year on the discretized state and moment state for that player (or players in the respective player group) in the respective year.

For appropriators, we find that the coefficient on own depth to groundwater is significant and negative for individual players, although there is significant range across players in these responses, and the magnitude is generally larger at wells outside of Beaumont. The sign is generally insignificant for the average depth to groundwater for individual players, and is not uniformly one sign. As expected the terms decrease in magnitude over time as the dynamic effects decrease in size. When we pool results we find that the sign on the term for depth to groundwater at wells inside the Beaumont Basin is now positive. Pooling using OLS allows variation between players to influence results. Thus if the value of groundwater use varies across players and is correlated with differences in location choices of wells across players, this can lead to perverse results. In this case we may infer that appropriators with high value uses for groundwater may have been willing to pay more for additional groundwater extraction during this period and may have drilled wells in areas where groundwater resources were more expensive to extract, creating positive correlation between the value function depth to groundwater. The pooled effect of the average depth to groundwater value is significant and positive. Variation in this variable should be expected acrosss players since wells varied in their proximity to other groundwater extraction wells in our sample.

Turning to farmers we see significant negative results across individual players, and negative but insignificant results for the pooled sample. Here again between player variation in value may be generating a perverse result in the pooled model, although less so since farmers can only drill wells on their land and thus have more limited options to add wells in more expensive locations when they have high value uses for groundwater. We see a prescisely estimated value of 0 for average depth to groundwater, suggesting that these players do not incoroporate the behavior of others in their decision making or expectations. Finally examining results for golf courses and housing developments we see results that mirror our results for appropriators. Individual regressions suggest a negative coefficient on own depth and a positive coefficient on average depth. These players may have larger landholdings and may have chosen loctions based on factors that are positively correlated with depth to groundwater, like elevation.

Taken together, our results suggest that appropriators tended to place a higher value on groundwater found outside of Beaumont. This suggests that they may have been better able to manage these stocks of groundwater due to lesser competition in the other neighboring basin areas. Since Beaumont was eventually adjudicated and these other basins were not, this makes sense. Our findings also suggest that appropriators placed a greater value on stock levels than others which is consistent with their generally higher welfare levels. Finally, our results suggest important differences across players in the way in which they incorporated information about the overall stock in the region, with farmers not incorporating any value on stock for their neighbors, and all other players actually negatively valuing additional stock in the region that was not on their land.

5.5 Long-Term Behavior

In our base case specification, the continuation value is 0 in the final period T (year 1996) of our open access finite-horizon game. For robustness, in an alternative specification, to further explore long-term behavior and long-term value functions, we make the continuation value in the final period T (year 1996) for each player a function of the player's own depth to groundwater x_{iT} at time T as well as the mean depth to groundwater $\hat{x}_T$ over all players inside and outside of Beaumont Basin at time T. Thus, the continuation value at time T is now a function of own state x_{iT} at time T and the mean state $\hat{x}_T$ at time T; and the coefficients on these terms in the continuation value in the final period T (year 1996) are additional parameters we will estimate along with the parameters in the per-period payoffs.

In particular, for appropriators, the continuation value at time T for each appropriator i is a linear function of own depth to groundwater inside Beaumont Basin at time T, own depth to groundwater outside Beaumont Basin at time T, and mean depth to groundwater at time T over all players inside and outside of Beaumont Basin at time T. For farmers, the continuation value at time T for each farmer i is a linear function of own depth to groundwater at time T and mean depth to groundwater at time T over all players inside and outside of Beaumont Basin at time T. For golf courses and housing developments, the continuation value at time T for each golf course or housing development i is a linear function of own depth to groundwater at time T and mean depth to groundwater at time T over all players inside and outside of Beaumont Basin at time T.

As seen in Table A.10 in Appendix A, the coefficients on own state and moment state in the continuation value in the final period T (year 1996) are all statistically significant and 0, and the parameters in the per-period payoffs are robust to whether the continuation value at time T is 0, or a function of own state and moment state at time T. We therefore use the base case specification in which the continuation value at time T is 0 for our counterfactual analysis.

5.6 Value of Information and Groundwater Stock Monitoring

As a novel way of estimating the welfare impacts of increased monitoring and publishing the depth to groundwater throughout the system, we simulate an alternate version of the dynamic game wherein each player knows the full state of the game, and how other players will extract based on this information; we call this alternative version the 'full state information' model. We can then compare welfare values under the full state information model, with the welfare values under a Markov Perfect Equilibrium from Sears et al. (2023), and with the welfare values under our baseline MME for different types of players.

Our procedure for solving for the action choices under the full state information model, wherein players have access to the full state vector, follows the following algorithm:

Table 3: Full State Information Simulation

1. Set simulation counter $k = 1$ and set time $t = 1$
2. While $k \leq K$ and $t \leq T$
   2a. Set state (x_t, z_t) to historical data state in period t.
   2b. Using baseline estimates for each player's action-dependent value function $v_{it}(a_{it}, x_{it}, \hat{x}_t, z_t, \hat{\theta})$ for each period t as solved using the backwards induction solution algorithm in Table 2 and a set of private information draws η_{tk}, solve for action choices under MME. Denote this as a_{tk}.
   2c. For each action choice m in the action set of player i
      2ci. Determine the true state transition density $x_{t+1} = T(x_t, (a_{it} = m, a_{itk}), z_t) + \epsilon_t$
      2cii. Set the full information action-dependent value function for player i in state x_{it} for action m to be $v_{it}^F(a_{it} = m, x_{it}, \hat{x}_t, z_t, \epsilon_t, \hat{\theta}) = \pi_i(a_{it} = m, x_{it}, z_t, \hat{\theta}) + E_i[\hat{V}_{i,t+1}(x_{i,t+1}, \hat{x}_{t+1}, z_{t+1})|a_{it} - m, x_{it}, \hat{x}_t, z_t, T, \epsilon_t]$
      2ciii. Using the random draw for η_{itk} determine the optimal action choice $\hat{a}_{itk}$ and simulate forward to determine the next period's state $x_{t+1,k}$. Track payoffs for player i in period t for simulation k.
   2d. Set $t = t + 1$ and $k = k + 1$
3. For each player i, set $\hat{V}_i = \frac{1}{K}\sum_{k=1}^{K}\left[\sum_{t=1}^{T}\left(\beta^{t-1}\pi(\hat{a}_{itk}, x_{tk}, z_t, \theta)\right)\right]$

Our full state information model does not encompass the full range of benefits associated with perfect information, since under assumed perfect information the player would adjust their expectations about the value of future states to incorporate any additional gains in value during those states from access to perfect information. Solving for the latter becomes prohitively expensive in computation as it would require integrating over the full set of future states, or approximating this set, and optimizing the value function in each of these states. Instead, our full state information model can rather be interpreted as a player gaining unexpected knowledge of the state vector each period, as well as knowledge of how other players will choose to act in the given period, and then optimizing based on this, their knowledge of how the groundwater stock will evolve, and their expected moment-state value function. We can then interpret our values here as a lower bound on the value of information to various players.

Table 11 presents the welfare for each player under the full state information model, under the MME, and under the MPE estimated in Sears et al. (2023). Since the full state information model involves unilateral deviation from the moment-state space strategies that we solved for using our backwards induction algorithm, we must simulate results individually for players and cannot treat the sum of player values as a total welfare count, nor can we sum over producer and consumer surplus generated to estimate a total value of additional consumer or producer surplus generated from access to information.

Our results suggest that players would not benefit from additional information in this case. Welfare values under the full state information model are very close to what we obtained in our baseline, as are the values we found in our open access model. This is consistent with our finding that players cared little for the future value of the stock, and thus would do little to change their behavior in response to more information. It suggests that information provision in cases like open access groundwater basins may not be particularly valuable, unless it is combined with policies that help to internalize social damages from groundwater extraction.

6 Sources of Inefficiency in Groundwater Management

Groundwater in our model is a common pool resource, extracted by players with payoffs that do not match with those of a social planner. We focus on three sources of inefficiency that arise in groundwater management in California. First, as a common pool resource, groundwater suffers from spatial pumping externalities whereby one user's groundwater extraction raises the extraction cost and lowers the total amount available to other nearby users (Lin Lawell, 2016; Sears and Lin Lawell, 2019). This uninternalized externality can generate social deadweight loss through overextraction (Provencher and Burt, 1993; Brozović et al., 2010; Pfeiffer and Lin, 2012; Lin Lawell, 2016; Sears et al., 2019).

Second, because water districts are not pure profit-maximizing organizations, and thus may price water to meet political objectives, rather than promoting long-run social welfare (Timmins, 2002; Sears et al., 2023). In Sears et al. (2023), we studied the implications of this phenomenon, which we referred to as "consumer surplus weighting", along with the spatial externalities from extraction, using a structural econometric model of a dynamic game played among a mix of cities, farmers, and other well owners in the region around the adjudicated Beaumont Basin in Southern California. We found evidence that both consumer surplus over-weighting and spatial externalities are sources of socially inefficient groundwater extraction, and that the property rights regime instituted to help manage groundwater resources did not correct these problems in the years immediately following their implementation.

Third, groundwater aquifers in California in many cases are located in arid regions with little natural recharge. As a consequence, groundwater resources should be managed dynamically, and extraction decisions should account for the marginal user cost, or the value to the user of leaving a marginal unit of the resource in the ground for future extraction. Pricing water to only recover the present costs of extraction, as is the case for private well owners, or pricing water to only meet an engineering cost of water supply in the present may not reflect the full social long-run value of groundwater, and thus may lead to overconsumption.

6.1 Theoretical Framework

In order to understand the inefficiencies that arise from spatial externalities and the over-weighting of consumer surplus, consider a simple dynamic game model of extraction. In the model there are I players i who all share the same aquifer, and who each extract groundwater for agricultural, recreational, or municipal use. One of these players, denoted as player A (for appropriator), is a municipal water utility that extracts water for sale to its consumers.

A social planner would choose extraction for each of the players i so as to maximize the present discounted sum of producer surplus and consumer surplus over infinite horizon, where producer surplus for each player i is the profit player i receives from groundwater extraction, and consumer surplus $CS(a_A)$ is the consumer surplus of the customers of the municipal water utility A. The social planner's value function is given by:

$$V_{SP}(x) = \max_a \left[\sum_{i \in I} \pi_i(a_i, x_i) + CS(a_A) + \beta E[V_{SP}(x')|a, x] \right],$$

where a represents the vector of extraction choices for each producer and x represents the vector of depth to groundwater for each player. Under the social optimum, the first-order condition for extraction by the municipal water utility A is given by:

$$\frac{\partial \pi_j(a_A, x_A)}{\partial a_A} + \frac{\partial CS(a_A)}{\partial a_A} + \beta E \left[\sum_{i \in I} \left(\frac{\partial V_{SP}(x')}{\partial x_i'} \frac{\partial x_i'}{\partial a_A} \right) \right] = 0. \tag{5}$$

The social planner considers the marginal effect of extraction on the current period sum of the profits of all players and consumer surplus as well as on the continuation value of the future sum of the profits of all players and consumer surplus in future periods derived from extraction by each of the players. Assuming that extraction has non-negative effects on depth to groundwater across producers, and assuming that the social planner's value function is non-increasing in depth to groundwater for each player, this marginal effect on the continuation value can be assumed to be non-negative. In addition, the weighting of the effect on producer profits and consumer surplus in the present period is equalized. We show this marginal condition in Figure 1, which plots the social welfare frontier from extraction at well j, which is made up of present period payoffs and discounted future period continuation value. Thus the social planner trades off future benefit for current period profits by extracting groundwater, which is graphically represented as tracing the frontier from the bottom right to the top left. The social planner then chooses the point on the frontier that reaches the highest social welfare isoline. The social welfare isoline balances the present period payoffs, made up of the sum of player A's producer surplus and consumer surplus equally with discounted future period continuation value.

In contrast to the social optimum, now consider the decision of agent A representing the water company in an open access dynamic game. To isolate the spatial externality, let's first assume that municipal water company A weighs consumer surplus equally with producer profits (so that there is no inefficiency from over- or under-weighting consumer surplus) but does not account for any spatial externalities. In other words, let's assume the municipal water company A places weights on consumer surplus and producer profits in the same way a social planner would, but, unlike a social planner, does not account for either the effect of other players on its own payoffs, nor the effect of its own decisions on the payoffs and actions of other players. Agent A's value function can then be written as:

$$V_A(x) = \max_{a_A} \left[\pi_A(a_A, x_A) + CS(a_A) + \beta E[V_A(x^{'})|a_A, \sigma_{-A}, x] \right], \tag{6}$$

where σ_{-A} is the strategy of all other players.

Then, assuming that there are no spatial externalities so that the value function is only directly affected through the player's own depth to groundwater state, the first-order condition can be written as:

$$\frac{\partial \pi_A(a_A, x_A)}{\partial a_A} + \frac{\partial CS(a_A)}{\partial a_A} + \beta E\left[\sum_{i \in I} \left(\frac{\partial V_A(x^{'})}{\partial x_i^{'}} \frac{\partial x_i^{'}}{\partial a_A} \right)\right] = 0. \tag{7}$$

We see that the term representing the marginal effect on continuation value now only contains the private continuation value for player A, and not the effect on the continuatison value for all other players in the game. Thus the player now equates marginal present period payoffs with the marginal effect on future discounted private payoffs. Graphically, in Figure 2, we represent this by having the player now choose the point on the production frontier that reaches the highest private welfare isoline. The private welfare isolines are flatter than the social welfare line, representing the fact that the private welfare function only considers the impact of extraction on future private payoffs, and not the payoffs of all players. Thus we find that this point lies on a lower social welfare isoline and generates deadweight loss. The deadweight loss can be measured graphically as the difference in the intercepts of the social welfare isolines that cross the two points in the figure. We term this the spatial externality effect in our model.

Next, consider the agent j's decision when we allow consumer surplus to be weighted differently than profits. In theory, consumer surplus can be weighted above or below the value of producer profits. Let ω represent the weight of consumer surplus in A's payoff function. Then the first-order condition now becomes:

$$\frac{\partial \pi_A(a_A, x_A)}{\partial a_A} + \omega \frac{\partial CS(a_A)}{\partial a_A} + \beta E\left[\sum_{i \in I} \left(\frac{\partial V_A(x^{'})}{\partial x_i^{'}} \frac{\partial x_i^{'}}{\partial a_A} \right)\right] = 0. \tag{8}$$

In Figure 3, we show the case in which $\omega > 1$. Here the slope of the private welfare isoline is flatter still. This is due to the fact that losses in present period consumer surplus are weighted more highly in the private payoff function. The effect of current period extraction on future payoffs goes only through the channel of extraction costs, which affect producer profits. Therefore the weighting of this term does not change. We see then that when consumer surplus is over-weighted, the deadweight loss grows. This effect is then termed the consumer surplus weighting effect.

6.2 Counterfactual Simulations

We run counterfactual simulations to analyze the understand the inefficiencies that arise from spatial externalities, the over-weighting of consumer surplus, and static rather than dynamic optimization.

Ideally we would like to solve a social planner problem and measure the full social welfare loss from these problems. However, our MME assumption unfortunately does not simplify the state space of a social planner, who would choose actions in a coordinated manner taking all information into account. What we can do instead is approximate the welfare loss from each of these sources of inefficiencies individually. This allows us to get a measure of the relative magnitudes of these problems. To do this we re-solve the dynamic game making counterfactual assumptions about the payoff functions of appropriators, and about the spatial flow of groundwater. Clearly the game will still be non-coopearative after we make these counterfactual assumptions. Moreover, these two inefficiency sources likely interact with one another, meaning that the combined effect should be larger than the sum of the two individual effects. Since both of these factors would work to make the efficiency loss under open access larger, we can interpret the combined effect to be a lower bound estimate of the full efficiency loss.

First we examine the effect of consumer surplus over-weighting. To do this we re-weight consumer surplus equally with water sale profits in the payoff function for appropriators. We re-solve the dynamic game backwards and simulate 25 trajectories. We produce standard errors using our bootstrap simulation method except that in each case we keep the consumer surplus weight constant. In Table 14 we present our social welfare results under this counterfactual assumption, alongside the quantities determined by the actual data, and their difference with simulation bias removed. To account for bias introduced by our simulation method we subtract the mean difference of baseline model simulated welfare quantities minus actual welfare quantities. We find striking results. With equal consumer surplus weighting, appropriators shift their extraction plans to produce significantly more producer surplus than consumer surplus. We find that after accounting for bias, the welfare gain relative to the actual data is just under \$7 million. We find that the spillover benefit to other players is small and insignificant. However, it is in line with results from a static optimization exercise that we conducted in Sears et al. (2023), where we found a lower bound on this effect of \$3.4 million in the years following the institution of property rights in the Beaumont Basin. Our result is larger, and likely reflects the fact that we are now allowing players to dynamically optimize. We are also using a different period of data, and examining a shorter time period, and so it is important not to draw too many conclusions from the relative sizes of these welfare gains until we can make more direct comparisons in future versions of this paper.

Next we examine the effect of removing spatial externalities. To do this we alter the state transition densities to exclude the effects of neighboring extraction. We then re-solve the dynamic game backwards and simulate 25 trajectories, and produce our standard errors. Since we are not altering the payoff functions in this counterfactual we allow the full parameter vector to vary in each bootstrap simulation. Our results for social welfare and its components can be found in Table 17. We find that after accounting for simulation bias, that the effects of these spatial spillovers are minor and insignificant. This is due in large part to the small effect that these spatial extraction terms play in the state transitions, and also the relatively small scale of extraction costs compared to consumer surplus and revenues from water sales. It is important to interpret these results in the context of our simulation period. We are only capturing the effect on payoffs over six years. Spatial extraction effects may indeed have a larger effect, especially if groundwater reaches levels at which it is impossible to extract in the short run without drilling new wells. To capture these effects we would need to model a significantly longer time frame.

Finally, we examine the role that dynamic optimization plays in the behavior of players in the game. We allow players to maximize static profits rather than solve a dynamic programming game. We re-simulate behavior and run 25 separate trajectories. We produce standard errors using our bootstrap simulation method, and allow the full parameter vector to vary in each simulation. In Table 20 we present our social welfare results under this counterfactual assumption, alongside the quantities determined by the actual data, and their difference with simulation bias removed. To account for bias introduced by our simulation method we subtract the mean difference of baseline model simulated welfare quantities minus actual welfare quantities. Our results are again very close to those that we found in our baseline. We only find a statistically significant difference for only one player and the difference is only around $10,000 per year. This suggests that behavior in the game is very close to what we would observe under static profit maximization. This is in line with a simple theory model suggesting that open access behavior is comparable to static profit maximization, and suggests that players did not have strong incentive to conserve water for future use.

7 Discussion, Next Steps, and Conclusion

Our preliminary results help to validate our modeling choice for this problem. Our baseline welfare results, and simulation statistics generated from behavior consistent with our model of an MME are largely in line with what we observe during this time period in the data, and the results we obtained using a full MPE-based approach. Thus we feel confident that our estimation procedure is producing a valid estimate of payoffs, and social welfare, and that any approximation error introduced by changing equilibrium concepts is relatively small.

Our finding suggest that under open access, consumer surplus weighting is a significant driver of social welfare loss. In line with prior results, we find that more efficient water pricing during this period would have produced significantly higher social welfare. Moreover, since the cumulative effects of groundwater conservation should be largest in the long term, when we would be most likely to observe players being forced to either drill new wells, or find alternative sources of water, our estimates of welfare loss from this source and from spatial externalities are likely underestimates. At the same time it is important that any pricing reform address equity concerns, as water costs still represent a significant burden for low income households (Cardoso and Wichman, 2021).

Our initial validation of our results has important implications both for the future path that we plan to take with this paper, and for the larger field of research on structural models of dynamic games. Using our MME modeling approach allows us to actually solve full versions of a large dynamic game, without risking significant approximation error. Indeed the information assumptions that we make by switching to MME may indeed be more realistic in cases like ours, when access to the full state vector is likely not available to all players. Moving forward this suggests that full solution estimation techniques like ours can be accomplished feasibly for large dynamic games, allowing counterfactual analysis that can be interpreted as a long run effect.

For our paper we plan to make significant updates in future versions. In particular we plan to solve a longer term version of the dynamic game. Adding additional periods to the solution does expand the moment state space size, however, this expansion occurs linearly, and thus it is feasible to make a much longer version of our model without hitting compuational limits. To do this we are working to address how to model long term weather conditions, regional economy, and well drilling. In this paper we do not treat well drilling as a choice variable, due to the limited variation in well drilling in our sample period. We could potentially use engineering cost estimates to incorporate well driling payoffs into our longer term model. Building in assumptions with weather is also a complex task. We could potentially use long term climate conditions for future years when data are not available. Alternatively we could incorporate a path for weather that is consistent with projected climate change in this region over the long term.

Finally, we would like to use our parameter results and a simple model of groundwater extraction permits, or property rights, to measure the potential benefits from strengthening property rights and instituting optimal managment. This will allow us to evaluate several alternative policy designs for managing groundwater resources over the long term.

Thus, our paper has important implications for structural modeling of dynamic games. We find that an MME approach produces results consistent with prior findings using a larger MPE approach. Moreover by being able to fully solve the dynamic game, we can conduct long run counterfactual analysis. In future versions of this paper we hope to take advantage of this to analyze the long run implications for groundwater extraction in this region of Southern California. By conducting this novel form of analysis, our paper will provide valuable insights to policymakers working to manage groundwater in California.

References

Andrews, D. W. K., Moreira, M. J., and Stock, J. H. (2019). Weak instruments in instrumental variables regression: Theory and practice. *Annual Review of Economics*, 11:727–753.

Angrist, J. and Pischke, J.-S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Bajari, P., Benkard, C. L., and Levin, J. (2007). Estimating dynamic models of imperfect competition. *Econometrica*, 75(5):1331–1370.

Benkard, C. L., Jeziorski, P., and Weintraub, G. Y. (2015). Oblivious equilibrium for concentrated industries. *RAND Journal of Economics*, 46(4):671–708.

Brozović, N., Sunding, D. L., and Zilberman, D. (2010). On the spatial nature of the groundwater pumping externality. *Resource and Energy Economics*, 32(2):154–164.

California Department of Food and Agriculture (2022). California agricultural production statistics. URL: `https://www.cdfa.ca.gov/Statistics/`.

California Department of Water Resources (2016). Management of the California State Water Project. Bulletin 132-16. URL: `https://water.ca.gov/-/media/DWR-Website/Web-Pages/Programs/State-Water-Project/Management/Cost-And-Revenue/Files/Bulletin-132-Management-of-the-California-State-Water-Project-2016.pdf`.

California Department of Water Resources (2022). Agricultural water use efficiency. URL: `https://water.ca.gov/Programs/Water-Use-And-Efficiency/Agricultural-Water-Use-Efficiency`.

California State Water Resources Control Board (2021). Groundwater recordation program. URL: `https://www.waterboards.ca.gov/waterrights/water_issues/programs/groundwater_recordation/`.

Cardoso, D. and Wichman, C. (2021). Water affordability in the united states. *Working Paper*.

Corbae, D. and D'Erasmo, P. (2021). Capital buffers in a quantitative model of banking industry dynamics. *Econometrica*, 89(6):2975–3023.

Ericson, R. and Pakes, A. (1995). Markov-perfect industry dynamics: A framework for empirical work. *The Review of Economic Studies*, 62(1):53–82.

Famiglietti, J. S. (2014). The global groundwater crisis. *Nature Climate Change*, 4(11):945 – 948.

Famiglietti, J. S., Lo, M., Ho, S. L., Bethune, J., Anderson, K. J., Syed, T. H., Swenson, S. C., de Linage, C. R., and Rodell, M. (2011). Satellites measure recent rates of groundwater depletion in california's central valley. *Geophysical Research Letters*, 38(3).

Fowlie, M., Reguant, M., and Ryan, S. P. (2016). Market-based emissions regulation and industry dynamics. *Journal of Political Economy*, 124(1):249–302.

Gerarden, T. (2023). Demanding innovation: The impact of consumer subsidies on solar panel production costs. *Management Science*, forthcoming.

Goettler, R. L. and Gordon, B. R. (2011). Does amd spur intel to innovate more?. *Journal of Political Economy*, 119(6):1141 – 1200.

Gowrisankaran, G., Langer, A., and Zhang, W. (2023). Policy uncertainty in the market for coal electricity: The case of air toxics standards. Working paper, Columbia University, University of Arizona, and Renmin University.

Hanson, R. T., Flint, L. E., Flint, A. L., Dettinger, M. D., Faunt, C. C., Cayan, D., and Schmid, W. (2012). A method for physically based model analysis of conjunctive use in response to potential climate changes. *Water Resources Research*, 48(6).

Hotz, V. J. and Miller, R. A. (1993). Conditional choice probabilities and the estimation of dynamic models. *Review of Economic Studies*, 60(3):497 – 529.

Ifrach, B. and Weintraub, G. Y. (2017). A framework for dynamic oligopoly in concentrated industries. *Review of Economic Studies*, 84(3):1106 – 1150.

Igami, M. (2017). Estimating the innovator's dilemma: Structural analysis of creative destruction in the hard disk drive industry, 1981-1998. *Journal of Political Economy*, 125(3):798 – 847.

Jeon, J. (2022). Learning and investment under demand uncertainty in container shipping. *RAND Journal of Economics*, 53(1):226–259.

Lee, D. S., McCrary, J., Moreira, M. J., and Porter, J. (2021). Valid t-ratio inference for IV. NBER Working Paper No. 29124.

Leyden, B. T. (2019). There's an app (update) for that: Understanding product updating under digitization. Working paper, Cornell University.

Lin Lawell, C.-Y. C. (2016). The management of groundwater: Irrigation efficiency, policy, institutions, and externalities. *Annual Review of Resource Economics*, 8:247–259.

Maskin, E. and Tirole, J. (1988a). A theory of dynamic oligopoly, i: Overview and quantity competition with large fixed costs. *Econometrica*, 56(3):549–569.

Maskin, E. and Tirole, J. (1988b). A theory of dynamic oligopoly, ii: Price competition, kinked demand curves, and edgeworth cycles. *Econometrica*, 56(3):571–599.

Pakes, A., Ostrovsky, M., and Berry, S. (2007). Simple estimators for the parameters of discrete dynamic games (with entry/exit examples). *RAND Journal of Economics*, 38(2):373–399.

Pfeiffer, L. and Lin, C.-Y. C. (2012). Groundwater pumping and spatial externalities in agriculture. *Journal of Environmental Economics and Management*, 64:16–30.

PRISM Climate Group and Oregon State University (2018). *PRISM Climate Data*. URL: http://prism.oregonstate.edu.

Provencher, B. and Burt, O. (1993). The externalities associated with the common property exploitation of groundwater. *Journal of Environmental Economics and Management*, 24(2):139–158.

Rojas Valdés, R. I., Lin Lawell, C.-Y. C., and Taylor, J. E. (2023). Migration dynamics, strategy, and policy. Working paper, Cornell University.

Rust, J. (1987). Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher. *Econometrica*, 55(5):999–1033.

Ryan, S. P. (2012). The costs of environmental regulation in a concentrated industry. *Econometrica*, 80(3):1019–1061.

Sanderson, E. and Windmeijer, F. (2016). A weak instrument F-test in linear IV models with multiple endogenous variables. *Journal of Econometrics*, 190(2):212–221.

Sears, L., Lim, D., and Lin Lawell, C.-Y. C. (2019). Spatial groundwater management: A dynamic game framework and application to California. *Water Economics and Policy*, 5:1850019.

Sears, L. and Lin Lawell, C.-Y. C. (2019). Water management and economics. In Cramer, G. L., Paudel, K. P., and Schmitz, A., editors, *The Routledge Handbook of Agricultural Economics*, pages 269–284. Routledge, London.

Sears, L., Lin Lawell, C.-Y. C., and Walter, M. T. (2023). Groundwater under open access: A structural model of the dynamic common pool extraction game. Working paper, Cornell University. URL: `http://clinlawell.dyson.cornell.edu/open_access_structural_paper.pdf`.

Seim, K. (2006). An empirical model of firm entry with endogenous product-type choices. *RAND Journal of Economics*, 37(3):619–640.

Staiger, D. and Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica*, 65(3):557–586.

Stock, J. H. and Yogo, M. (2005). Testing for weak instruments in linear IV regression. In Andrews, D. W. and Stock, J. H., editors, *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, pages 80–108. Cambridge University Press, Cambridge, UK.

Stockstad, E. (2020). Deep deficit. *"Science"*. URL: `https://www.science.org/content/article/droughts-exposed-california-s-thirst-groundwater-now-state-hopes-refill-its-aquifers`.

Taylor, R. G., Scanlon, B., Doell, P., Rodell, M., van Beek, R., Wada, Y., Longuevergne, L., Leblanc, M., Famiglietti, J. S., Edmunds, M., Konikow, L., Green, T. R., Chen, J., Taniguchi, M., Bierkens, M. F. P., MacDonald, A. M., Fan, Y., Maxwell, R. M., Yechieli, Y., Gurdak, J. J., Allen, D. M., Shamsudduha, M., Hiscock, K., Yeh, P. J. F., Holman, I., and Treidel, H. (2013). Ground water and climate change. *Nature Climate Change*, 3(4):322 – 329.

Timmins, C. (2002). Measuring the dynamic efficiency costs of regulators' preferences: Municipal water utilities in the arid West. *Econometrica*, 70(2):603–629.

Weintraub, G. Y., Benkard, C. L., and Van Roy, B. (2008). Markov perfect industry dynamics with many firms. *Econometrica*, 76(6):1375–1411.

Worthington, A. and Hoffman, M. (2008). An empirical survey of residential water demand modelling. *Journal of Economic Surveys*, 22:842–871.

Yi, F., Lin Lawell, C.-Y. C., and Thome, K. E. (2023). A dynamic model of subsidies: Theory and application to ethanol industry. Working paper, Cornell University.

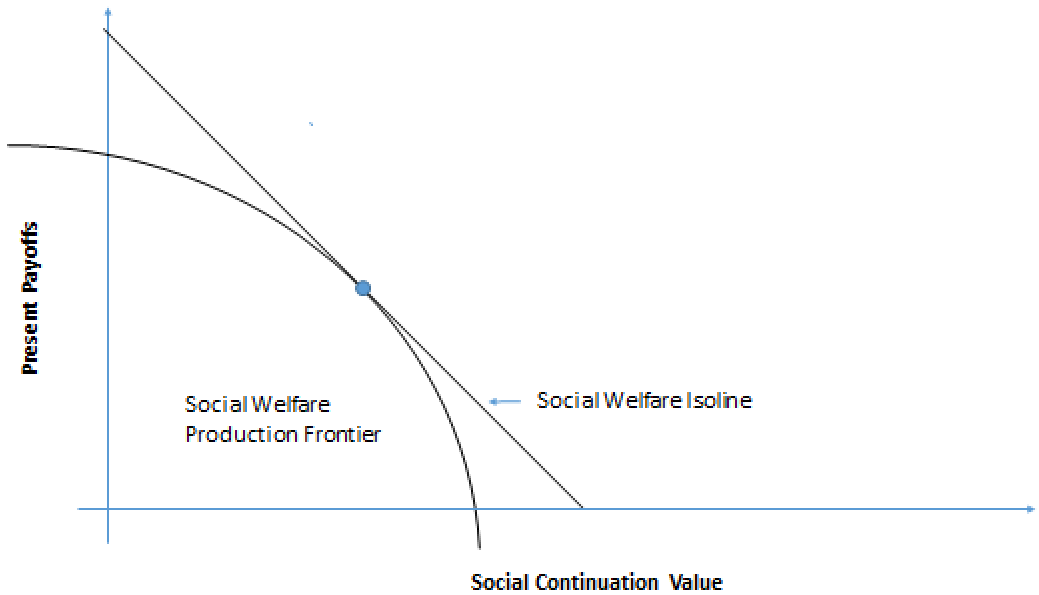


Figure 1: Appropriator Extraction Decision: Social Planner's Problem

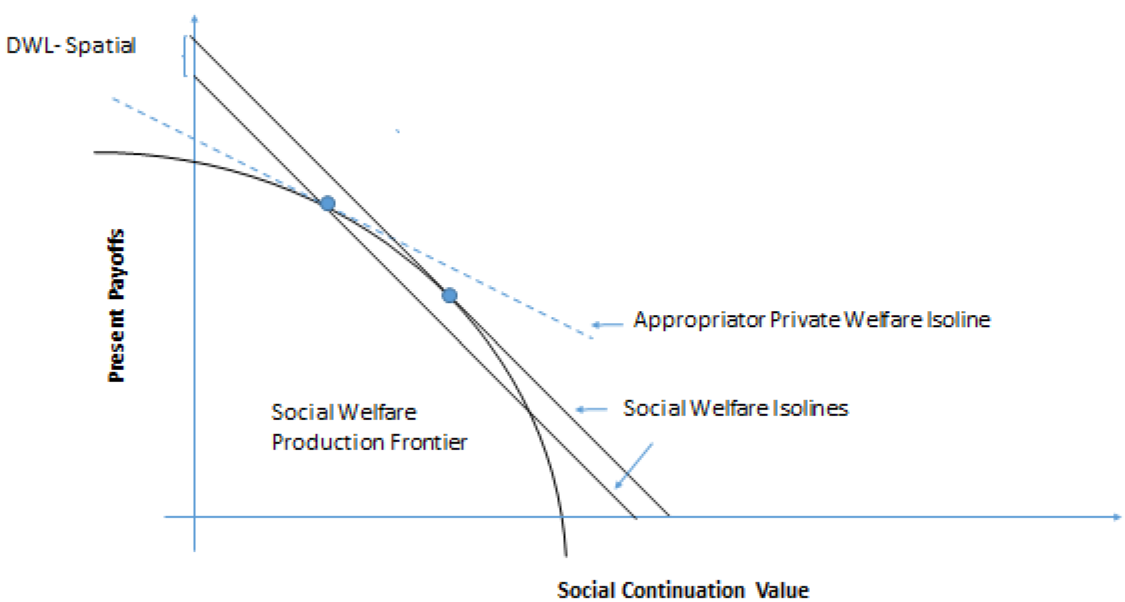


Figure 2: Appropriator Extraction Decision: Spatial Externality Effect

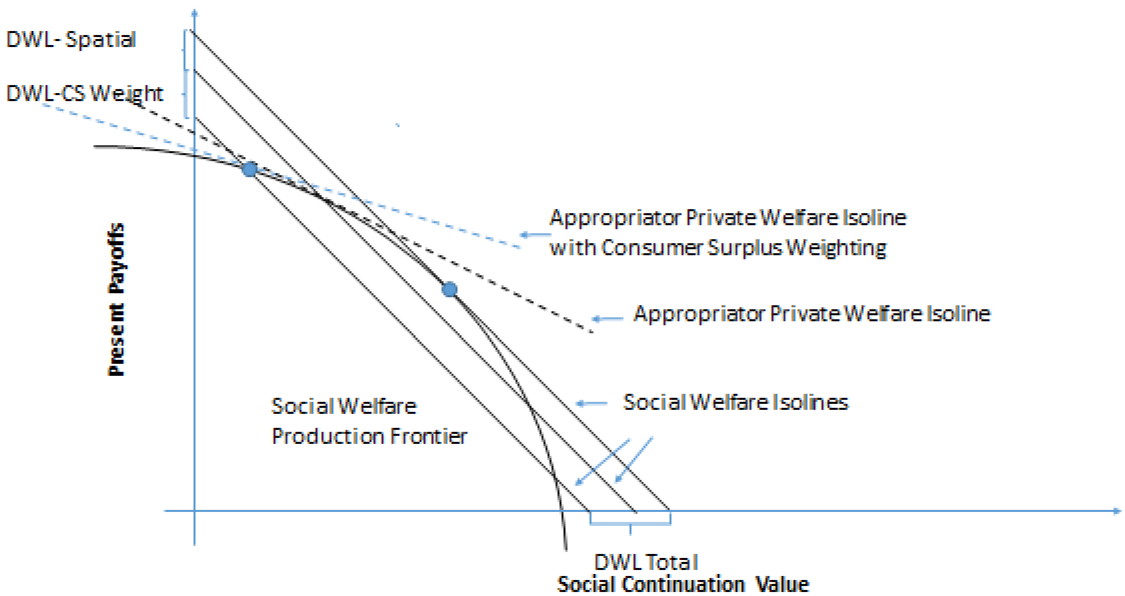


Figure 3: Appropriator Extraction Decision: Consumer Surplus Weighting Effect

Table 4: State Transition Results, 1991-1996

	Dependent variable is depth to groundwater (feet) for:			
	Farmer	Golf/ Housing	Appropriator inside Beaumont	Appropriator outside Beaumont
	(1)	(2)	(3)	(4)
Lagged values of:				
Saturated hydraulic conductivity (feet per day) X Extraction (acre-feet)	0.00319	0.000185*		
	(0.00371)	(0.000074)		
Saturated hydraulic conductivity X Neighbor extraction, 3 to 4 miles	0.000106**			
	(0.000038)			
Saturated hydraulic conductivity X Neighbor extraction, 2 to 3 miles	0.000138***			
	(0.000038)			
Depth to groundwater (feet) X Electricity price (dollars/kwh)	1.789***	1.381**		
	(0.540)	(0.481)		
Precipitation, Apr-Oct (inches)	-1.584*		1.673	
	(0.788)		(1.245)	
CA real GDP per capita (1997 chained dollars)	0.00237*		0.00839***	0.00125*
	(0.000996)		(0.00198)	(0.000521)
Depth to groundwater (feet)		0.808***		
		(0.0480)		
Number of high heat days (> 90 F), Apr-Oct		0.0982*	-0.358**	
		(0.0482)	(0.127)	
Saturated hydraulic conductivity X Extraction in Beaumont			0.000191**	
			(0.000068)	
Retail price of untreated water (dollars/acre-foot)			0.0922***	
			(0.0218)	
Saturated hydraulic conductivity X Neighbor extraction in Beaumont, 3 to 4 miles				-0.000369**
				(0.000135)
Depth to groundwater outside management zone (feet)				0.806***
				(0.0764)
Saturated hydraulic conductivity X Extraction outside Beaumont				-0.000005
				(0.000004)
Saturated hydraulic conductivity X Neighbor extraction in Beaumont, 1 to 2 miles				0.000046
				(0.000054)
Saturated hydraulic conductivity X Neighbor extraction in Beaumont, 0.5 to 1 miles			8.71E-05*	
			(4.34E-05)	
Average pump strength outside management zone (gallons per minute)				-0.00758*
				(0.00355)
Difference GMM	Y	N	Y	N
System GMM	N	Y	N	Y
# Observations	30	25	24	24
# Players	5	5	4	4
p-value (Prob>F)	0.000	0.000	0.000	0.000
RMSE	4.047	2.715	5.558	4.166

Notes: Results were obtained originally in Sears et al. (2023). Standard errors in parentheses. Significance codes: *** p<0.001, ** p<0.01, * p<0.05

Table 5: Structural Parameter Estimates

Player Group	Parameter Estimate
Appropriators	
Consumer surplus	2.21***
Consumer surplus, squared	-3.98E-08***
Extraction inside Beaumont Basin (acre-ft) × Depth to groundwater ×:	
Beaumont or Banning dummy ×:	
Log(Population)	1.91***
Regional price untreated water imports	-0.08***
Yucaipa Valley Water District	-75.65***
Extraction outside Beaumont Basin (acre-ft) × Depth to groundwater ×:	
Beaumont Cherry Valley Water District dummy × 1/Number of wells	-60.36***
City of Banning dummy × 1/Number of wells	-384.00***
Yucaipa Valley Water District dummy	-164.03***
All extraction (acre-ft) × Depth to groundwater ×:	
South Mesa Water Company dummy	-323.41***
Farmers	
Extraction (acre-ft) ×:	
Average crop price	0.23
Average crop price ×:	
Number of days with high temperature ≥ 90 degrees F	-0.01
Precipitation, inches (April-October)	-0.34
Precipitation, inches (April-October) × Number of degree days	0.01
Precipitation, inches (April-October)	24.63***
Total number of wells in Beaumont Basin	18.81***
Total number of wells in all locations	12.10***
Location in Beaumont Basin dummy	18.82***
Extraction per well, squared	-0.03
Golf Course/Housing Development	
Extraction (acre-ft) ×:	
Number of wells	-134.42***
Number of wells ×:	
Golf course dummy	-67.73***
Saturated hydraulic conductivity (ft/day)	1.68***
Retirement home dummy	-64.22***
CA Real GDP per capita	8.09***
Planned construction dummy	230.36***
Population, City of Beaumont	4.36***
Extraction per well, squared	-0.12***

Notes: Table reports the structural parameter estimates for the player group payoff functions. Each player group's payoff function is a linear function of the state variables. Standard errors are computed using 100 bootstrapped estimates of the structural parameters. Bootstrap estimates are computed using counterfactual sets of players chosen by random draws from the group of players in the dataset. Significance codes: * p <0.05, ** p<0.01, *** p< 0.001

Table 6: Model Fit: Mean Depth to Groundwater, 1991-1996

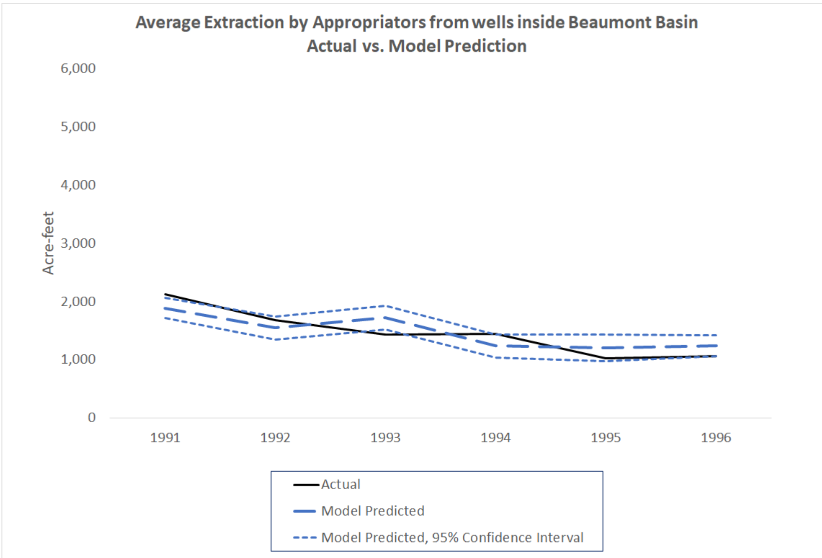
Appropriators in Beaumont Basin	Appropriators outside Beaumont Basin	Farmers	Golf courses/ Housing Developments
	Simulated Data		
186.43	128.66	205.91	228.41
(0.57)	(0.44)	(0.52)	(0.32)
	Actual Data		
185.32	131.37	205.74	227.53

Notes: Table reports the model predicted and actual mean depth to groundwater (ft) for each group of player wells. Simulated dataset is composed of 100 simulated paths of the years 1991-1996 using random draws to determine action choices and state transitions. Standard deviations of the group means are presented in parentheses.

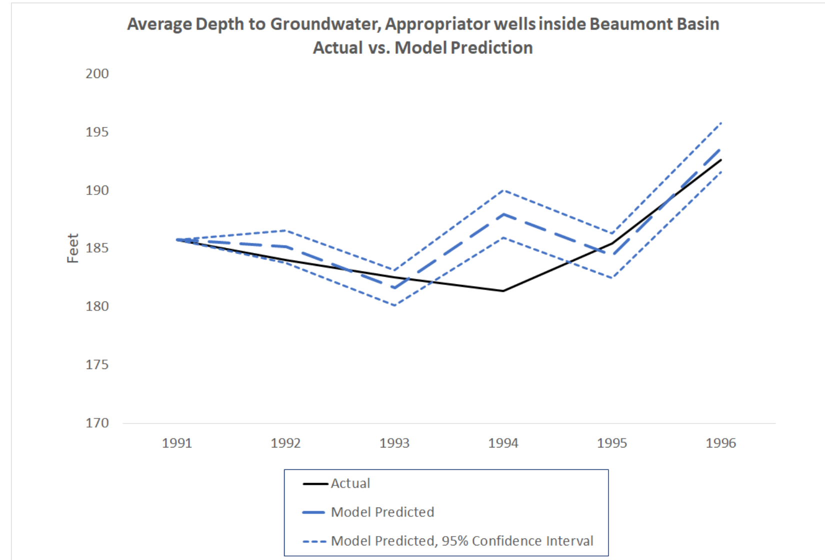
Table 7: Model Fit: Mean Extraction, 1991-1996

Appropriators in Beaumont Basin	Appropriators outside Beaumont Basin	Farmers	Golf courses/ Housing Developments
	Simulated Data		
1,475.83	3,904.58	205.69	428.08
(39.35)	(56.06)	(33.86)	(3.30)
	Actual Data		
1,461.13	3,944.25	208.80	430.59

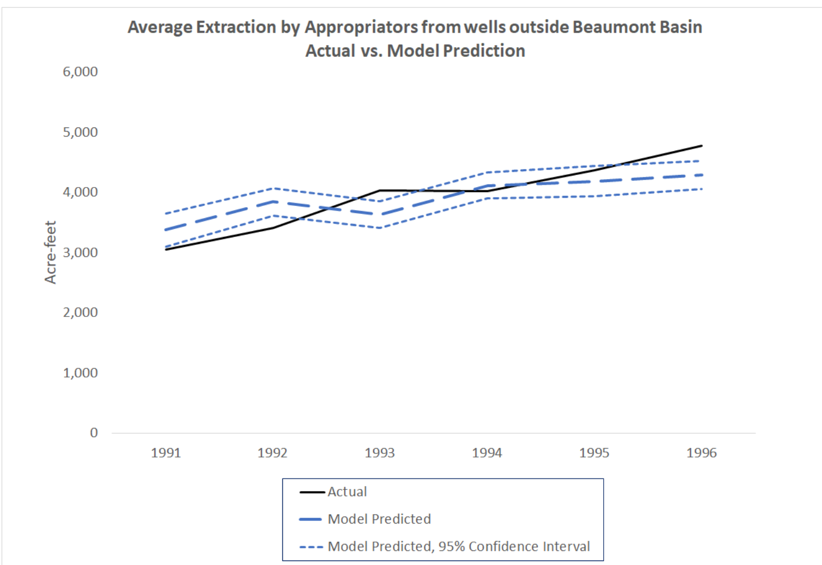
Notes: Table reports the model predicted and actual mean extraction (acre-ft) for each group of player wells. Simulated dataset is composed of 100 simulated paths of the years 1991-1996 using random draws to determine action choices and state transitions. Standard deviations of the group means are presented in parentheses.



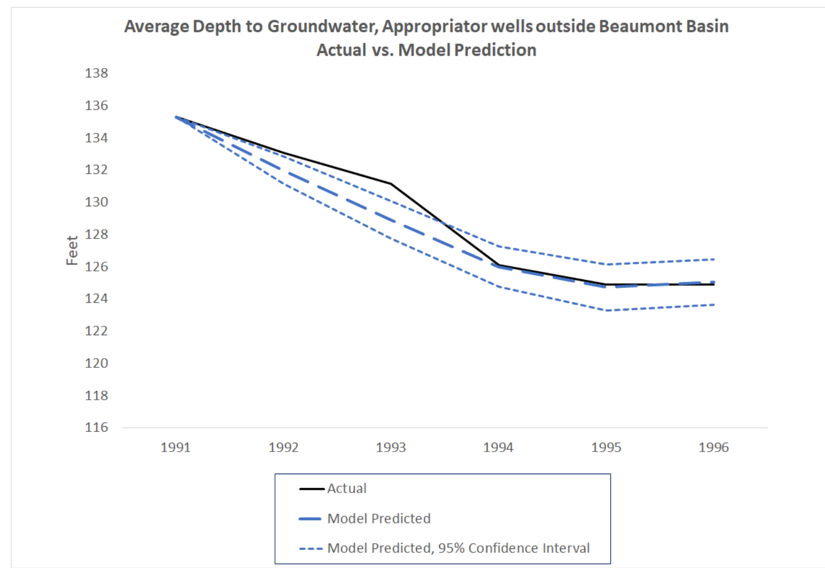
(a) Appropriator Extraction in Beaumont Basin



(b) Appropriator Depth to Groundwater in Beaumont Basin

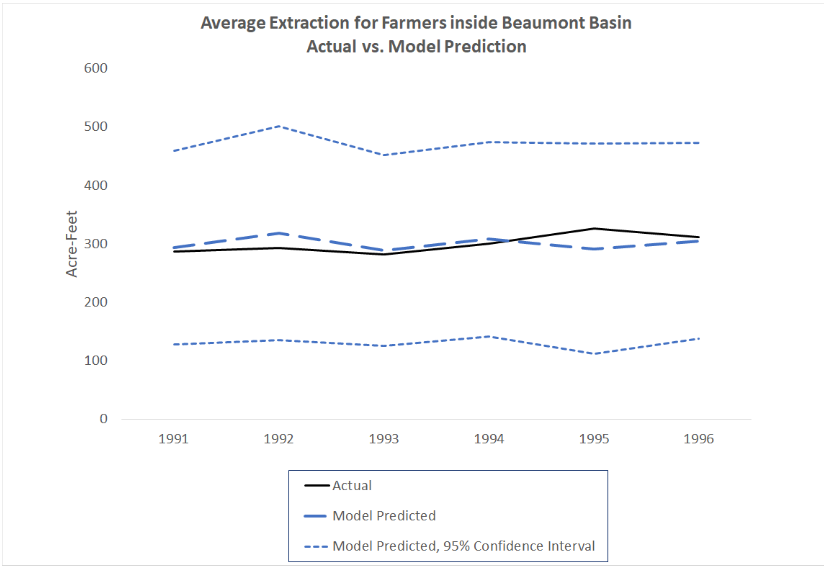


(c) Appropriator Extraction outside Beaumont Basin

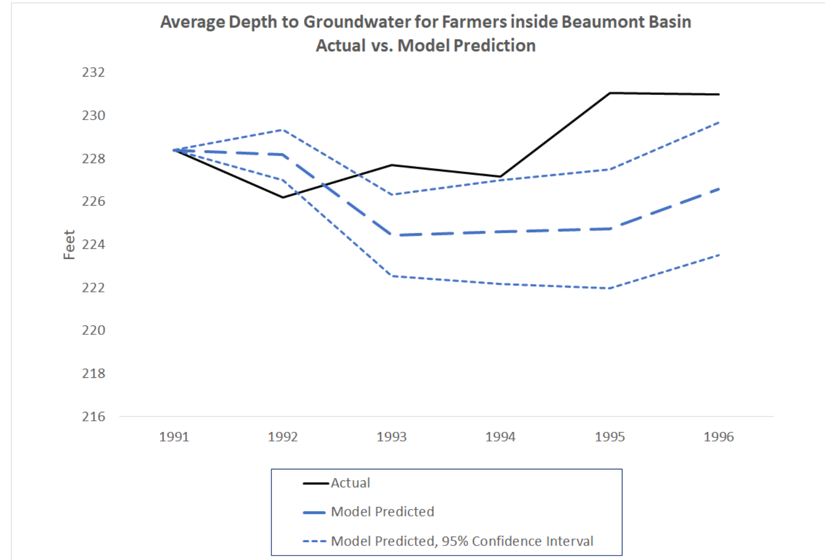


(d) Appropriator Depth to Groundwater outside Beaumont Basin

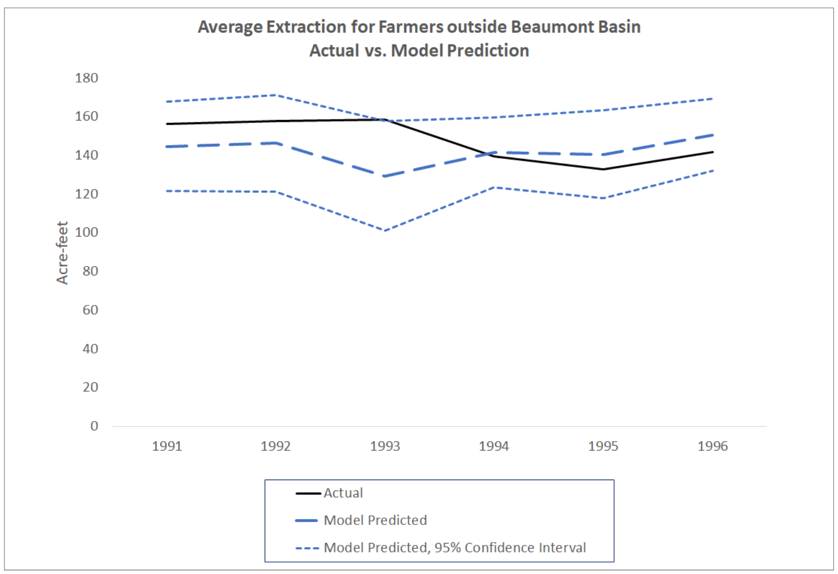
Figure 4: Model Simulated vs. Actual Data, Appropriators, 1991-1996



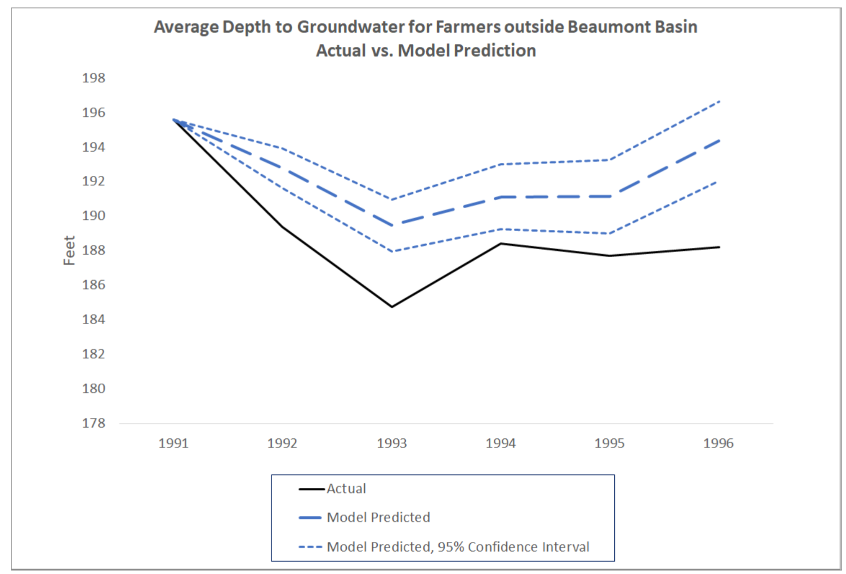
(a) Farmer Extraction in Beaumont Basin



(b) Farmer Depth to Groundwater in Beaumont Basin

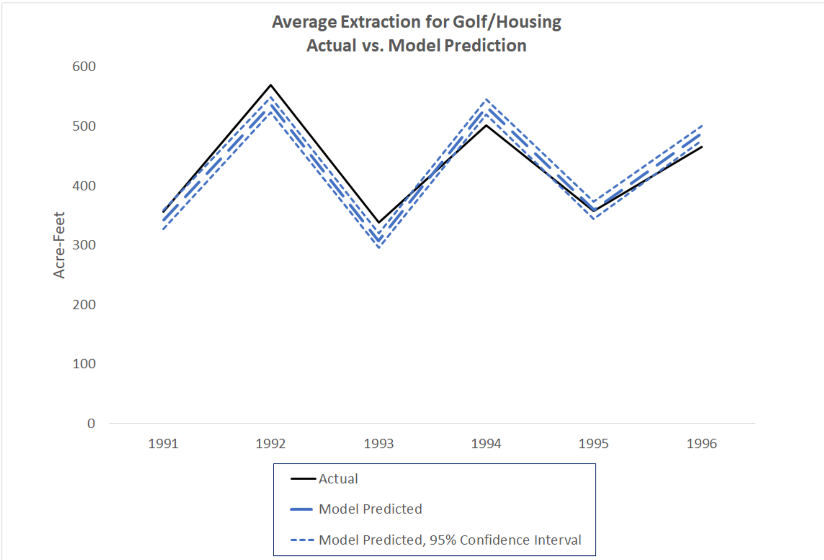


(c) Farmer Extraction outside Beaumont Basin

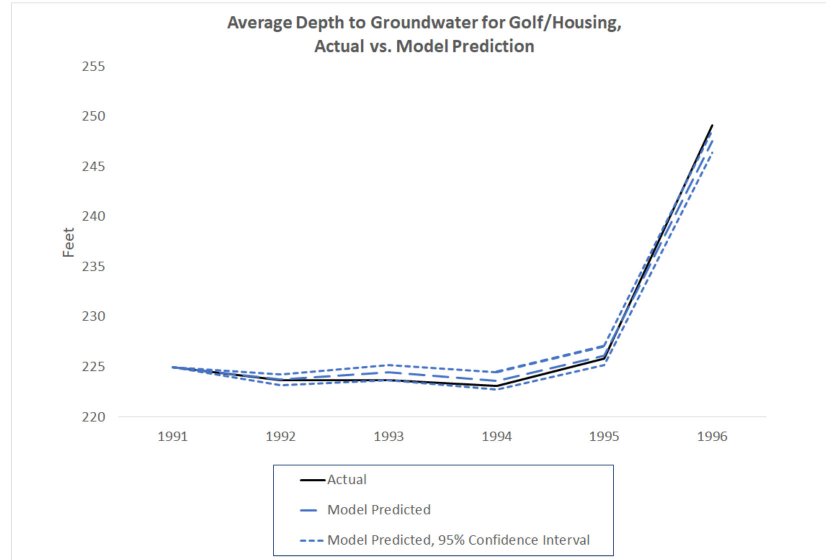


(d) Farmer Depth to Groundwater outside Beaumont Basin

Figure 5: Model Simulated vs. Actual Data, Farmers, 1991-1996



(a) Golf Course/Housing Development Extraction



(b) Golf Course/Housing Development Depth to Groundwater

Figure 6: Model Simulated vs. Actual Data, Golf Course/Housing Developments, 1991-1996

Table 8: Average Annual Welfare, 1991-1996

	Actual	Model Predicted	Model Predicted Minus Actual
Appropriators			
Beaumont-Cherry Valley Water District	7.17 million	7.33 million	0.16 million***
City of Banning	13.54 million	13.77 million	0.23 million***
South Mesa Water Company	4.50 million	4.81 million	-0.310 million***
Yucaipa Valley Water District	17.41 million	18.36 million	0.95 million***
Total appropriators	42.62 million	44.27 million	1.66 million***
Farmers			
Dowling	0.27 thousand	0.17 thousand	-0.09 thousand
Illy	3.61 thousand	3.42 thousand	-0.18 thousand
Murray	1.73 thousand	1.98 thousand	0.25 thousand
Riedman	8.54 thousand	8.39 thousand	-0.15 thousand
Summit	0.50 thousand	0.47 thousand	-0.04 thousand
Total farmers	14.65 thousand	14.22 thousand	-0.43 thousand
Golf course/Housing Development			
California Oak Valley Golf and Resort	49.22 thousand	49.40 thousand	0.17 thousand
Coscan Stewart Partnership	-0.25 thousand	-0.25 thousand	-0.05 thousand
Oak Valley Partners	45.02 thousand	85.74 thousand	40.72 thousand***
Plantation on the Lake	5.85 thousand	5.61 thousand	-0.23 thousand
Sharondale Mesa Owners Association	1.40 thousand	1.17 thousand	-0.22 thousand
Total golf course/housing developments	101.23 thousand	141.55 thousand	40.32 thousand

Notes: Table reports the mean annual welfare for players. Mean annual welfare is computed by dividing the present discounted value of total payoffs for the years 1991-1996 by the number of years in which the player participated in the extraction game. Payoffs are computed using the structural parameters for both actual and model simulated quantities. For actual payoffs we use the observed state variables and action choices in the observed data. For model simulated payoffs we use 100 simulated trajectories in which we take random draws to determine action choices and state transitions based on the observed state transition densities and the solution to the action dependent expected value functions. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Average Annual Social Welfare, 1991-1996

	Actual	Model Predicted	Model Predicted Minus Actual
Consumer Surplus			
Beaumont-Cherry Valley Water District	3.55 million	3.63 million	0.07 million***
City of Banning	7.39 million	7.57 million	0.18 million***
South Mesa Water Company	2.38 million	2.51 million	0.13 million***
Yucaipa Valley Water District	9.63 million	10.25 million	0.62 million***
Total Consumer Surplus	22.96 million	23.96 million	1.00 million***
Producer Surplus			
Appropriators	0.31 million	0.53 million	0.22 million
Farmers	14.65 thousand	14.22 thousand	-0.43 thousand
Golf course/Housing Developments	101.23 thousand	141.55 thousand	40.32 thousand
Total Producer Surplus	0.42 million	0.68 million	0.26 million
Total Social Welfare	23.38 million	24.64 million	1.26 million

Notes: Table reports the mean annual components of social welfare for players and groups of players. Social welfare is defined as unweighted sum of producer surplus plus consumer surplus. Consumer surplus is computed using the model of residential water demand. Producer surplus is computed using the payoff functions for each player and does not include consumer surplus related components. Mean annual social welfare components are computed by dividing the present discounted value of the total quantity for the years 1991-1996 by the number of years in which the player participated in the extraction game. For actual values we use the observed state variables and action choices in the observed data. For model simulated payoffs we use 100 simulated trajectories in which we take random draws to determine action choices and state transitions based on the observed state transition densities and the solution to the action dependent expected value functions. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Value Function Fixed Effects Regression Results

	Player's own private state			
	Depth to Groundwater (ft)	Depth to Groundwater Wells in Beaumont Basin (ft)	Depth to Groundwater Wells outside Beaumont Basin (ft)	Moment State Average Depth to Groundwater (ft) All Wells
Appropriators				
1991		-1,955***	-17,392***	353.7
1992		-1,824***	-15,525***	237.4
1993		-1,588***	-13,987***	131.6
1994		-1,664***	-10,910***	171.0
1995		-1,126***	-8,028***	142.6
1996		-714.3***	-3,916***	90.50*
All Years Pooled		-1,599***	-12,626***	205.2***
Farmers				
1991	-87.17***			0.00
1992	-72.98***			0.00
1993	-72.52***			0.00
1994	-60.48***			0.00
1995	-47.50***			0.00
1996	-24.56***			0.00
All Years Pooled	-62.55***			0.00
Golf Course/Housing Developments				
1991	-223.8***			67.74***
1992	-246.5***			63.71***
1993	-206.1***			39.34***
1994	-208.6***			29.81**
1995	-127.3***			9.755
1996	-70.21***			0.00
All Years Pooled	-192.7***			41.91***

Notes: Table reports regression results from fixed effects regressions for each player group of the value function for players in that player group in that year on the discretized state and moment state for players in that player group in that year. Each row reports the results of a separate regression of the value function for the respective player group in the respective year on the discretized state and moment state for that player group in that year. Regressions by year include player fixed effects. Regressions that pool over all years for a player group include player-year fixed effects. For each player, the value function in year t is the present discounted value of the entire stream of expected per-period payoffs expected to be earned by the player from year t onwards. The value of the value function at a particular state and moment state is the present discounted value of the entire stream of expected per-period payoffs expected to be earned by the player from year t onwards upon reaching the state and moment state in year t. Value functions and policy functions are solved for by solving the dynamic game using backwards induction using the estimated structural parameters and state transition densities. Intercept coefficients are not included in the table. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Value of Information: Average Annual Welfare, 1991-1996

	Full State Information Model Predicted	MME Model Predicted	MPE Model Predicted
Appropriators			
Beaumont-Cherry Valley Water District	7.3 million	7.3 million	8.0 million
City of Banning	13.8 million	13.8 million	14.2 million
South Mesa Water Company	4.8 million	4.8 million	5.6 million
Yucaipa Valley Water District	18.4 million	18.4 million	19.4 million
Farmers			
Dowling	0.2 thousand	0.2 thousand	0.3 thousand
Illy	3.7 thousand	3.4 thousand	0.8 thousand
Murray	2.0 thousand	2.0 thousand	0.4 thousand
Riedman	8.2 thousand	8.4 thousand	5.0 thousand
Summit	0.4 thousand	0.5 thousand	0.0 thousand
Golf course/Housing Development			
California Oak Valley Golf and Resort	49.3 thousand	49.4 thousand	8.2 thousand
Coscan Stewart Partnership	-0.3 thousand	-0.3 thousand	0.3 thousand
Oak Valley Partners	85.8 thousand	85.7 thousand	24.3 thousand
Plantation on the Lake	5.7 thousand	5.6 thousand	2.0 thousand
Sharondale Mesa Owners Association	1.2 thousand	1.2 thousand	1.3 thousand

Notes: Table reports the mean annual welfare for players. Mean annual welfare is computed by dividing the present discounted value of total payoffs for the years 1991-1996 by the number of years in which the player participated in the extraction game. Payoffs form MME and Full State Information quantities are computed using the structural parameters from this paper and model simulated quantities as described in the text. MPE values are calculated using model simulated actions and state values and structural parameters estimated in Sears et al. (2023) under an assumption of Markov Perfect Equilibrium.

Table 12: Equal Consumer Surplus Weighting Counterfactual: Mean Depth to Groundwater, 1991-1996

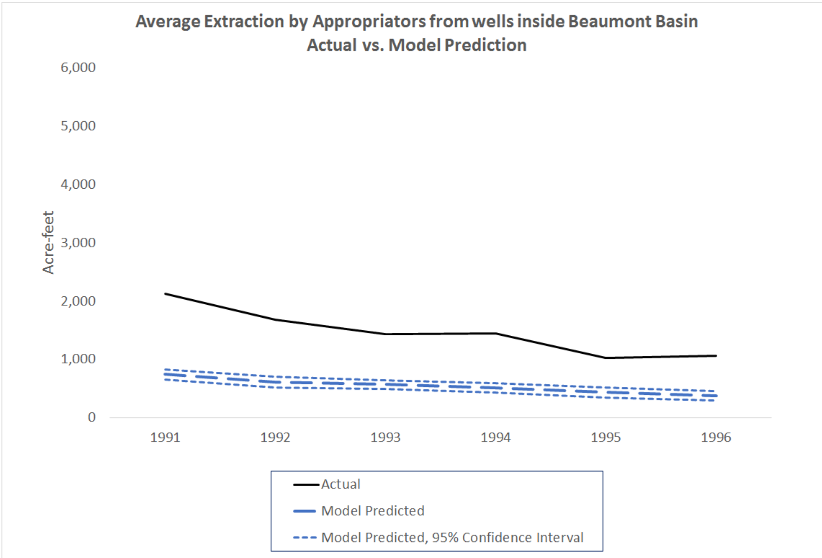
Appropriators in Beaumont Basin	Appropriators outside Beaumont Basin	Farmers	Golf courses/ Housing Developments
Equal Consumer Surplus Weighting Counterfactual			
183.23	129.28	195.44	228.54
(0.65)	(0.43)	(0.60)	(0.27)
Actual Data			
185.32	131.37	205.74	227.53

Notes: Table reports the counterfactual and actual mean depth to groundwater level (ft) for each group of player wells. Simulated dataset is composed of 100 simulated paths of the years 1991-1996 using random draws to determine action choices and state transitions. Payoff functions for appropriators are adjusted to weight consumer surplus equally with producer profits from water sales. Standard deviations of the group means are presented in parentheses.

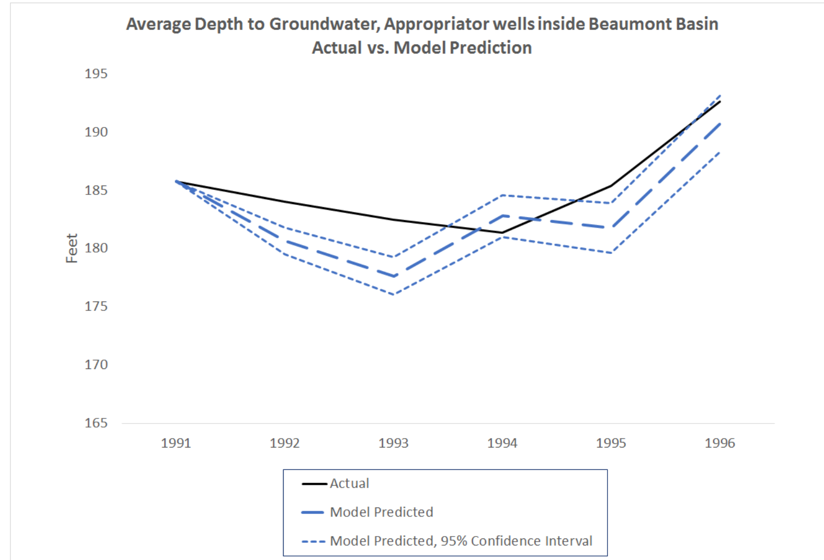
Table 13: Equal Consumer Surplus Weighting Counterfactual: Mean Extraction, 1991-1996

Appropriators in Beaumont Basin	Appropriators outside Beaumont Basin	Farmers	Golf courses/ Housing Developments
Equal Consumer Surplus Weighting Counterfactual			
542.92	939.17	212.08	429.30
(18.66)	(18.45)	(34.36)	(3.24)
Actual Data			
1,461.13	3,944.25	208.80	430.59

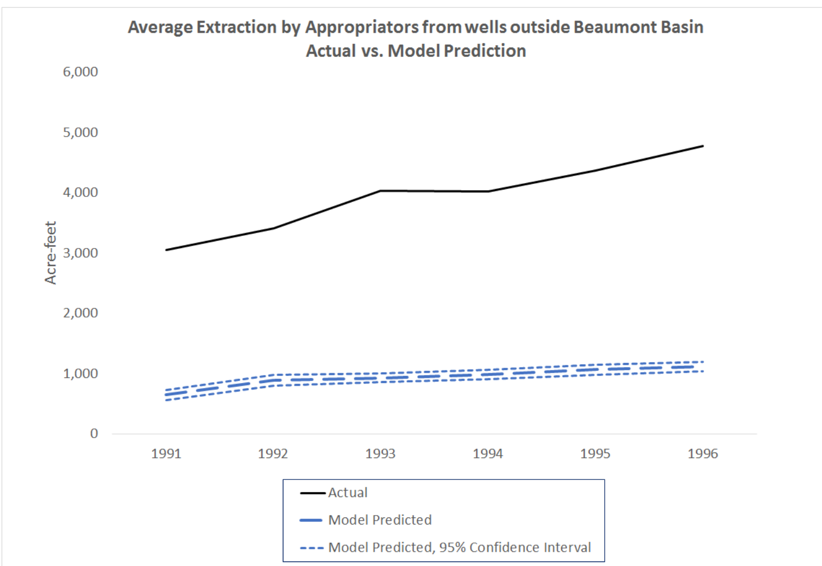
Notes: Table reports the counterfactual and actual mean extraction (acre-ft) for each group of player wells. Simulated dataset is composed of 100 simulated paths of the years 1991-1996 using random draws to determine action choices and state transitions. Payoff functions for appropriators are adjusted to weight consumer surplus equally with producer profits from water sales. Standard deviations of the group means are presented in parentheses.



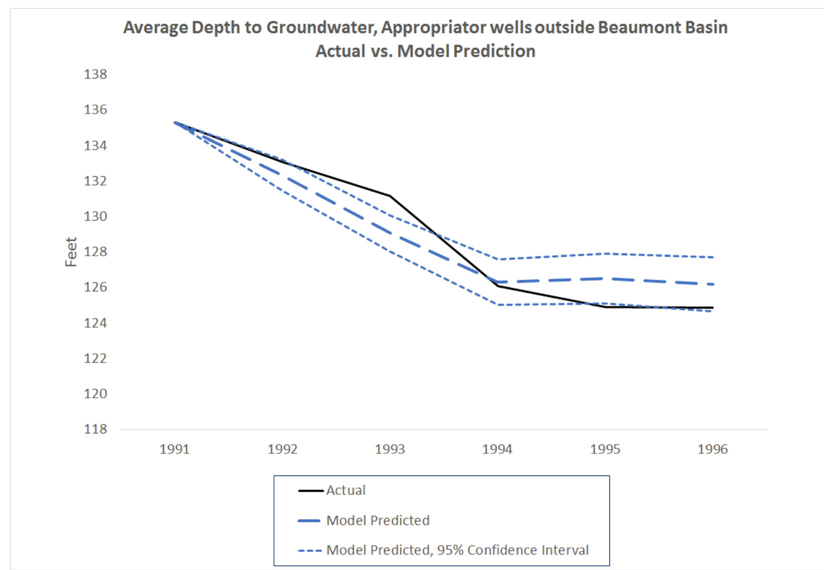
(a) Appropriator Extraction in Beaumont Basin



(b) Appropriator Depth to Groundwater in Beaumont Basin

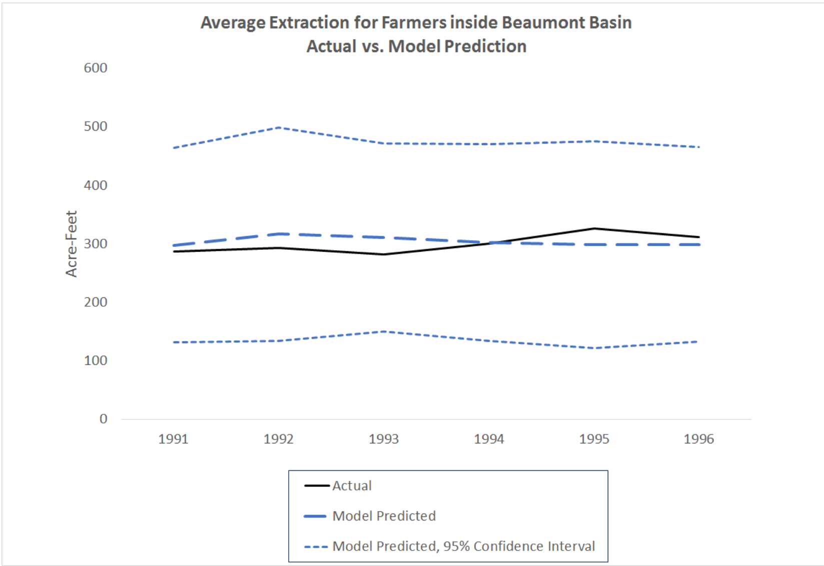


(c) Appropriator Extraction outside Beaumont Basin

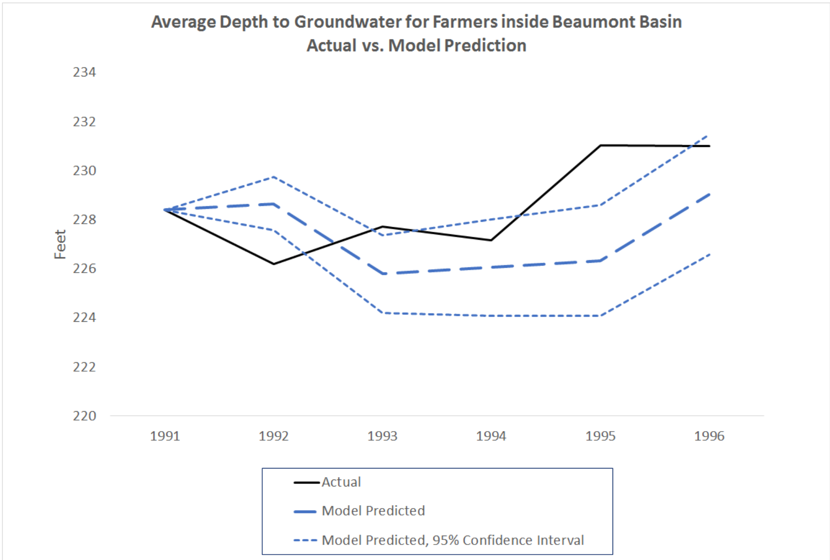


(d) Appropriator Depth to Groundwater outside Beaumont Basin

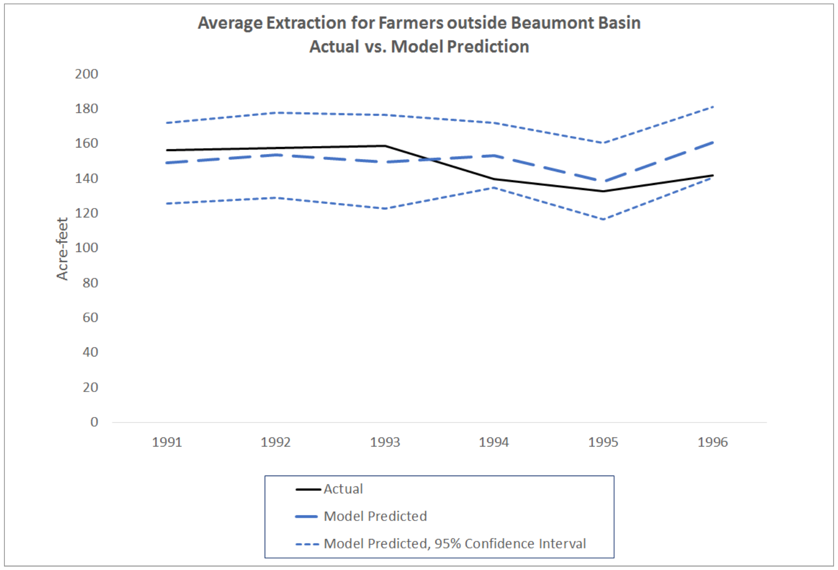
Figure 7: Equal Consumer Surplus Weighting Counterfactual vs. Actual Data, Appropriators, 1991-1996



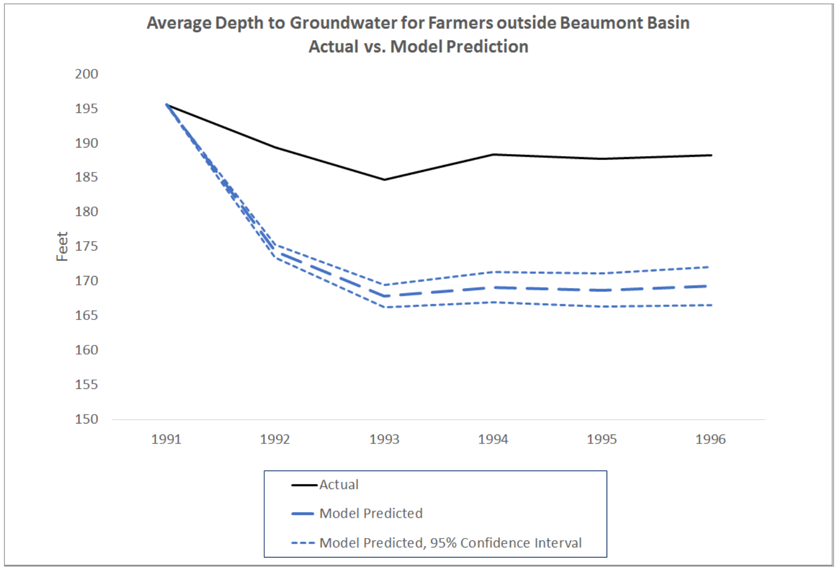
(a) Farmer Extraction in Beaumont Basin



(b) Farmer Depth to Groundwater in Beaumont Basin

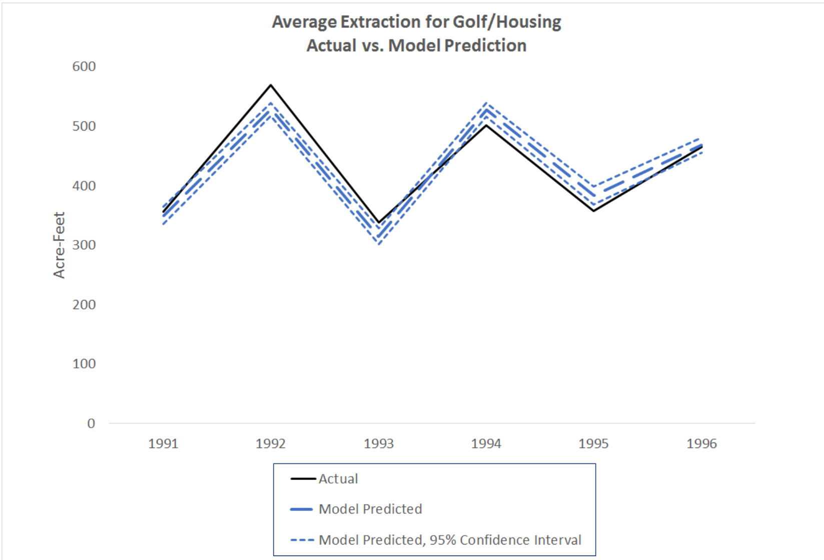


(c) Farmer Extraction outside Beaumont Basin

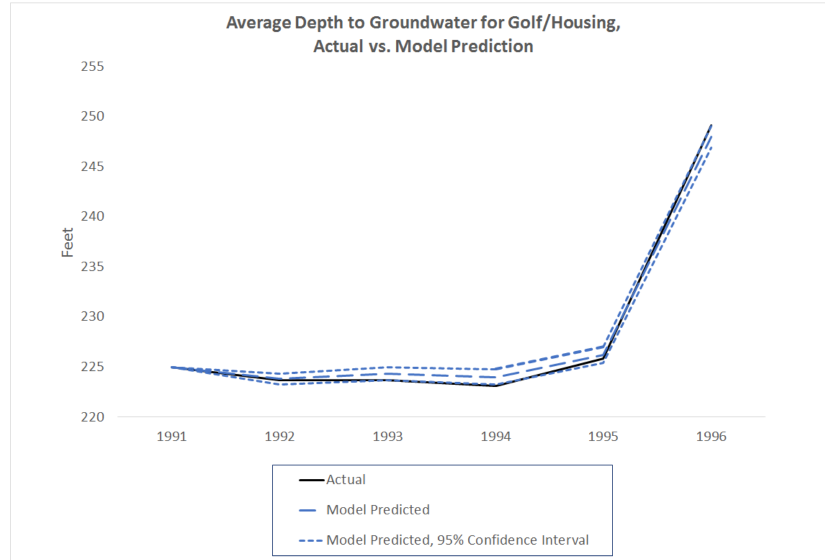


(d) Farmer Depth to Groundwater outside Beaumont Basin

Figure 8: Equal Consumer Surplus Weighting Counterfactual vs. Actual Data, Farmers, 1991-1996



(a) Golf Course/Housing Development Extraction



(b) Golf Course/Housing Development Depth to Groundwater

Figure 9: Equal Consumer Surplus Weighting Counterfactual vs. Actual Data, Golf Course/Housing Developments, 1991-1996

Table 14: Equal Consumer Surplus Weighting Counterfactual: Average Annual Social Welfare, 1991-1996

	Actual	Equal CS Weighting Counterfactual	Equal CS Weighting Counterfactual Minus Actual
Consumer Surplus			
Beaumont-Cherry Valley Water District	3.55 million	0.91 million	-2.72 million***
City of Banning	7.39 million	2.46 million	0.-5.11 million***
South Mesa Water Company	2.38 million	1.02 million	-1.49 million***
Yucaipa Valley Water District	9.63 million	2.85 million	-7.40 million***
Total Consumer Surplus	22.96 million	7.24 million	-16.7 million***
Producer Surplus			
Appropriators	0.31 million	24.05 million	23.52*** million
Farmers	14.65 thousand	15.25 thousand	1.04 thousand
Golf course/Housing Developments	101.23 thousand	141.66 thousand	0.11 thousand
Total Producer Surplus	0.42 million	24.20 million	23.52 million
Total Social Welfare	23.38 million	31.44 million	6.80 million

Notes: Table reports the mean annual components of social welfare for players and groups of players. Social welfare is defined as unweighted sum of producer surplus plus consumer surplus. Consumer surplus is computed using the model of residential water demand. Producer surplus is computed using the payoff functions for each player and does not include consumer surplus related components. Mean annual social welfare components are computed by dividing the present discounted value of the total quantity for the years 1991-1996 by the number of years in which the player participated in the extraction game. For actual values we use the observed state variables and action choices in the observed data. For no consumer surplus weighting counterfactual simulated payoffs we use 100 simulated trajectories in which we take random draws to determine action choices and state transitions based on the observed state transition densities and the solution to the action dependent expected value functions. Consumer surplus is weighted at an equal rate with producer costs and revenues from water sales in the payoff functions of appropriators. Bias is defined as the mean difference between baseline simulated values and the actual value. Significance codes: * p <0.05, ** p<0.01, *** p< 0.001

Table 15: No Spatial Externalities Counterfactual: Mean Depth to Groundwater, 1991-1996

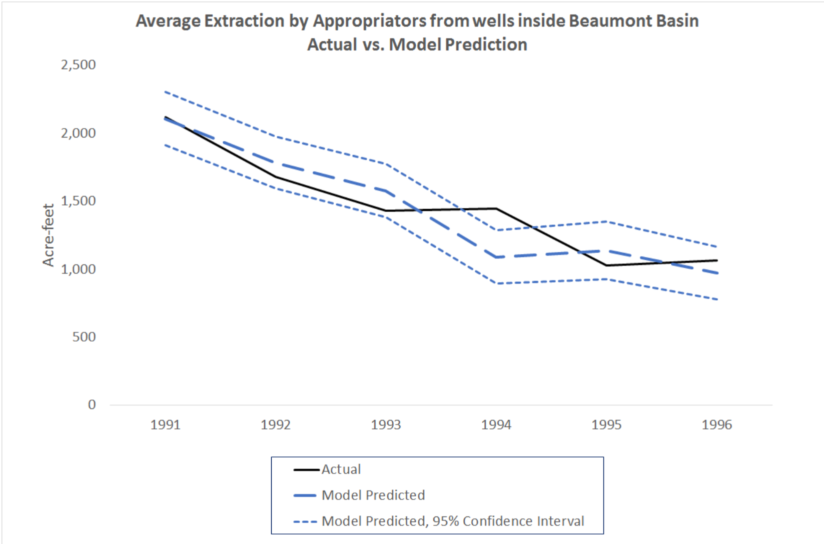
Appropriators in Beaumont Basin	Appropriators outside Beaumont Basin	Farmers	Golf courses/ Housing Developments
No Spatial Externalities Counterfactual			
185.15	128.47	205.34	228.22
(0.57)	(0.44)	(0.53)	(0.31)
Actual Data			
185.32	131.37	205.74	227.53

Notes: Table reports the counterfactual and actual mean depth to groundwater level (ft) for each group of player wells. Simulated dataset is composed of 100 simulated paths of the years 1991-1996 using random draws to determine action choices and state transitions. State transition densities are altered to not include the effects of variables related to nearby extraction by other players. Standard deviations of the group means are presented in parentheses.

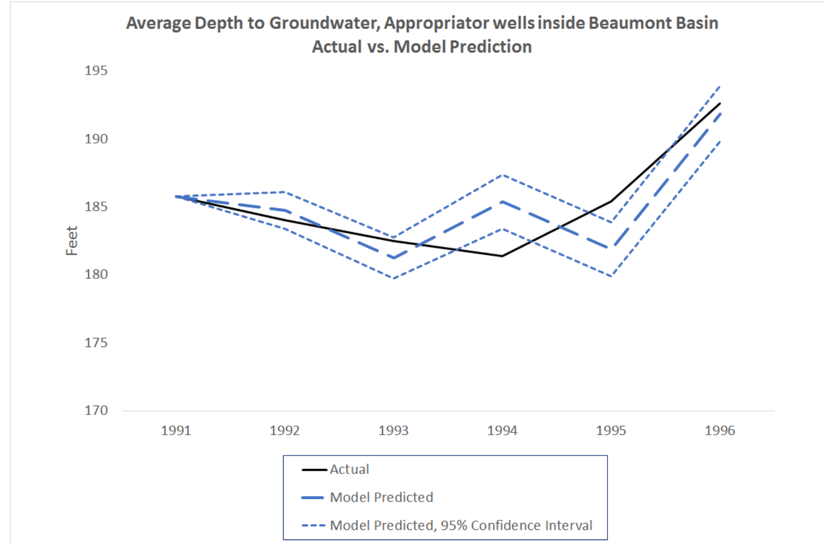
Table 16: No Spatial Externalities Counterfactual: Mean Extraction, 1991-1996

Appropriators in Beaumont Basin	Appropriators outside Beaumont Basin	Farmers	Golf courses/ Housing Developments
No Spatial Externalities Counterfactual			
1,444.58	3,958.33	206.53	431.69
(39.35)	(56.06)	(33.79)	(3.37)
Actual Data			
1,461.13	3,944.25	208.80	430.59

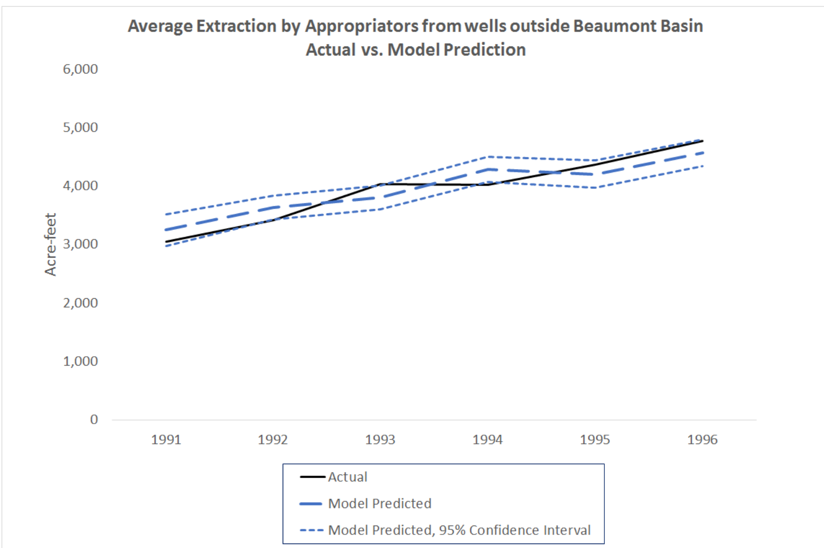
Notes: Table reports the counterfactual and actual mean extraction (acre-ft) for each group of player wells. Simulated dataset is composed of 100 simulated paths of the years 1991-1996 using random draws to determine action choices and state transitions. State transition densities are altered to not include the effects of variables related to nearby extraction by other players. Standard deviations of the group means are presented in parentheses.



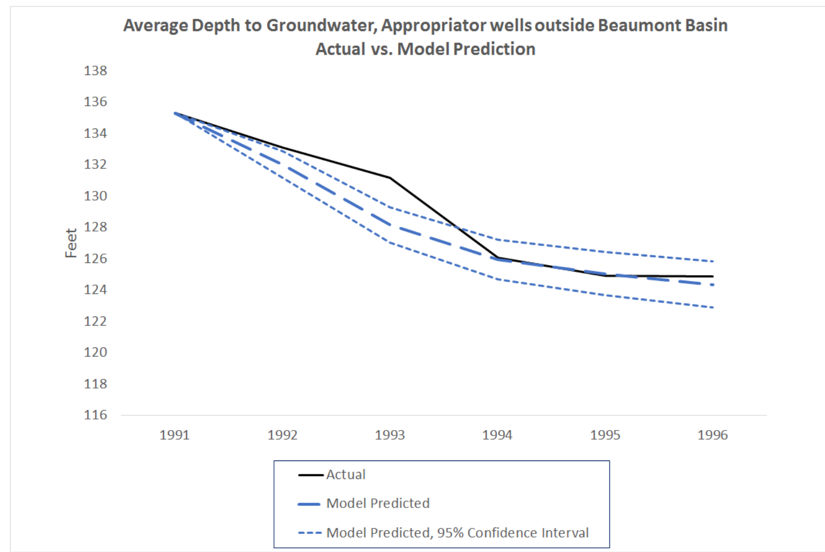
(a) Appropriator Extraction in Beaumont Basin



(b) Appropriator Depth to Groundwater in Beaumont Basin

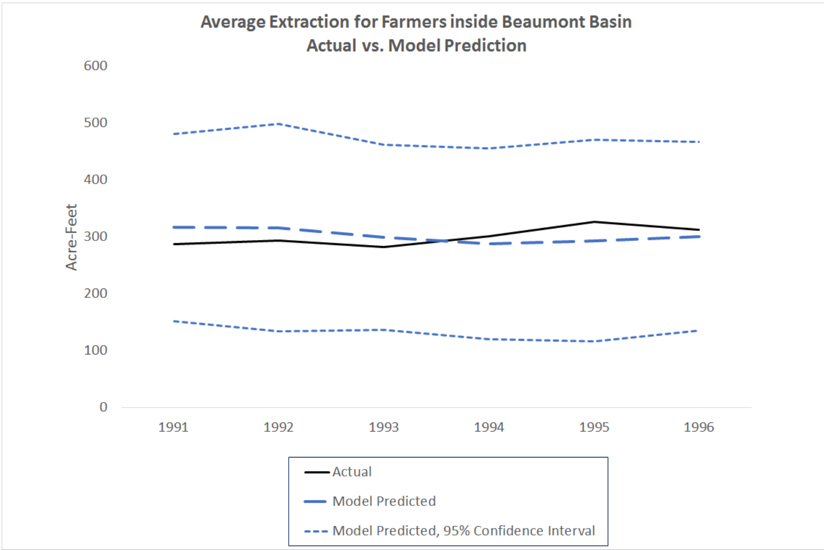


(c) Appropriator Extraction outside Beaumont Basin

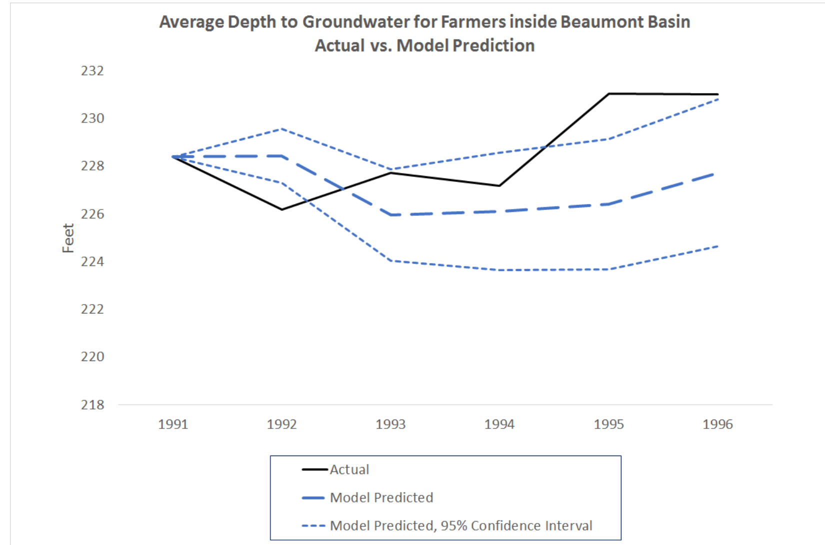


(d) Appropriator Depth to Groundwater outside Beaumont Basin

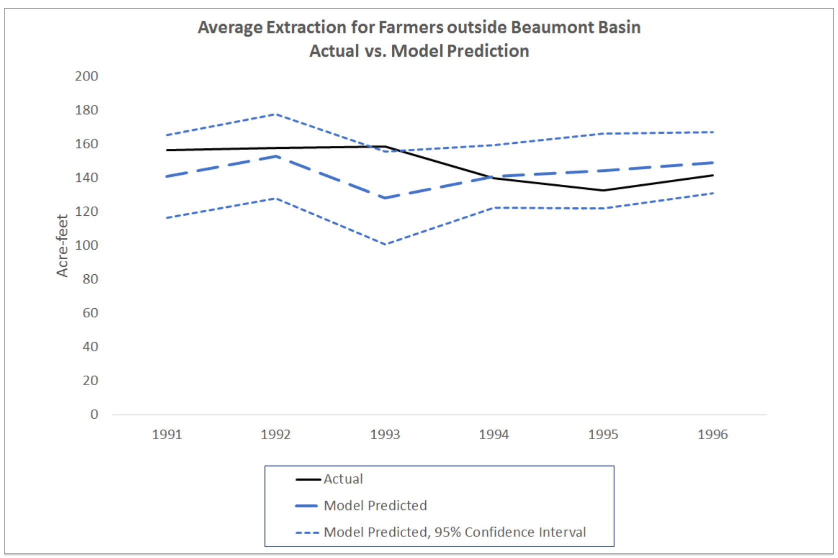
Figure 10: No Spatial Externalities Counterfactual vs. Actual Data, Appropriators, 1991-1996



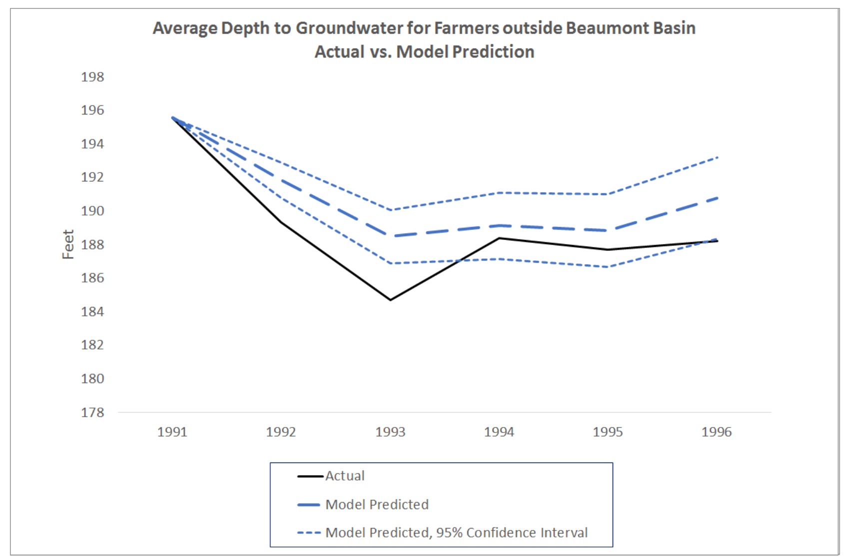
(a) Farmer Extraction in Beaumont Basin



(b) Farmer Depth to Groundwater in Beaumont Basin

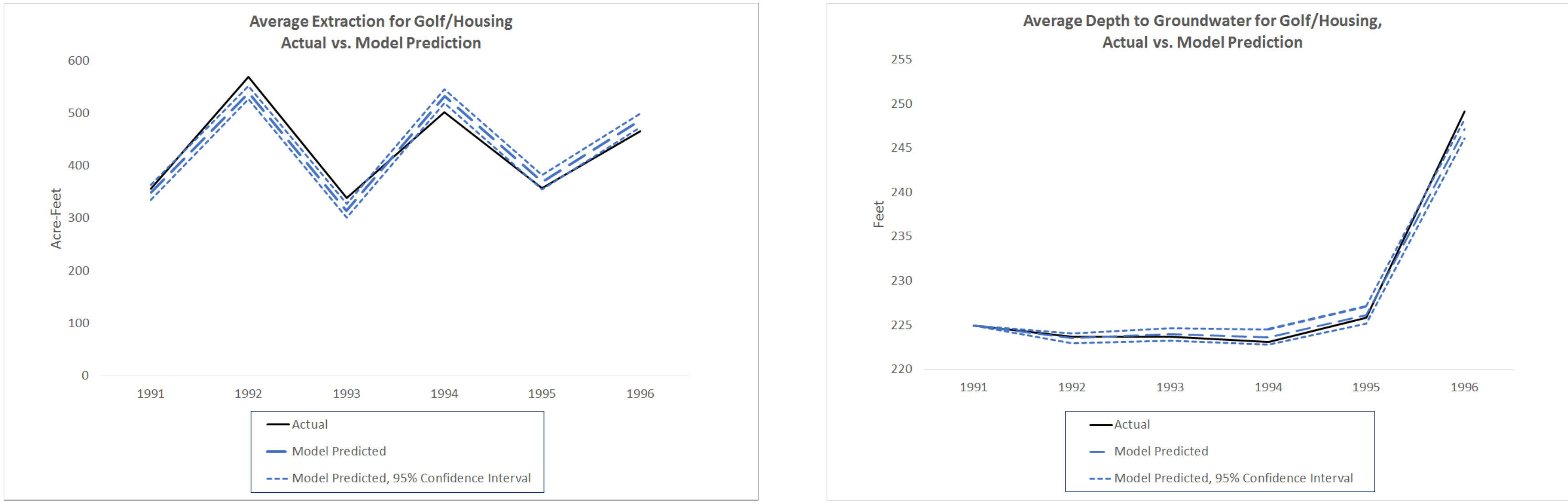


(c) Farmer Extraction outside Beaumont Basin



(d) Farmer Depth to Groundwater outside Beaumont Basin

Figure 11: No Spatial Externalities Counterfactual vs. Actual Data, Farmers, 1991-1996



(a) Golf Course/Housing Development Extraction

(b) Golf Course/Housing Development Depth to Groundwater

Figure 12: No Spatial Externalities Counterfactual vs. Actual Data, Golf Course/Housing Developments, 1991-1996

Table 17: No Spatial Externalities Counterfactual: Average Annual Social Welfare, 1991-1996

	Actual	No Spatial Externalities Counterfactual	No Spatial Externalities Counterfactual Minus Actual
Consumer Surplus			
Beaumont-Cherry Valley Water District	3.55 million	3.63 million	0.00 million
City of Banning	7.39 million	7.57 million	0.00 million
South Mesa Water Company	2.38 million	2.49 million	-0.01 million*
Yucaipa Valley Water District	9.63 million	10.24 million	-0.01 million
Total Consumer Surplus	22.96 million	23.94 million	-0.02 million
Producer Surplus			
Appropriators	0.31 million	0.55 million	0.03 million
Farmers	14.65 thousand	14.52 thousand	0.31 thousand
Golf course/Housing Developments	101.23 thousand	141.75 thousand	0.20 thousand
Total Producer Surplus	0.42 million	0.71 million	0.03 million
Total Social Welfare	23.38 million	24.65 million	0.01 million

Notes: Table reports the mean annual components of social welfare for players and groups of players. Social welfare is defined as unweighted sum of producer surplus plus consumer surplus. Consumer surplus is computed using the model of residential water demand. Producer surplus is computed using the payoff functions for each player and does not include consumer surplus related components. Mean annual social welfare components are computed by dividing the present discounted value of the total quantity for the years 1991-1996 by the number of years in which the player participated in the extraction game. For actual values we use the observed state variables and action choices in the observed data. For no spatial effects counterfactual simulated payoffs we use 100 simulated trajectories in which we take random draws to determine action choices and state transitions based on the observed state transition densities and the solution to the action dependent expected value functions. Spatial effects are defined as neighbor extraction effects on the next period's depth to groundwater level in the state transition densities. Bias is defined as the mean difference between baseline simulated values and the actual value. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18: No Dynamic Behavior Counterfactual: Mean Depth to Groundwater, 1991-1996

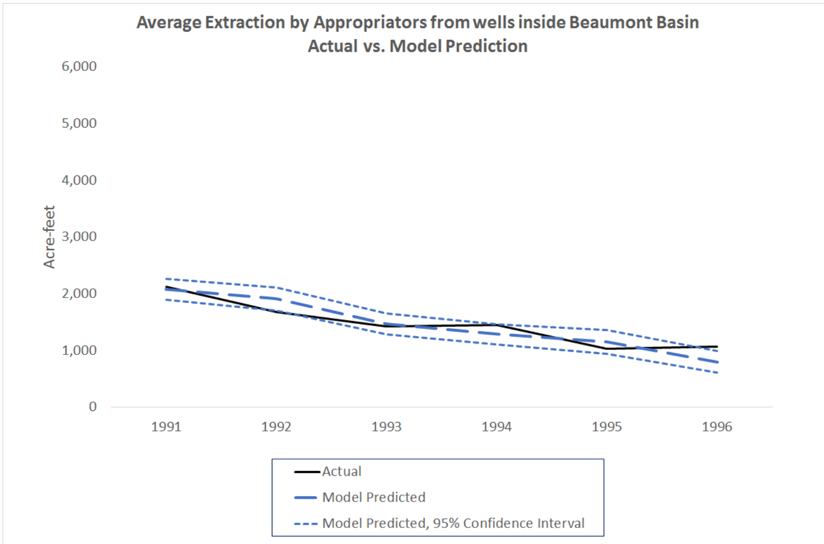
Appropriators in Beaumont Basin	Appropriators outside Beaumont Basin	Farmers	Golf courses/ Housing Developments
	No Dynamic Behavior Counterfactual		
186.09	129.26	206.22	228.64
(0.65)	(0.44)	(0.60)	(0.27)
	Actual Data		
185.32	131.37	205.74	227.53

Notes: Table reports the counterfactual and actual mean depth to groundwater level (ft) for each group of player wells. Simulated dataset is composed of 100 simulated paths of the years 1991-1996 using random draws to determine action choices and state transitions. Players are assumed to choose period payoff maximizing action choices, and do not consider present discounted expected future payoffs. Standard deviations of the group means are presented in parentheses.

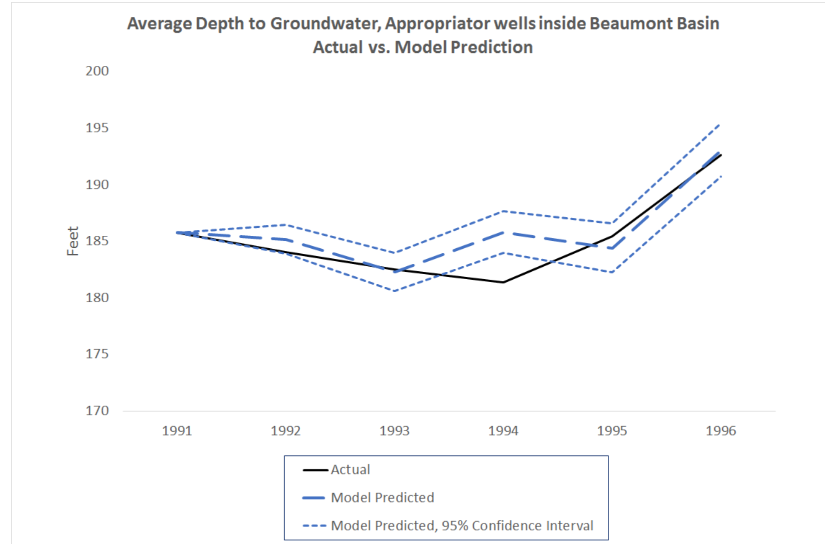
Table 19: No Dynamic Behavior Counterfactual: Mean Extraction, 1991-1996

Appropriators in Beaumont Basin	Appropriators outside Beaumont Basin	Farmers	Golf courses/ Housing Developments
	No Dynamic Behavior Counterfactual		
1,448.33	3,913.75	209.49	431.42
(43.85)	(55.96)	(33.84)	(3.19)
	Actual Data		
1,461.13	3,944.25	208.80	430.59

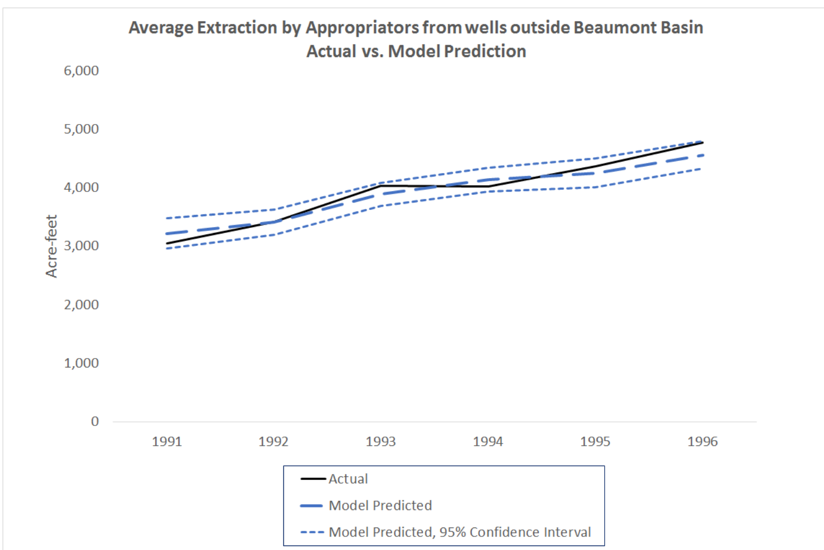
Notes: Table reports the counterfactual and actual mean extraction (acre-ft) for each group of player wells. Simulated dataset is composed of 100 simulated paths of the years 1991-1996 using random draws to determine action choices and state transitions. Players are assumed to choose period payoff maximizing action choices, and do not consider present discounted expected future payoffs. Standard deviations of the group means are presented in parentheses.



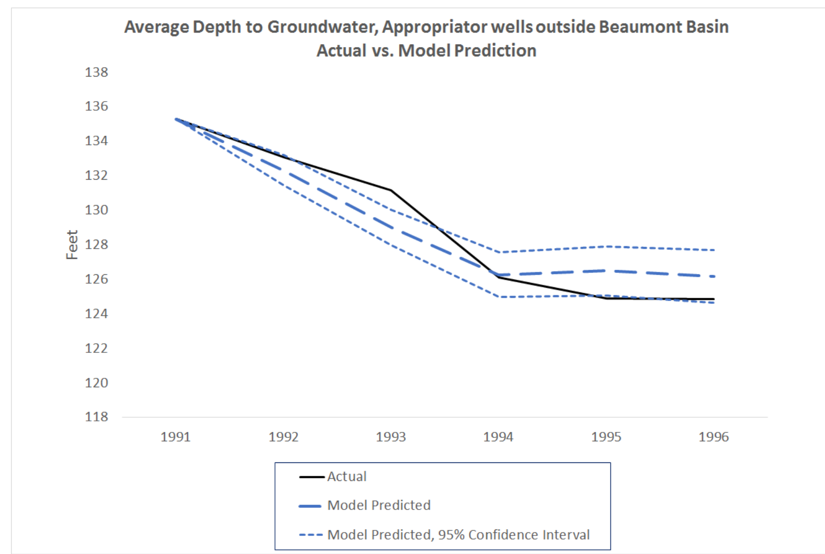
(a) Appropriator Extraction in Beaumont Basin



(b) Appropriator Depth to Groundwater in Beaumont Basin

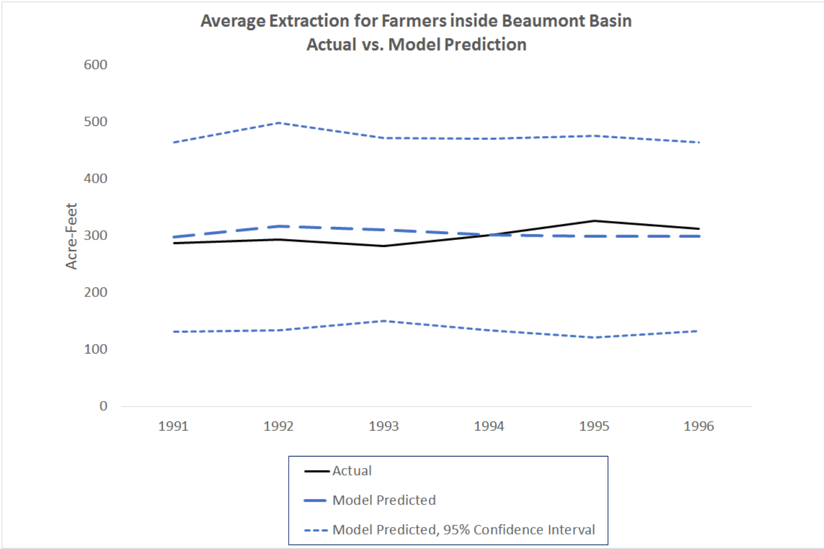


(c) Appropriator Extraction outside Beaumont Basin

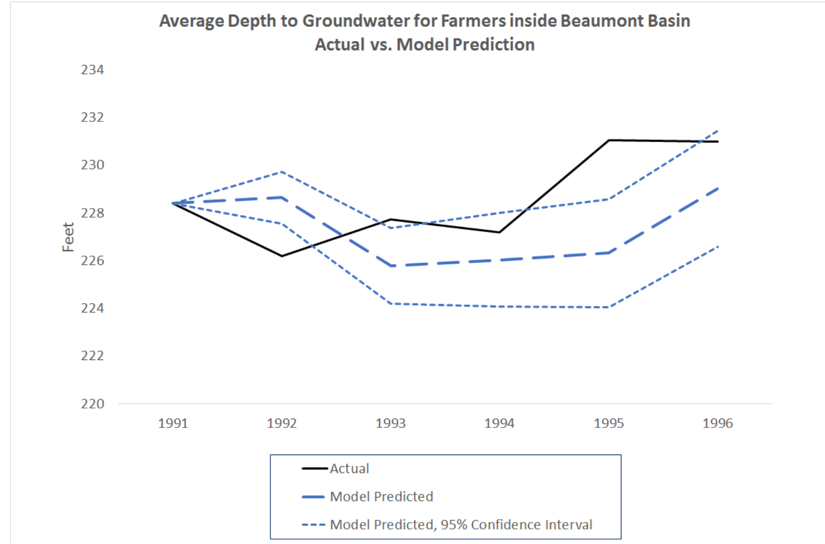


(d) Appropriator Depth to Groundwater outside Beaumont Basin

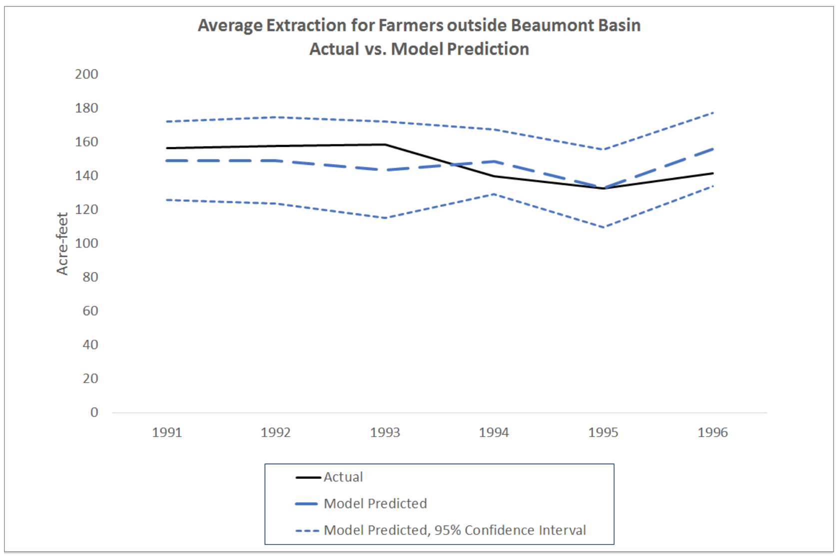
Figure 13: No Dynamic Behavior Counterfactual vs. Actual Data, Appropriators, 1991-1996



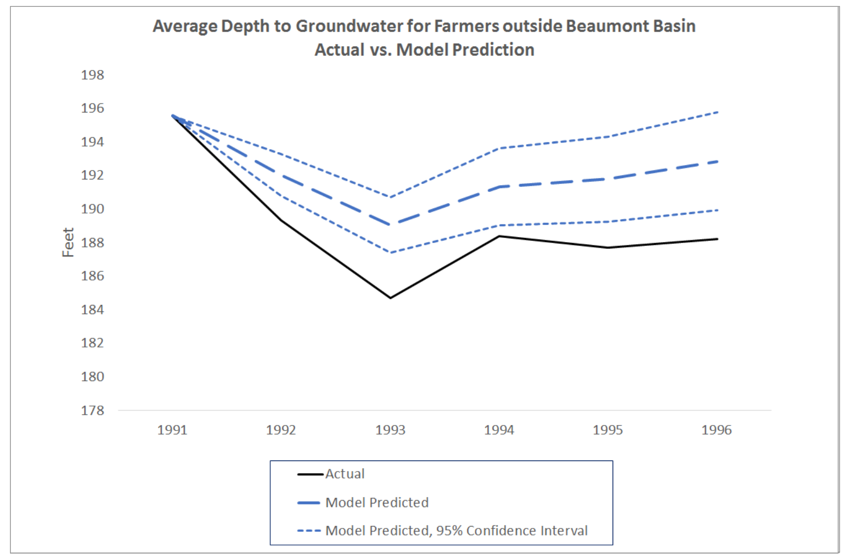
(a) Farmer Extraction in Beaumont Basin



(b) Farmer Depth to Groundwater in Beaumont Basin

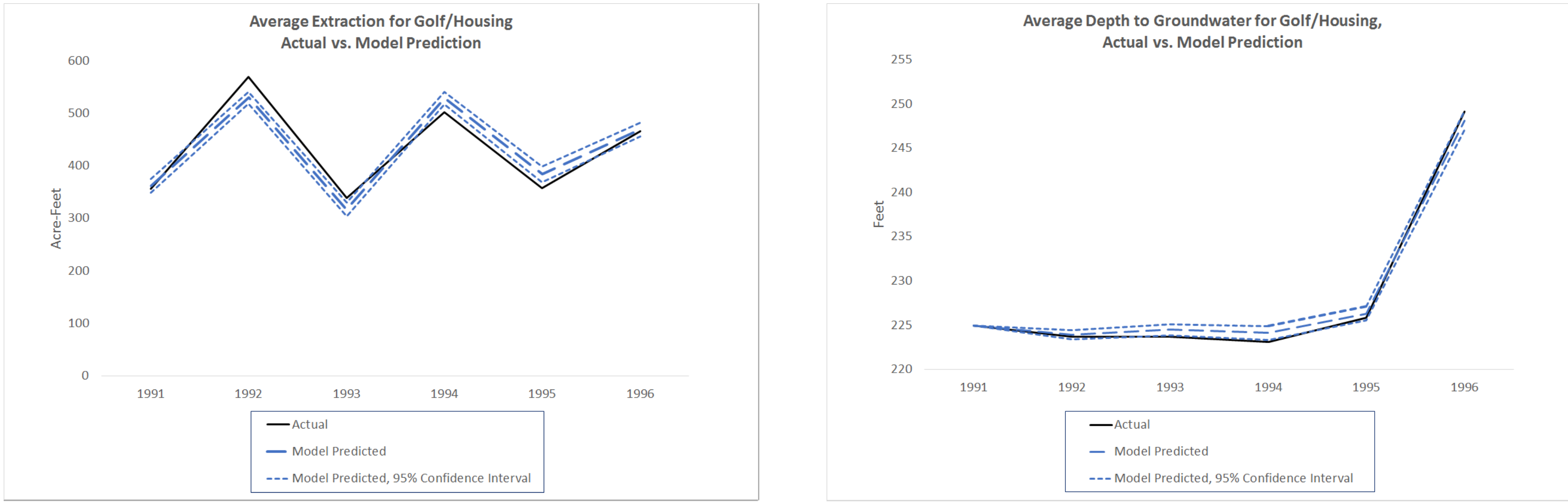


(c) Farmer Extraction outside Beaumont Basin



(d) Farmer Depth to Groundwater outside Beaumont Basin

Figure 14: No Dynamic Behavior Counterfactual vs. Actual Data, Farmers, 1991-1996



(a) Golf Course/Housing Development Extraction

(b) Golf Course/Housing Development Depth to Groundwater

Figure 15: No Dynamic Behavior Counterfactual vs. Actual Data, Golf Course/Housing Developments, 1991-1996

Table 20: No Dynamic Behavior Counterfactual: Average Annual Social Welfare, 1991-1996

	Actual	No Dynamic Behavior Counterfactual	No Dynamic Behavior Counterfactual Minus Actual
Consumer Surplus			
Beaumont-Cherry Valley Water District	3.55 million	3.63 million	0.00 million
City of Banning	7.39 million	7.57 million	0.00 million
South Mesa Water Company	2.38 million	2.50 million	-0.01 million*
Yucaipa Valley Water District	9.63 million	10.17 million	-0.08 million
Total Consumer Surplus	22.96 million	23.87 million	-0.09 million
Producer Surplus			
Appropriators	0.31 million	0.63 million	0.04 million
Farmers	14.65 thousand	14.62 thousand	0.40 thousand
Golf course/Housing Developments	101.23 thousand	141.73 thousand	0.19 thousand
Total Producer Surplus	0.40 million	0.78 million	0.10 million
Total Social Welfare	23.38 million	24.65 million	0.01 million

Notes: Table reports the mean annual components of social welfare for players and groups of players. Social welfare is defined as unweighted sum of producer surplus plus consumer surplus. Consumer surplus is computed using the model of residential water demand. Producer surplus is computed using the payoff functions for each player and does not include consumer surplus related components. Mean annual social welfare components are computed by dividing the present discounted value of the total quantity for the years 1991-1996 by the number of years in which the player participated in the extraction game. For actual values we use the observed state variables and action choices in the observed data. In the counterfactual simulation players are assumed to choose period payoff maximizing action choices, and do not consider present discounted expected future payoffs. Bias is defined as the mean difference between baseline simulated values and the actual value. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix

A Supplementary Tables and Figures

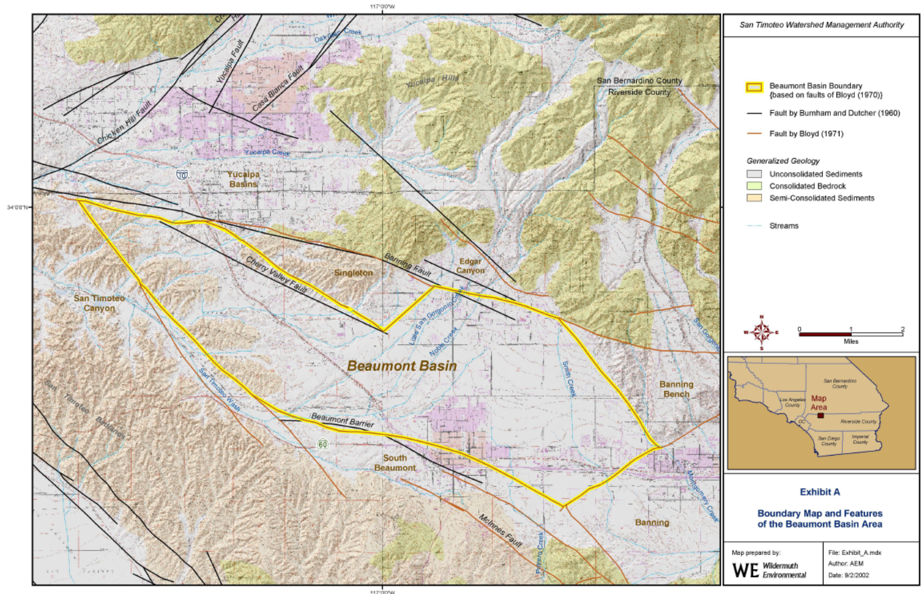


Figure A.1: Adjudicated Boundaries of the Beaumont Basin
Source: Exhibit A of Beaumont Basin Adjudication Judgment

Table A.1: Summary Statistics for Groundwater Variables by Player Type, 1991-1996

	Mean	Min	Max	Std.Dev.	Obs
Appropriators					
Appropriator extraction in Beaumont (acre-feet)	1,461.13	387.00	4,219.00	1,012.82	24
Appropriator extraction outside Beaumont (acre-feet)	3,944.25	932.00	8,317.00	2,260.33	24
Average depth to groundwater (feet)	143.94	103.93	196.38	30.19	24
Average depth to groundwater, wells in Beaumont Basin (feet)	185.29	123.82	237.82	36.87	24
Average depth to groundwater, wells outside Beaumont Basin (feet)	129.23	94.23	194.74	36.55	24
Wells per player	21.38	5.00	45.00	12.08	24
Wells inside of Beaumont Basin per player	5.75	2.00	11.00	3.64	24
Wells outside of Beaumont Basin per player	15.63	3.00	42.00	11.85	24
Average depth of wells (feet)	668.51	598.58	753.56	64.20	24
Appropriator population	18,932.11	7,502.95	36,789.55	11,171.08	24
Appropriator average household size	2.65	2.50	2.78	0.09	24
Farmers					
Farmer extraction (acre-feet)	208.80	55.00	550.00	170.63	30
Average depth to groundwater (feet)	204.83	100.60	269.41	54.41	30
Average depth to groundwater, wells in Beaumont Basin (feet)	228.59	187.83	269.41	40.11	12
Average depth to groundwater, wells outside Beaumont Basin (feet)	189.00	100.60	244.06	57.84	18
Wells per player	1.60	1.00	3.00	0.81	30
Wells inside of Beaumont Basin per player	0.40	0.00	1.00	0.50	30
Wells outside of Beaumont Basin per player	1.20	0.00	3.00	1.19	30
Average depth of wells (feet)	235.50	171.00	300.00	67.37	12
Golf course / Housing development action and state variables					
Golf course / Housing development extraction (acre-feet)	430.59	13.00	1,570.00	380.94	29
Average depth to groundwater (feet)	225.24	143.49	382.67	77.72	30
Average depth to groundwater, wells in Beaumont Basin (feet)	225.24	143.49	382.67	77.72	30
Average depth to groundwater, wells outside Beaumont Basin (feet)	.	.	.	.	0
Wells per player	1.40	1.00	2.00	0.50	30
Wells inside of Beaumont Basin per player	1.40	1.00	2.00	0.50	30
Wells outside of Beaumont Basin per player	0.00	0.00	0.00	0.00	30
Average depth of wells (feet)	941.50	415.00	1,370.00	407.47	18

Data Sources: AWWA CA/Nevada Survey 2007-2015; CA Franchise Tax Board; USGS; CA-SWP; CA Dept. Finance; PRISM; FRED; BEA; USDA; SGPWA; STWMA; Beaumont Watermaster; Groundwater Recordation Program.

Table A.2: Summary Statistics for Additional State Variables, 1991-1996

	Mean	Min	Max	Std.Dev.	Obs
Annual state variables					
Agricultural price of electricity (dollars per kwh)	0.10	0.10	0.11	0.01	6
Price alfalfa (dollars per ton)	88.17	73.70	97.30	8.37	6
Price grapes (dollars per ton)	129.17	123.00	135.00	4.71	6
Price untreated imported water (dollars per acre-foot)	295.25	213.00	344.00	53.11	6
Price strawberries (dollars per pound)	0.78	0.65	0.90	0.09	6
Price cherries (dollars per ton)	126.00	115.00	140.00	10.08	6
Price olives (dollars per ton)	96.50	94.40	99.10	1.68	6
Average crop price (dollars per unit)	96.50	94.40	99.10	1.68	6
Price untreated imported water (dollars per acre-foot)	295.25	213.00	344.00	53.11	6
Population of Beaumont	10,422.83	9,996	10,673	264.05	6
Other player-level state variables					
Saturated hydraulic conductivity (feet per day)	33.00	4.61	92.00	33.53	84
Saturated hydraulic conductivity in Beaumont Basin (feet per day)	29.71	4.61	92.00	29.28	66
Saturated hydraulic conductivity outside Beaumont Basin (feet per day)	40.16	5.85	120.67	43.90	42
Extraction by neighbors within 3 miles (acre-feet)	410.46	0.00	1,971.00	560.65	84
Extraction by neighbors in the Beaumont Basin within 1 mile (acre-feet)	547.15	0.00	2,351.00	717.05	84
Extraction by neighbors in the Beaumont Basin within 2 miles (acre-feet)	754.43	0.00	4,869.00	1,067.76	84
Extraction by neighbors in the Beaumont Basin within 3 miles (acre-feet)	491.20	0.00	4,219.00	838.95	84
Extraction by neighbors in the Beaumont Basin within 4 miles (acre-feet)	978.63	0.00	4,807.00	1,296.27	84
Extraction by neighbors outside the Beaumont Basin within 2 miles (acre-feet)	339.85	0.00	6,511.00	1,287.07	84
Extraction by neighbors outside the Beaumont Basin within 4 miles (acre-feet)	1,473.19	0.00	9,964.00	2,652.12	84
Precipitation, growing season (inches)	2.44	0.79	5.03	1.00	84
Precipitation, full year (inches)	22.67	10.74	42.72	7.57	84
Number of high heat days (> 90 F), growing season (Apr-Oct)	79.85	36.76	104.00	16.68	84

Data Sources: AWWA CA/Nevada Survey 2007-2015; CA Franchise Tax Board; USGS; CA-SWP; CA Dept. Finance; PRISM; FRED; BEA; USDA; SGPWA; STWMA; Beaumont Watermaster; Groundwater Recordation Program.

Table A.3: Summary Statistics for Residential Water Demand Estimation

	Mean	Min	Max	Std.Dev.	Obs
Demand estimation sample					
Household monthly consumption (hundred cubic feet)	17.38	1.00	38.00	6.66	210
Average water price (dollars per hundred cubic feet)	1.71	0.25	19.77	2.36	210
State Water Project equivalent unit charge (dollars per acre-foot)	334.26	31.46	2,164.80	296.16	210
Electricity price (dollars per kwh) x Depth to groundwater (feet)	5.21	0.05	30.83	5.28	210
Household size	2.84	1.94	4.53	0.47	210
Median adjusted gross income (dollars)	15,986.30	11,135.96	25,277.77	2,749.63	210
Unemployment rate (percent)	8.43	5.38	11.71	2.67	210
Precipitation, full year (inches)	12.78	1.60	56.16	9.57	210

Data Sources: AWWA CA/Nevada Survey 2007-2015; CA Franchise Tax Board; USGS; CA-SWP; CA Dept. Finance; PRISM; FRED; BEA; USDA; SGPWA; STWMA; Beaumont Watermaster; Groundwater Recordation Program.

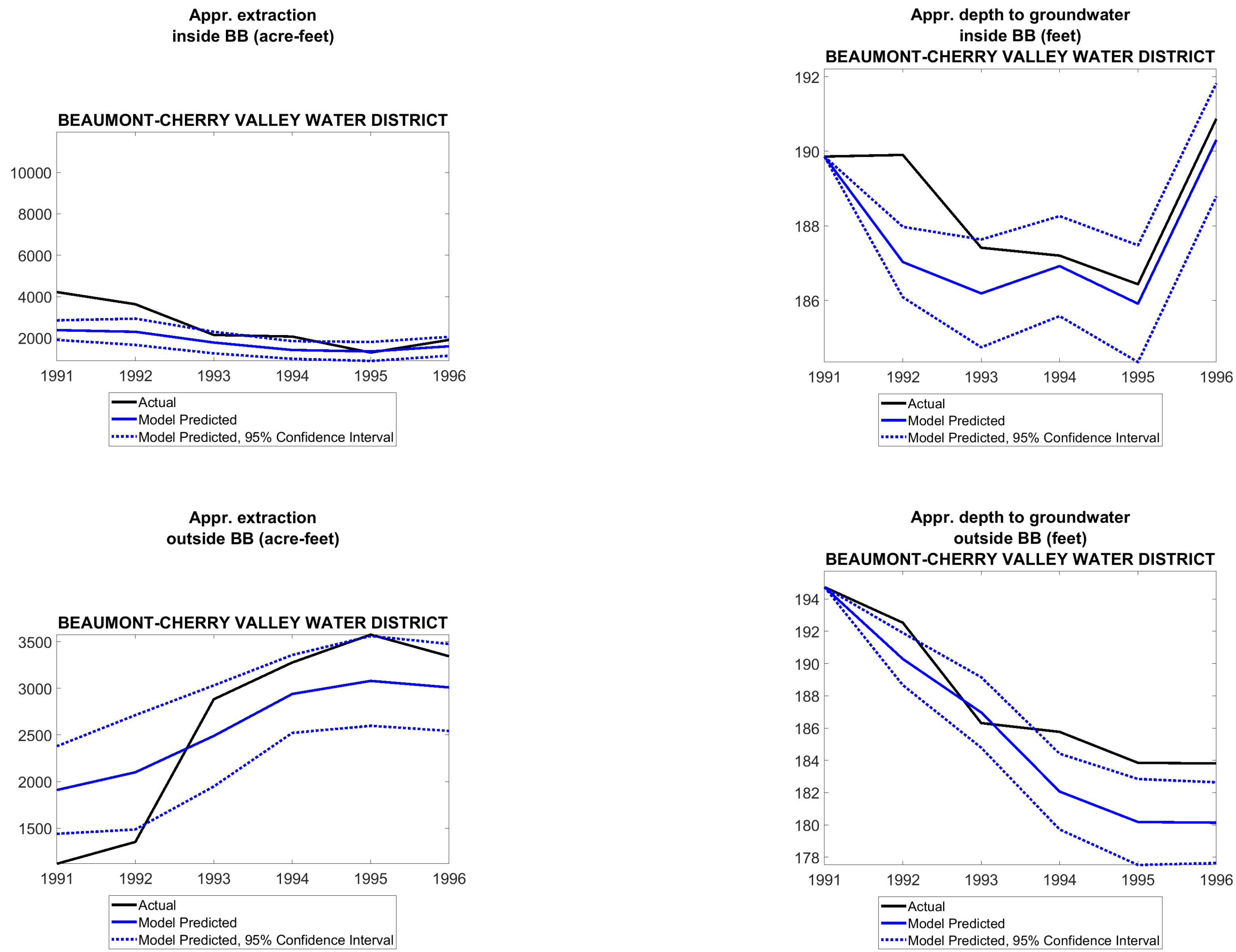


Figure A.2: Model Simulated vs. Actual Data, Beaumont Cherry-Valley Water District, 1991-1996

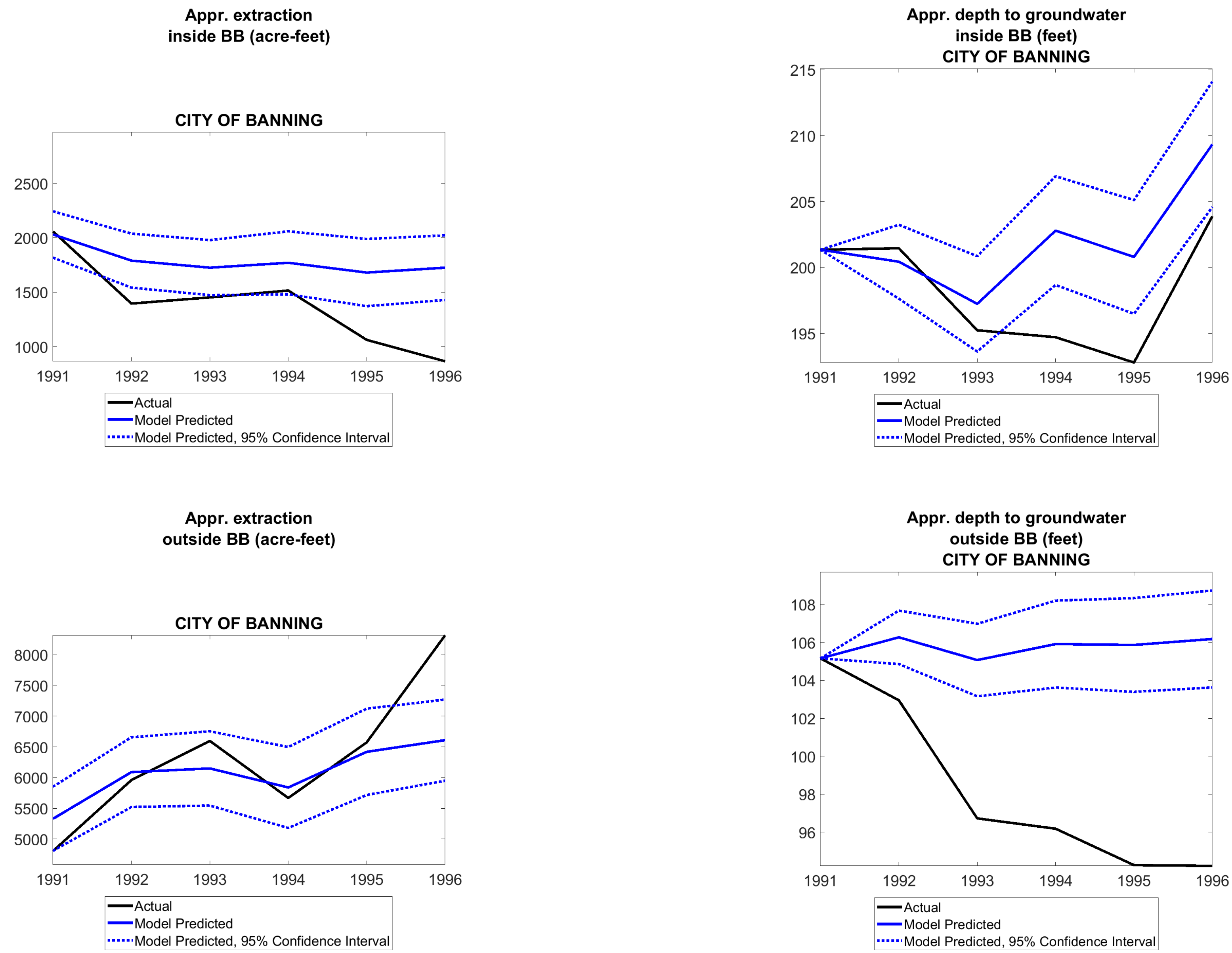


Figure A.3: Model Simulated vs. Actual Data, City of Banning, 1991-1996

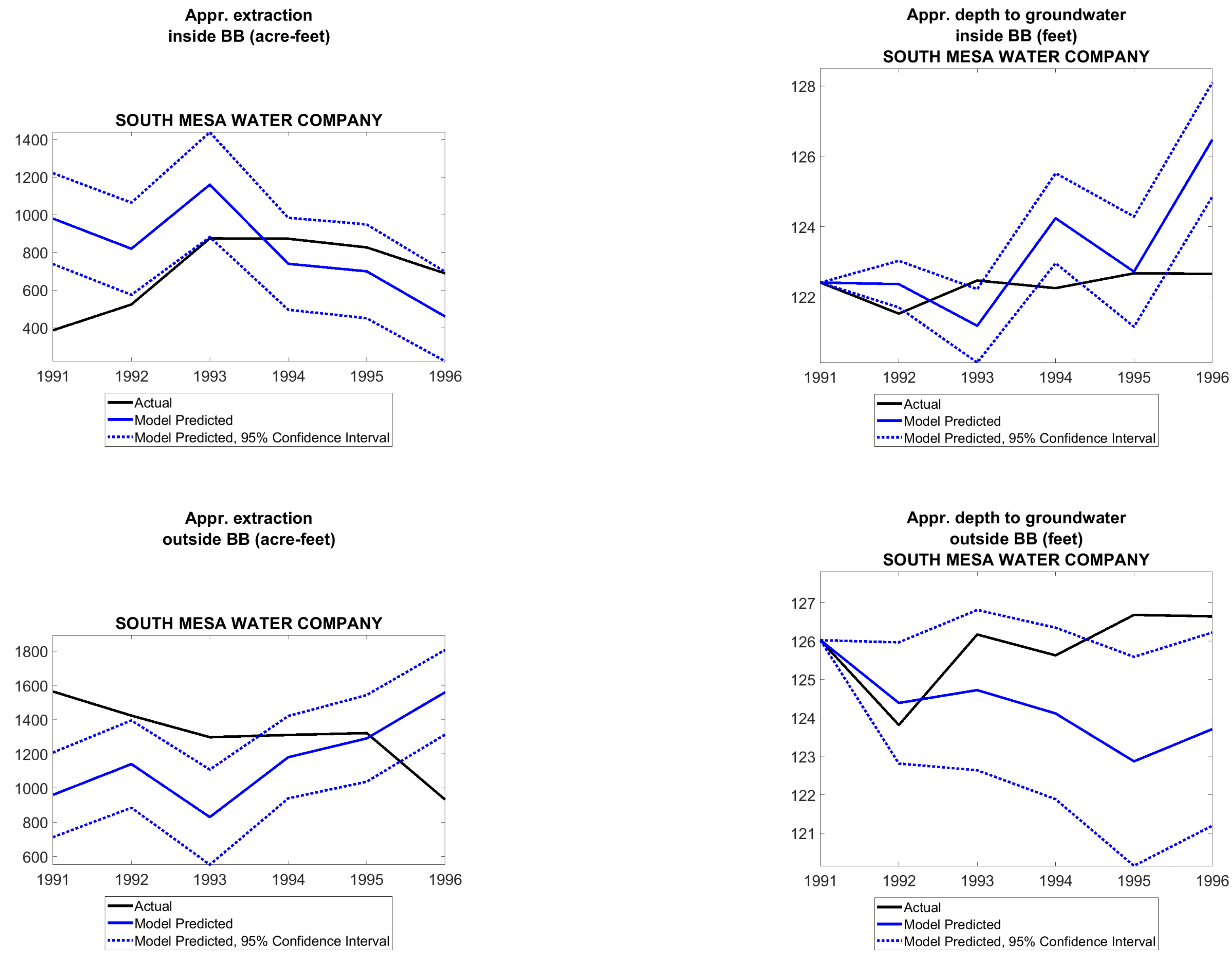


Figure A.4: Model Simulated vs. Actual Data, South Mesa Water Co., 1991-1996

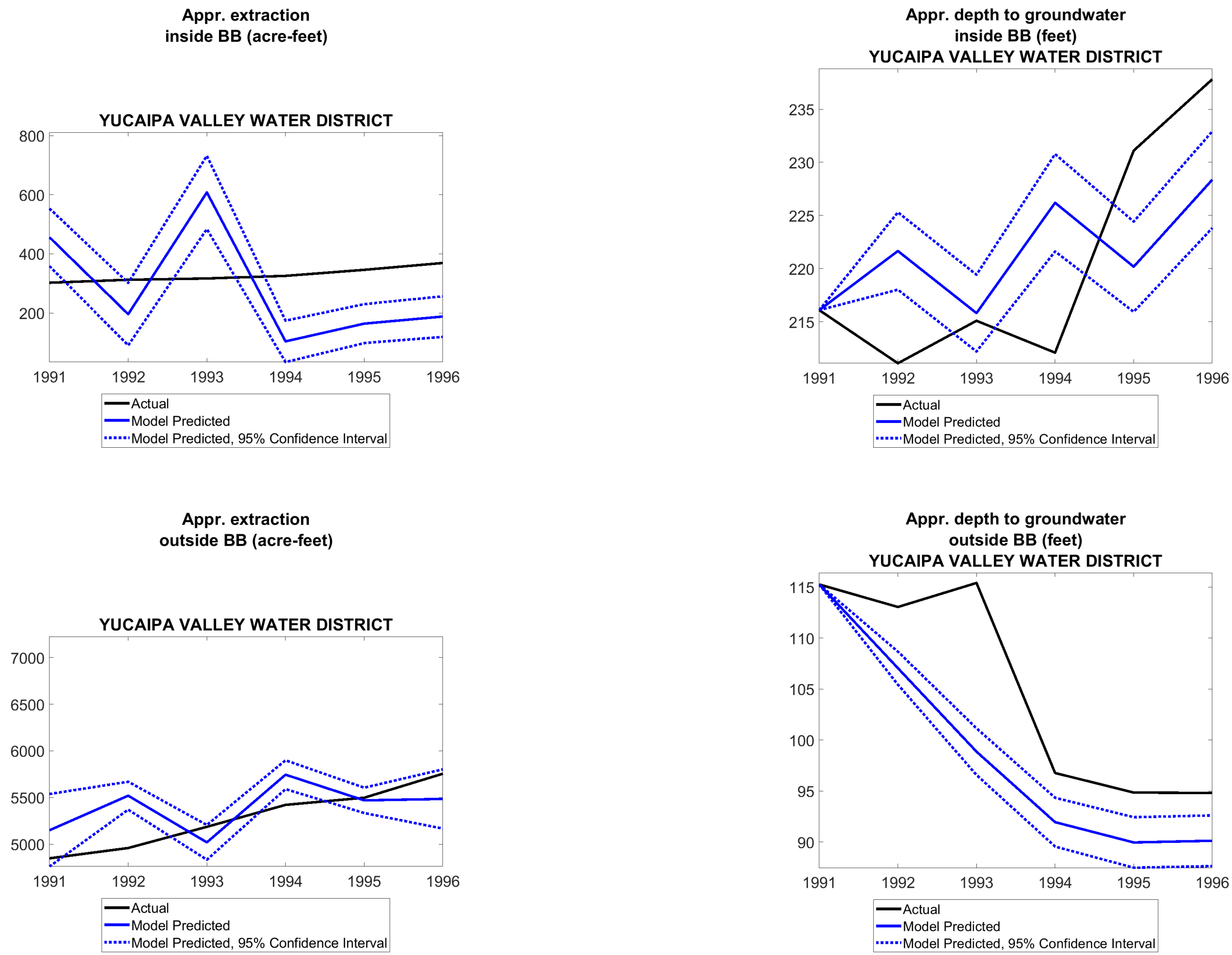


Figure A.5: Model Simulated vs. Actual Data, Yucaipa Valley Water District, 1991-1996

Figure A.6: Model Simulated vs. Actual Data, Dowling, 1991-1996

Figure A.7: Model Simulated vs. Actual Data, Illy, 1991-1996

Figure A.8: Model Simulated vs. Actual Data, Murray, 1991-1996

Figure A.9: Model Simulated vs. Actual Data, Riedman, 1991-1996

Figure A.10: Model Simulated vs. Actual Data, Summit, 1991-1996

Figure A.11: Model Simulated vs. Actual Data, California Oak Valley Golf and Resort, 1991-1996

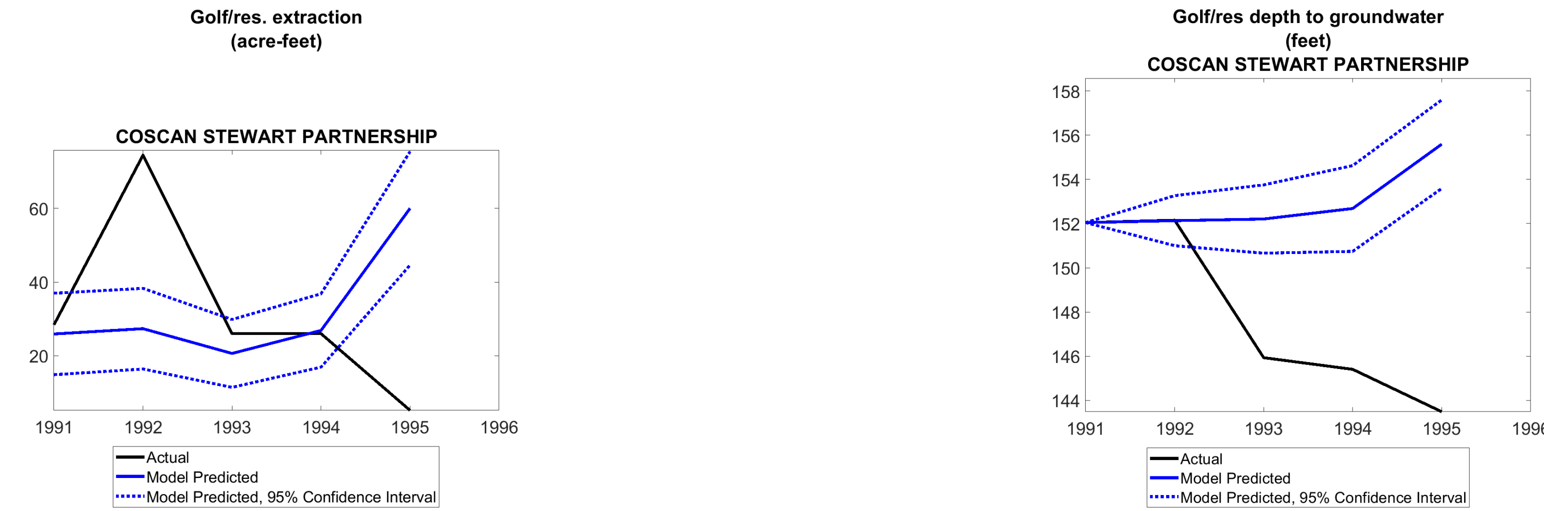


Figure A.12: Model Simulated vs. Actual Data, Coscan Stewart Partnership, 1991-1996

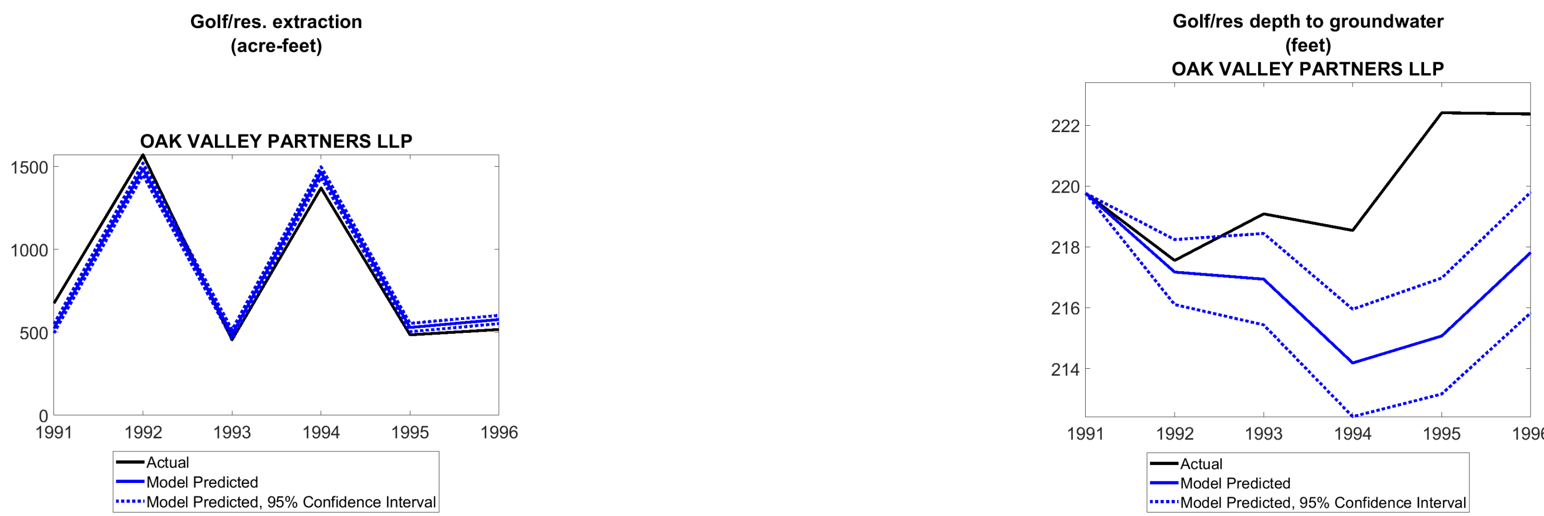


Figure A.13: Model Simulated vs. Actual Data, Oak Valley Partners, 1991-1996

Figure A.14: Model Simulated vs. Actual Data, Plantation on the Lake, 1991-1996

Figure A.15: Model Simulated vs. Actual Data, Sharondale Mesa Owners Association, 1991-1996

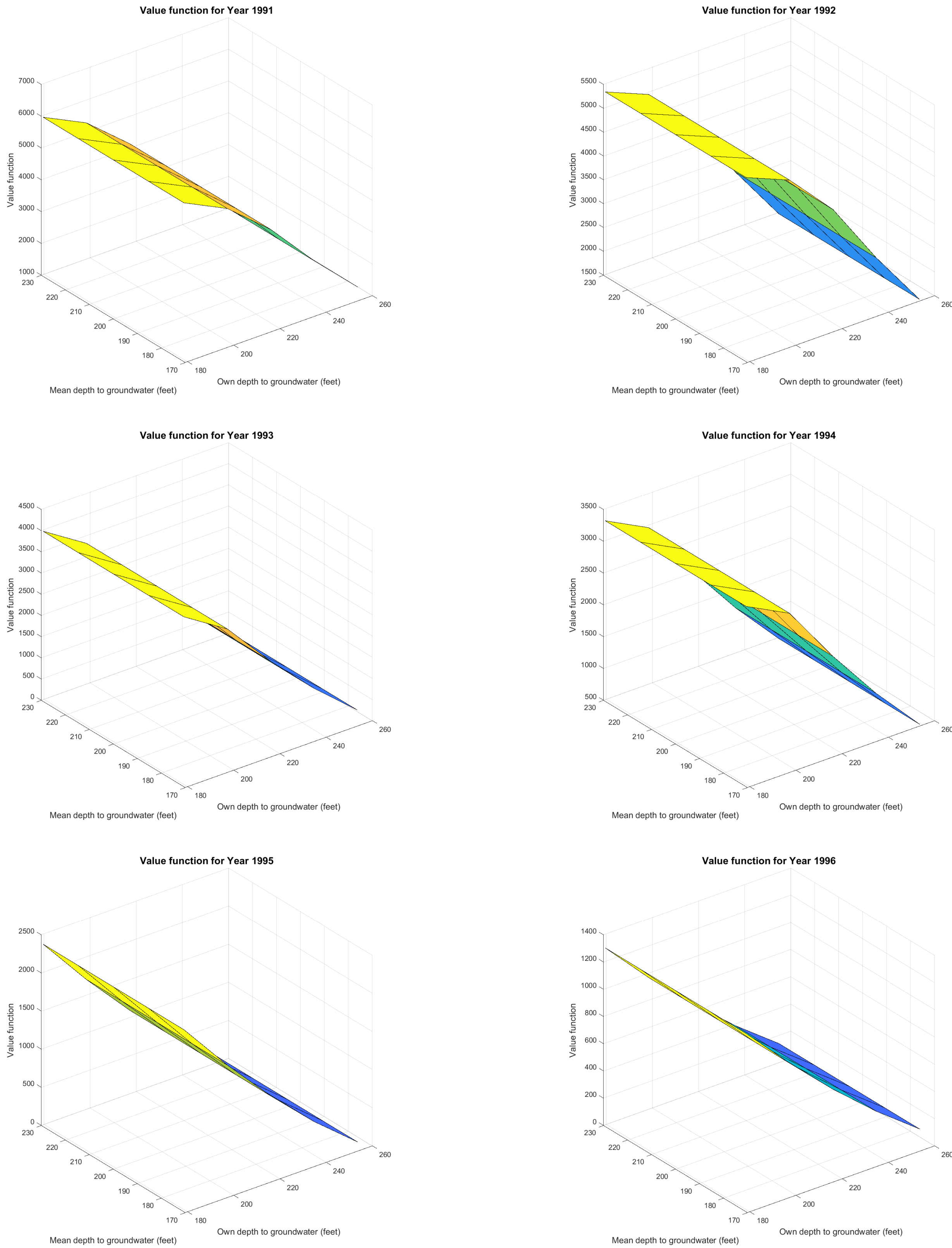


Figure A.16: Value Function, Dowling, 1991-1996

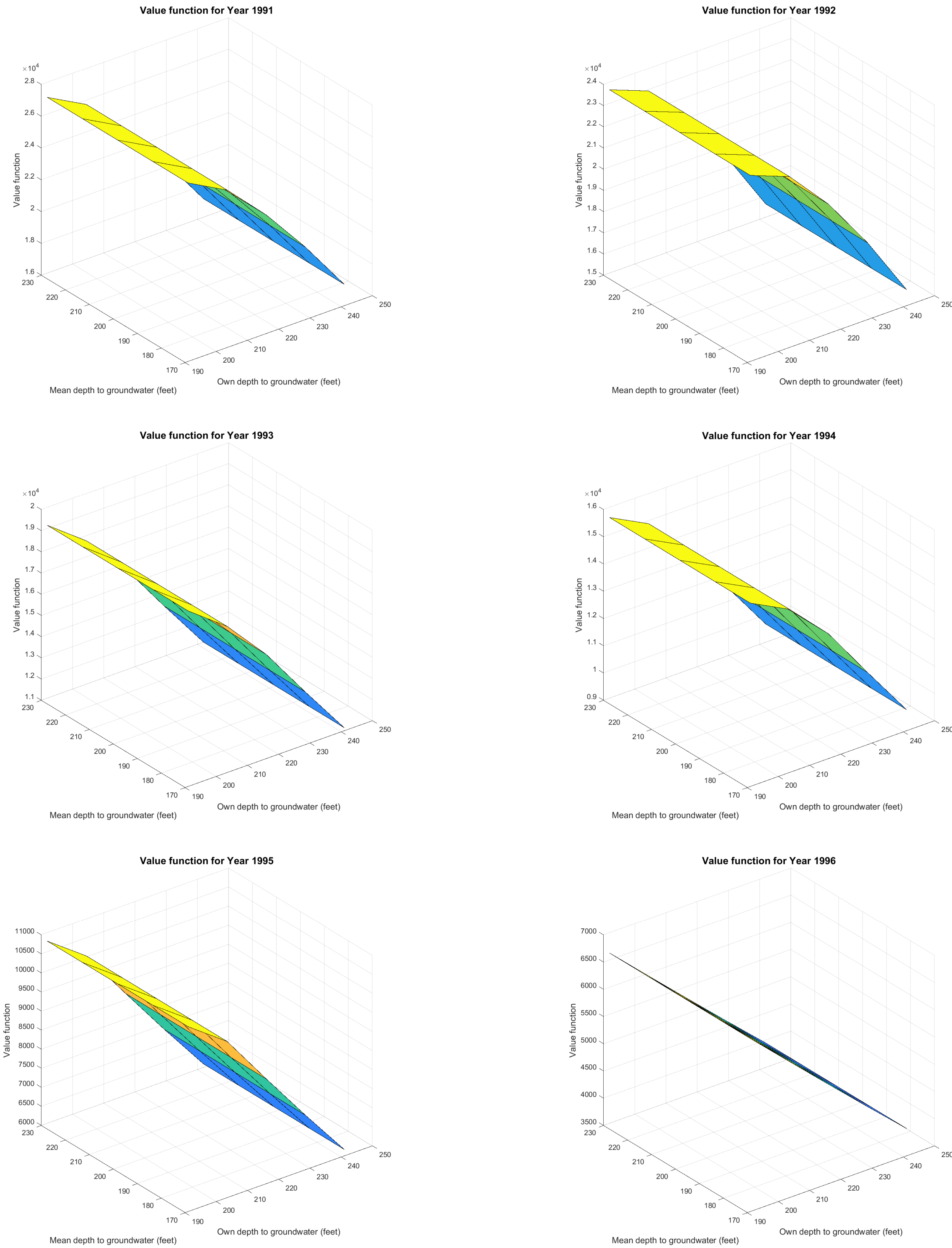


Figure A.17: Value Function, Illy, 1991-1996

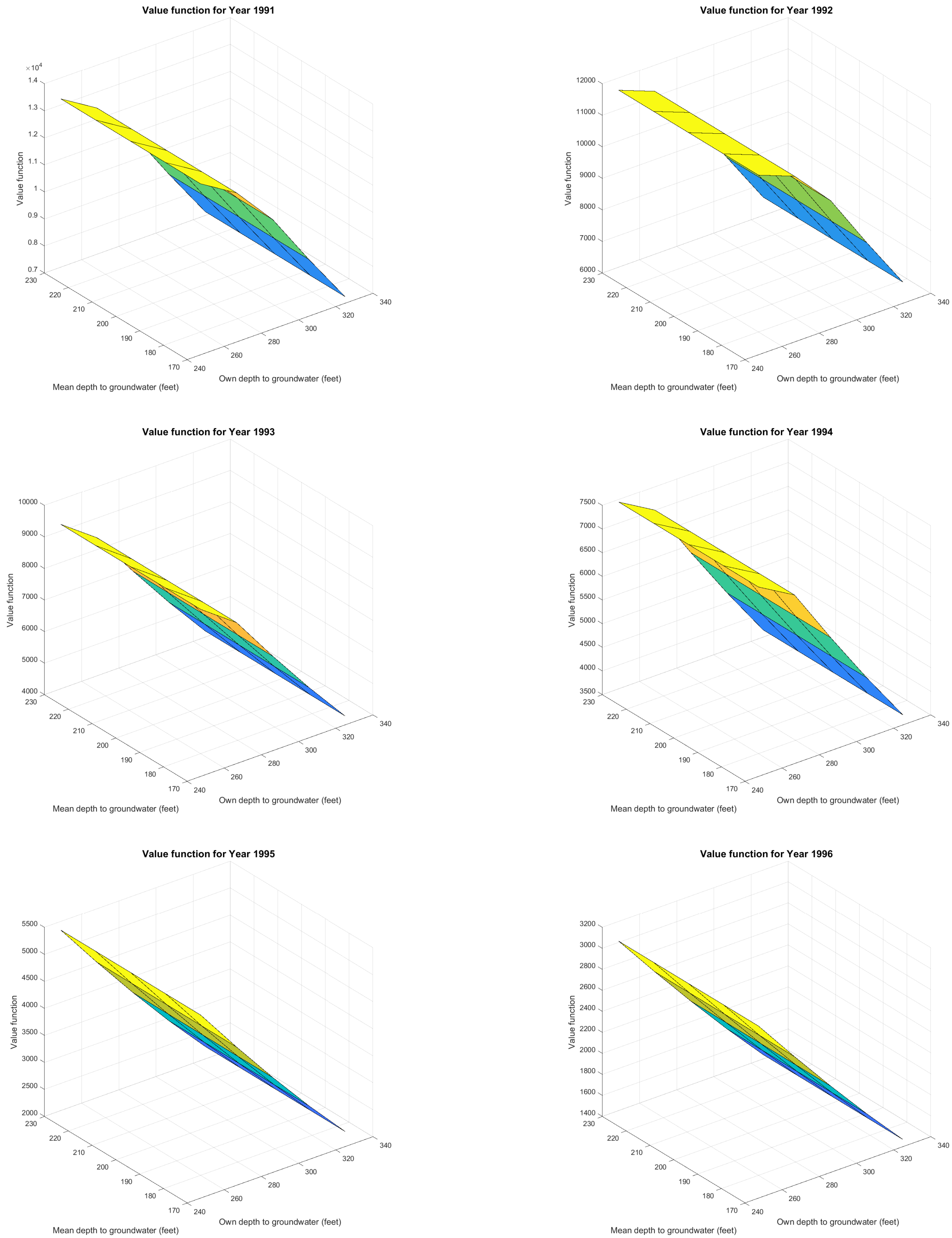


Figure A.18: Value Function, Murray, 1991-1996

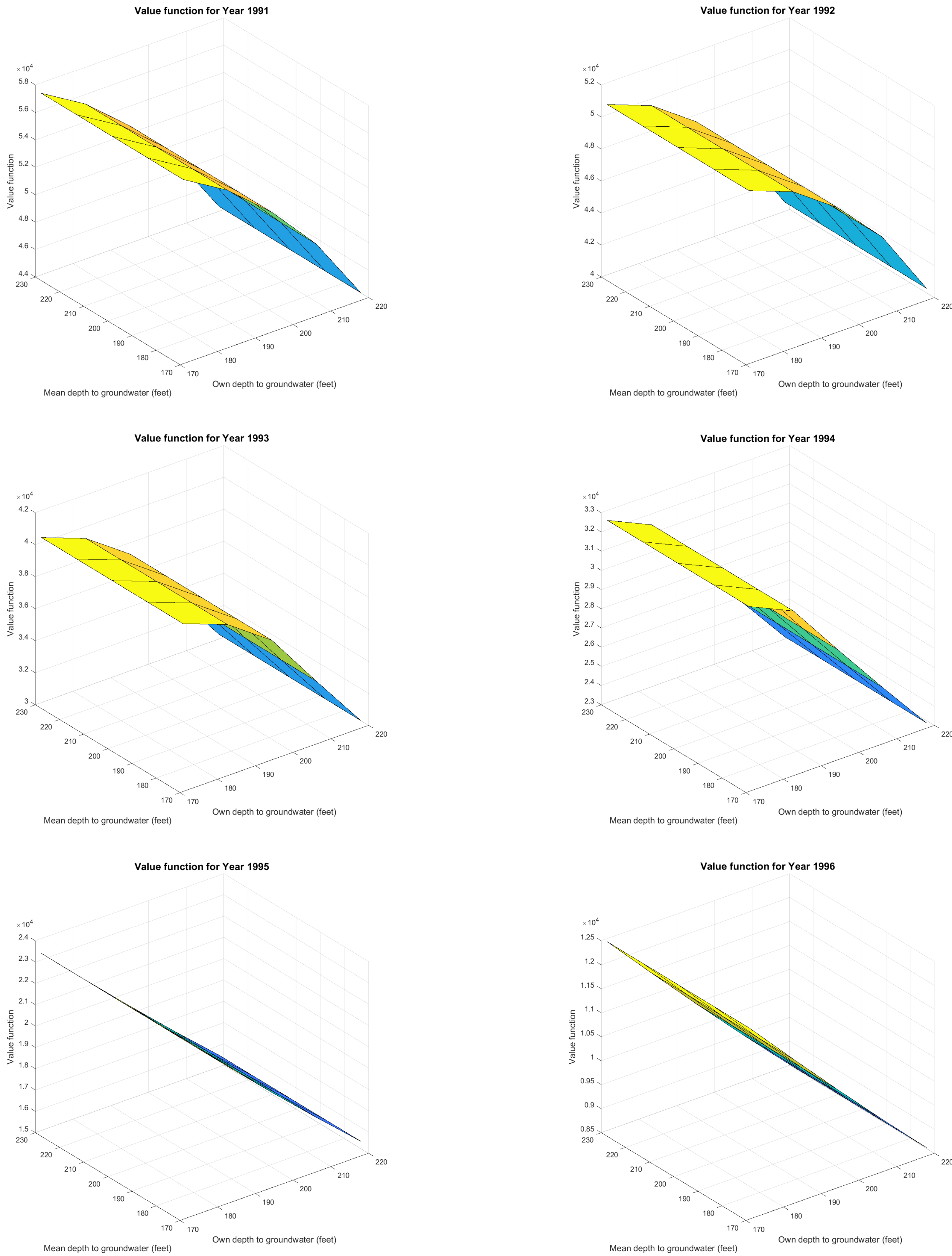


Figure A.19: Value Function, Riedman, 1991-1996

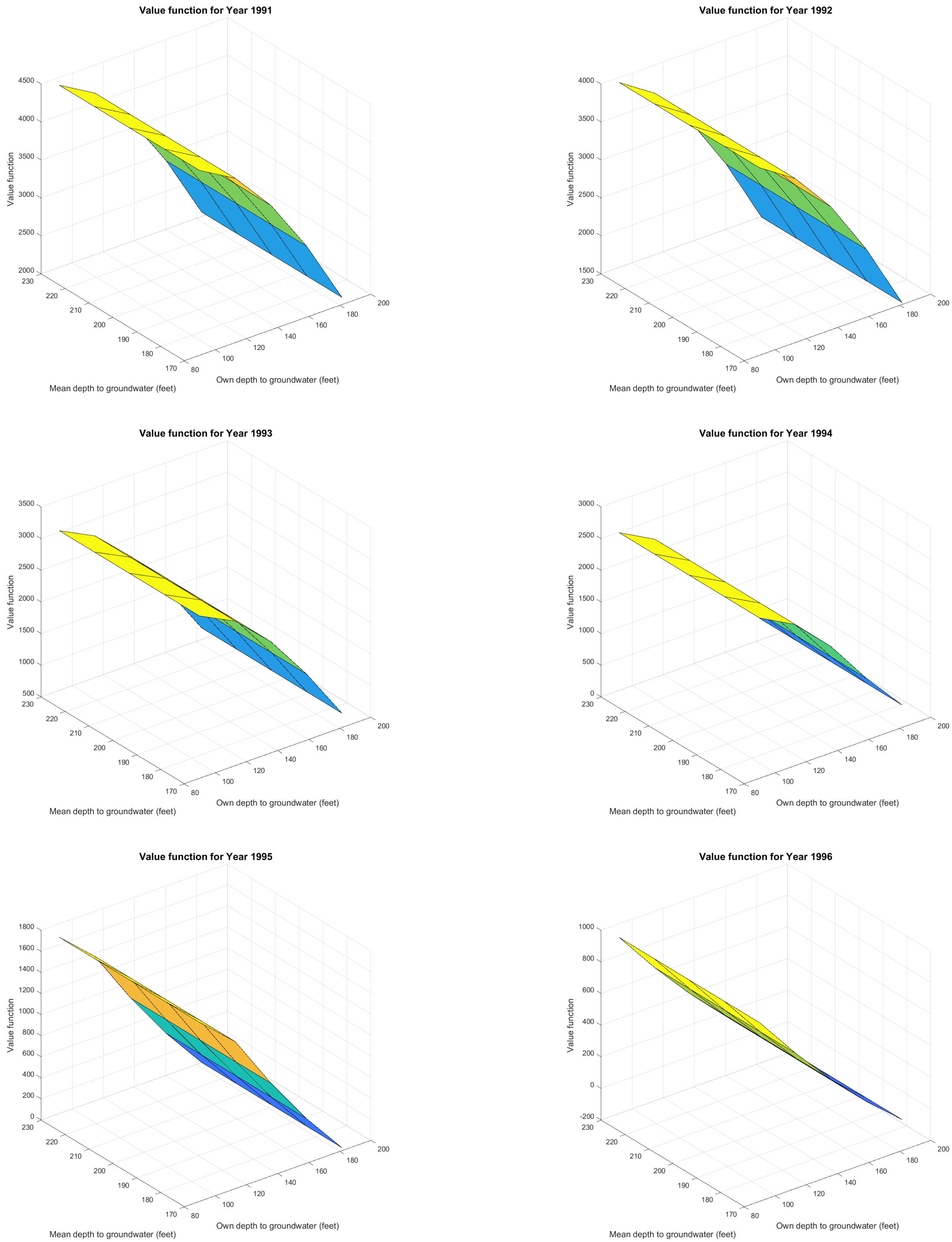


Figure A.20: Value Function, Summit, 1991-1996

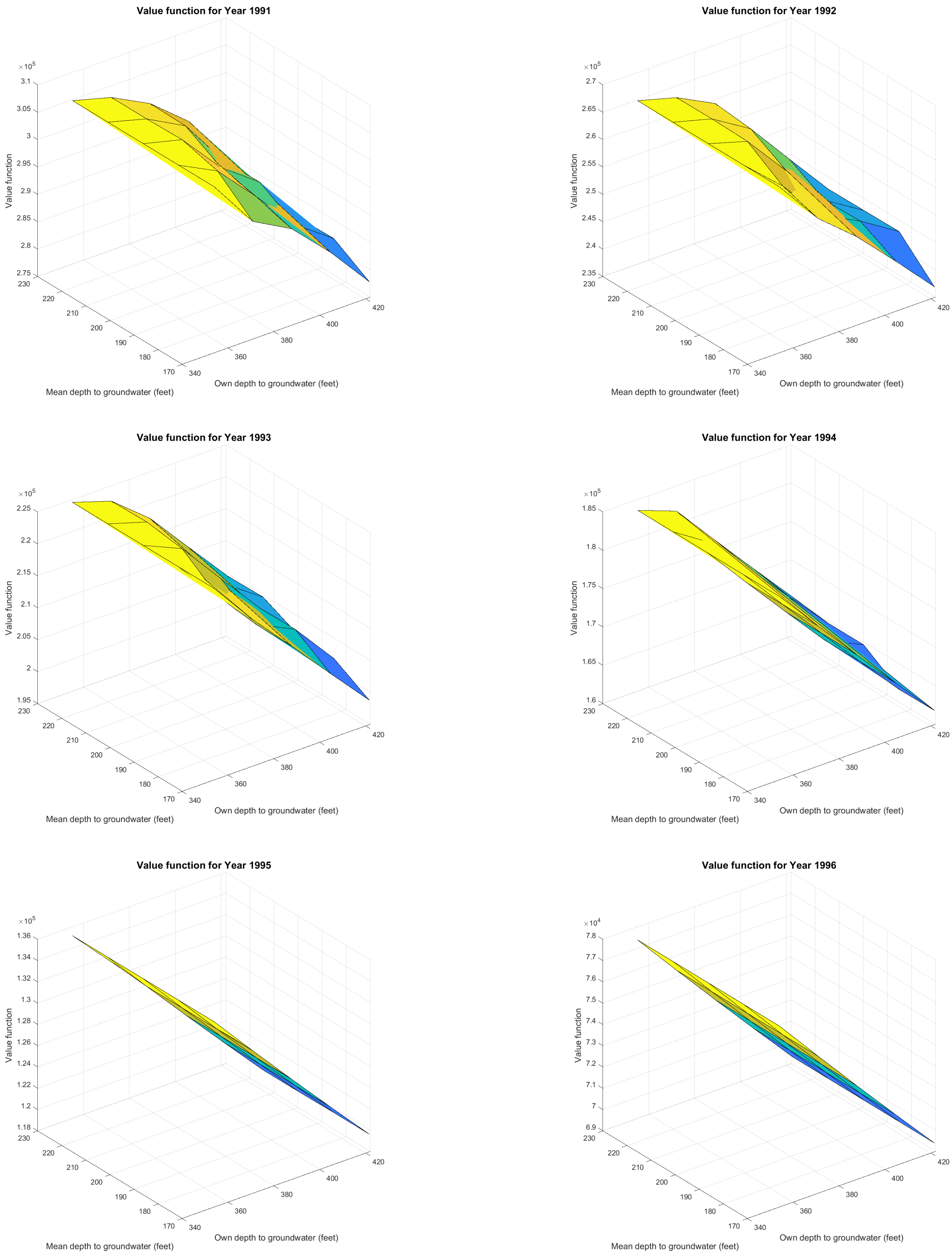


Figure A.21: Value Function, California Oak Valley Golf and Resort LLC, 1991-1996

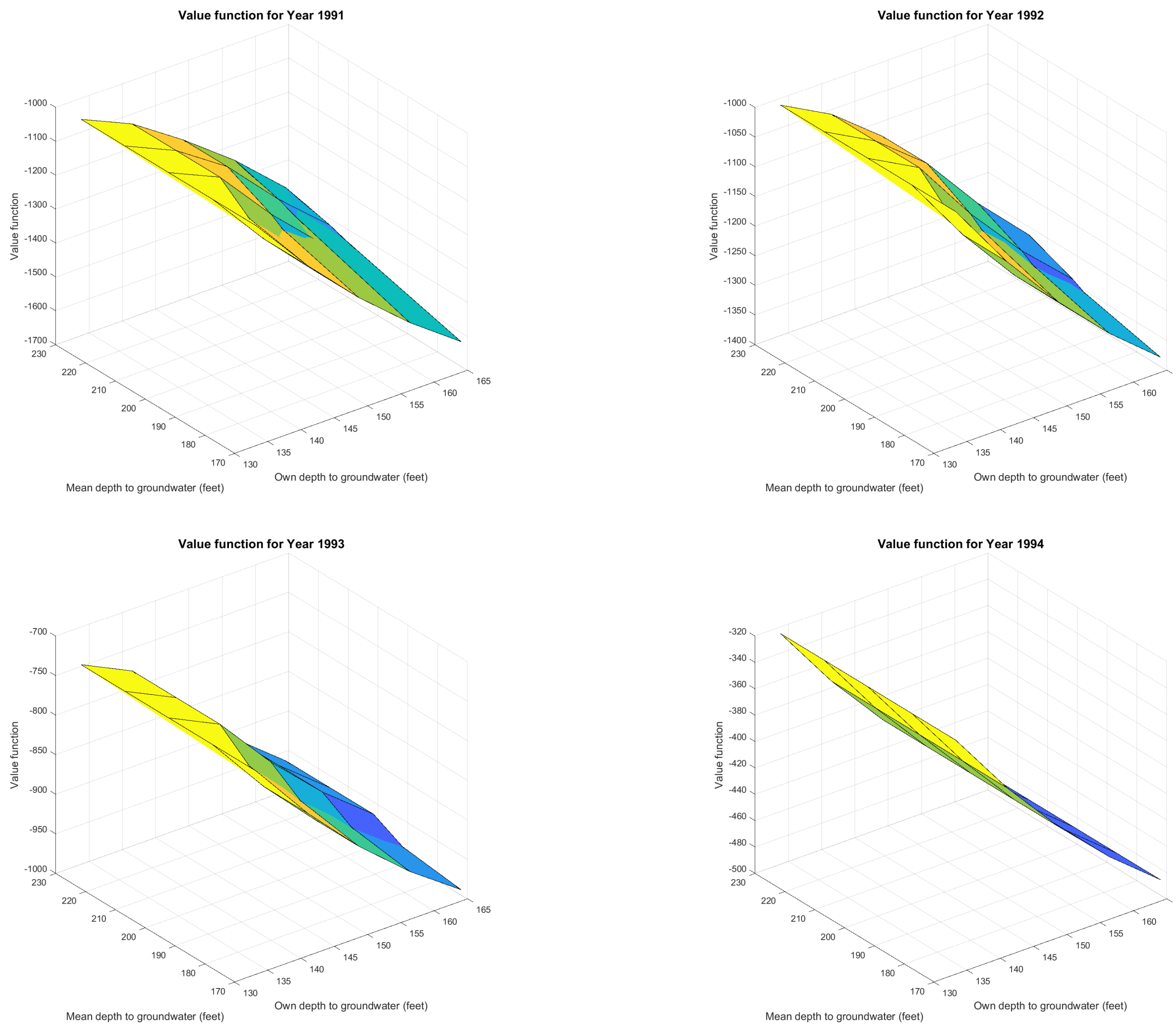


Figure A.22: Value Function, Coscan Stewart Partnership, 1991-1996

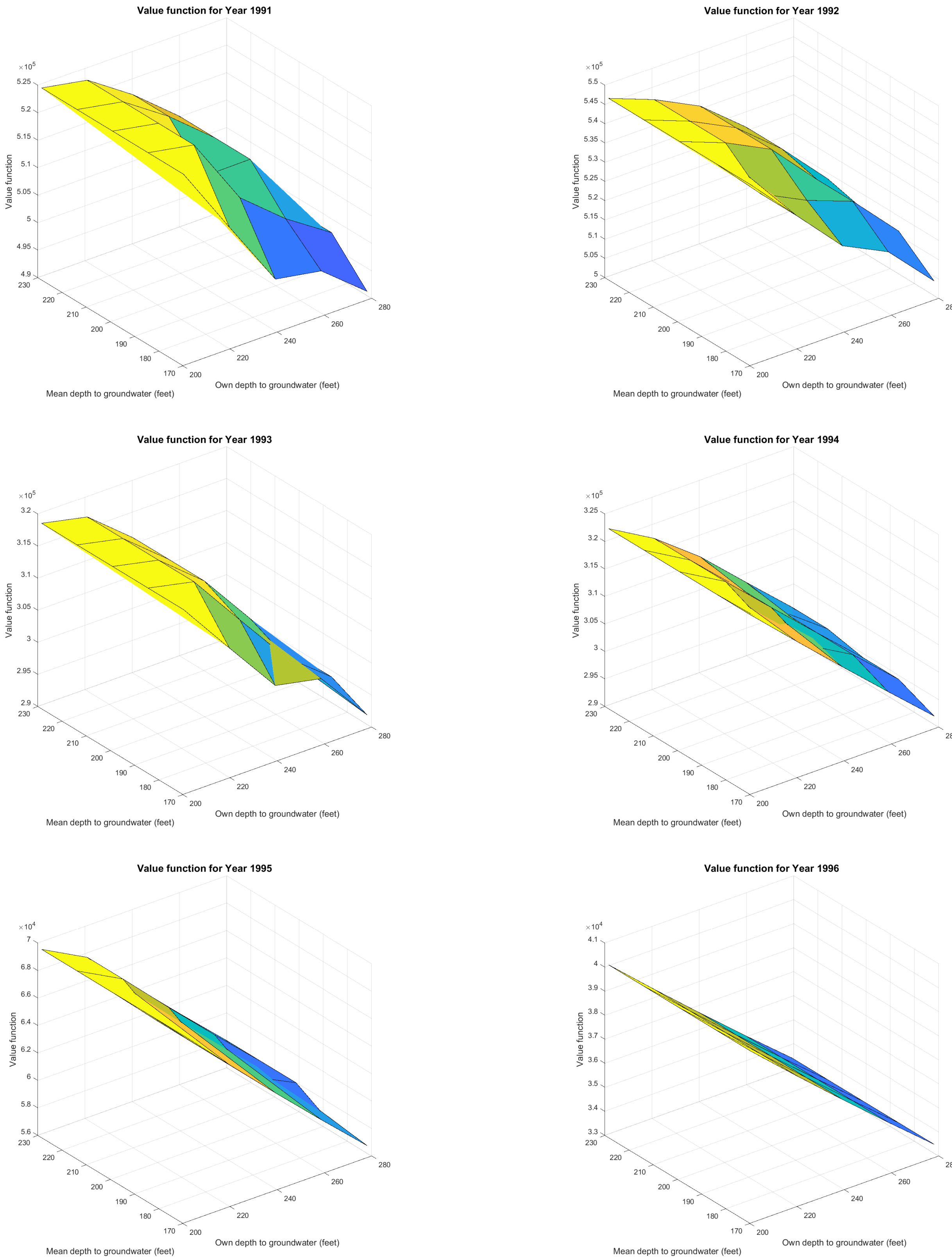


Figure A.23: Value Function, Oak Valley Partners LLP, 1991-1996

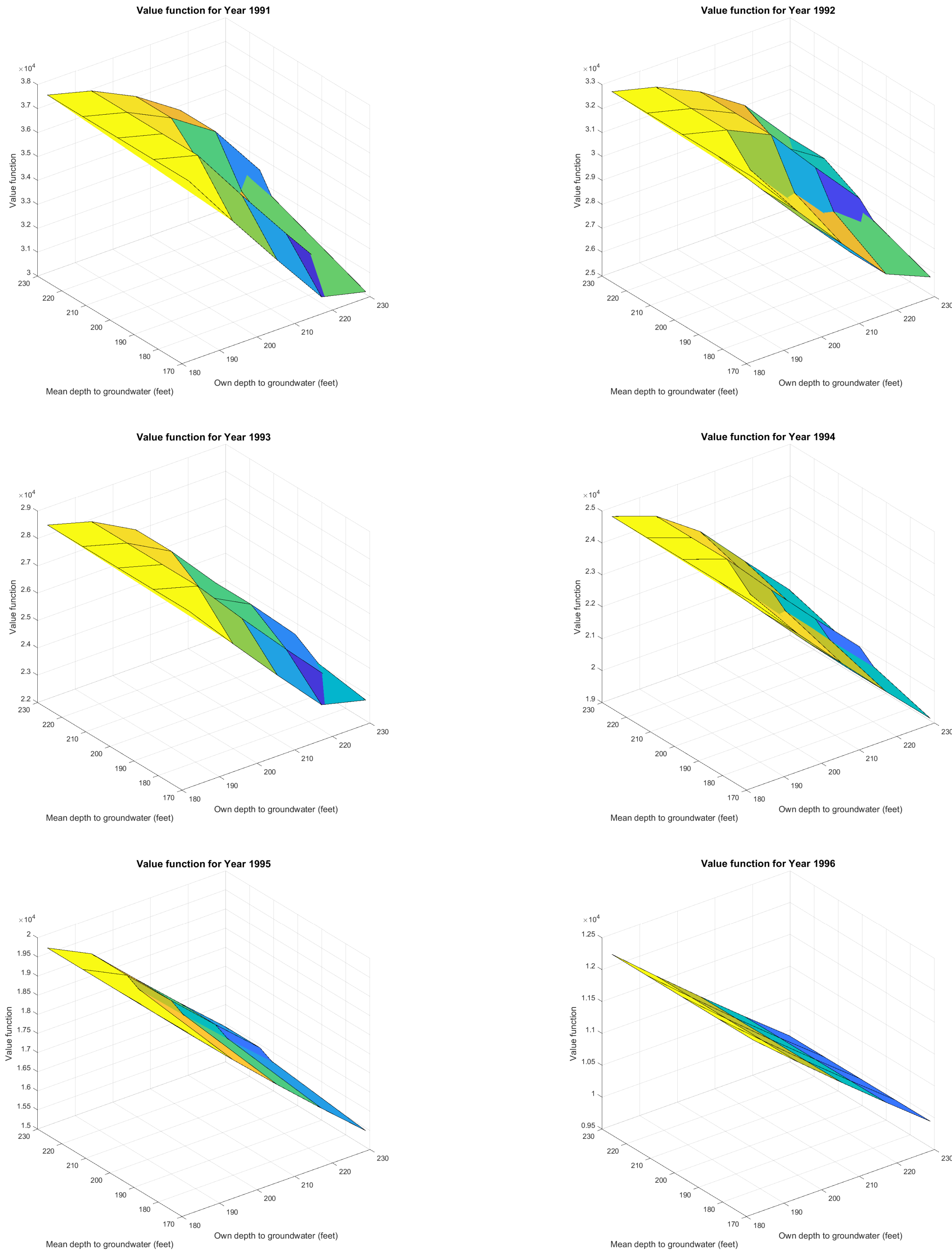


Figure A.24: Value Function, Plantation on the Lake, 1991-1996

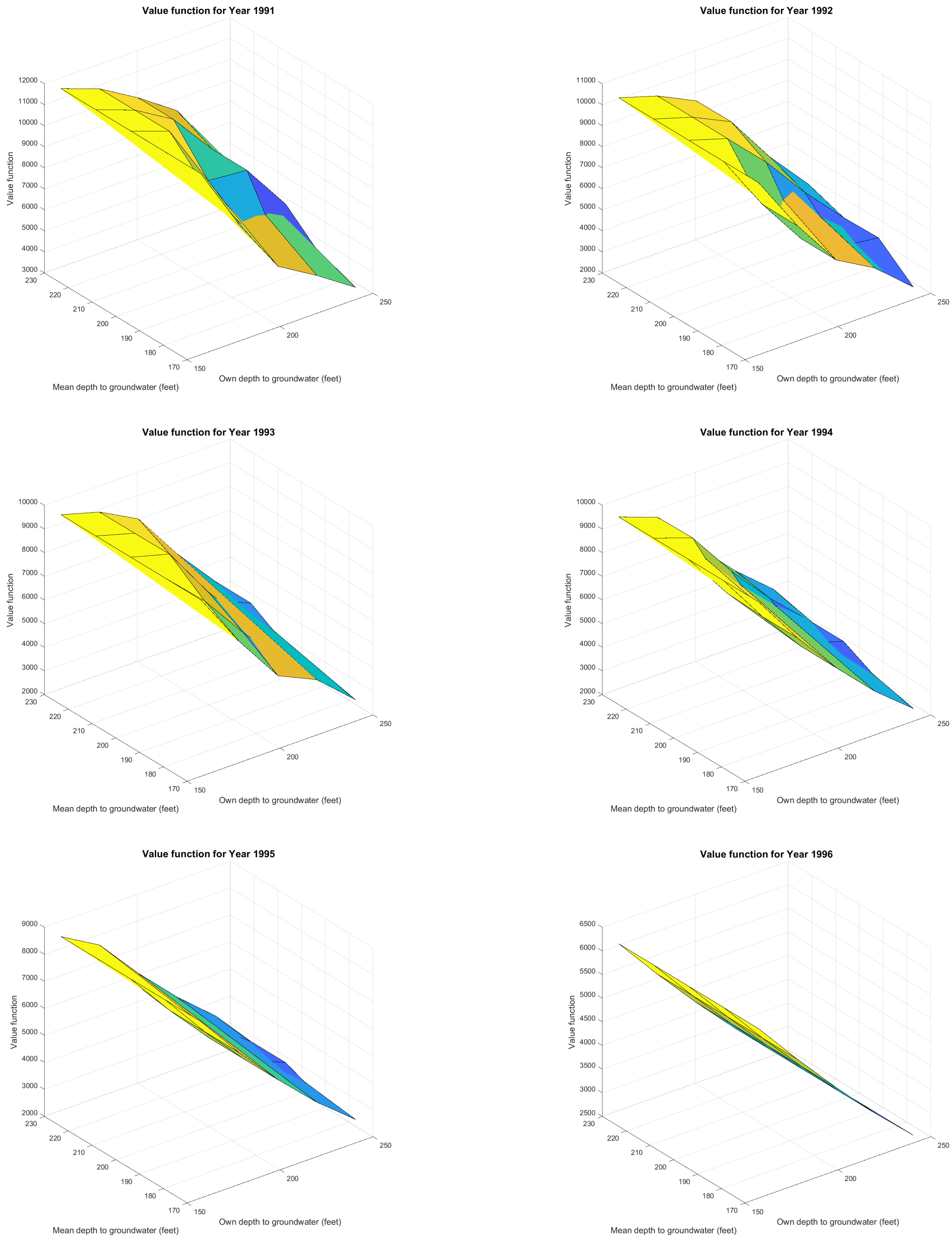


Figure A.25: Value Function, Sharondale Mesa Owners Association, 1991-1996

Table A.4: Value Function Regression Results: Value Function, 1991

	Player's own private state			
	Depth to Groundwater (ft)	Depth to Groundwater Wells in Beaumont Basin (ft)	Depth to Groundwater Wells outside Beaumont Basin (ft)	Moment State Average Depth to Groundwater (ft) All Wells
Appropriators				
Beaumont-Cherry Valley Water District		-1,025***	-1,195***	-32.61
City of Banning		-1,531***	-13,214***	-29.85
South Mesa Water Company		-7,495***	-7,144***	1,019***
Yucaipa Valley Water District		-650.9**	-45,254***	307.8**
All Appropriators Pooled		504,384***	-340,843***	50,317***
Farmers				
Dowling	-62.86***			0.00
Illy	-200.9***			0.00
Murray	-80.22***			0.00
Riedman	-271.9***			0.00
Summit	-25.81***			0.00
All Farmers Pooled	-23.40			0.00
Golf Course/Housing Developments				
California Oak Valley Golf and Resort	-353.0***			93.32***
Coscan Stewart Partnership	-16.33***			2.190***
Oak Valley Partners	-354.9***			155.7***
Plantation on the Lake	-137.9***			40.49***
Sharondale Mesa Owners Association	-80.28***			47.03***
All Golf Course/Housing Developments Pooled	1,252***			67.74

Notes: Table reports regression results from an ordinary least squares (OLS) regressions for each player of the value function for that player in 1991 on the discretized state and moment state for that player in 1991. Each row reports the results of a separate regression of the value function for the respective player (or players in the respective player group) in 1991 on the discretized state and moment state for that player (or players in the respective player group) in 1991. For each player, the value function in 1991 is the present discounted value of the entire stream of expected per-period payoffs expected to be earned by the player from 1991 onwards. The value of the value function at a particular state and moment state is the present discounted value of the entire stream of expected per-period payoffs expected to be earned by the player from 1991 onwards upon reaching the state and moment state in 1991. Value functions and policy functions are solved for by solving the dynamic game using backwards induction using the estimated structural parameters and state transition densities. Intercept coefficients are not included in the table. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.5: Value Function Regression Results: Value Function, 1992

	Player's own private state			
	Depth to Groundwater (ft)	Depth to Groundwater Wells in Beaumont Basin (ft)	Depth to Groundwater Wells outside Beaumont Basin (ft)	Moment State Average Depth to Groundwater (ft) All Wells
Appropriators				
Beaumont-Cherry Valley Water District		-759.4***	-1,465***	-30.05
City of Banning		-1,530***	-11,846***	8.754
South Mesa Water Company		-8,340***	-8,220***	648.2***
Yucaipa Valley Water District		-270.1	-38,287***	85.53
All Appropriators Pooled		444,542***	-299,628***	44,181***
Farmers				
Dowling	-53.20***			0.00
Illy	-163.8***			0.00
Murray	-66.83***			0.00
Riedman	-212.0***			0.00
Summit	-26.89***			0.00
All Farmers Pooled	-18.98			0.00
Golf Course/Housing Developments				
California Oak Valley Golf and Resort	-353.5***			99.56***
Coscan Stewart Partnership	-10.98***			1.322***
Oak Valley Partners	-442.8***			139.7***
Plantation on the Lake	-122.0***			40.01***
Sharondale Mesa Owners Association	-77.07***			38.01***
All Golf Course/Housing Developments Pooled	1,084***			63.71

Notes: Table reports regression results from an ordinary least squares (OLS) regressions for each player of the value function for that player in 1992 on the discretized state and moment state for that player in 1992. Each row reports the results of a separate regression of the value function for the respective player (or players in the respective player group) in 1992 on the discretized state and moment state for that player (or players in the respective player group) in 1992. For each player, the value function in 1992 is the present discounted value of the entire stream of expected per-period payoffs expected to be earned by the player from 1992 onwards. The value of the value function at a particular state and moment state is the present discounted value of the entire stream of expected per-period payoffs expected to be earned by the player from 1992 onwards upon reaching the state and moment state in 1992. Value functions and policy functions are solved for by solving the dynamic game using backwards induction using the estimated structural parameters and state transition densities. Intercept coefficients are not included in the table. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.6: Value Function Regression Results: Value Function, 1993

	Player's own private state			
	Depth to Groundwater (ft)	Depth to Groundwater Wells in Beaumont Basin (ft)	Depth to Groundwater Wells outside Beaumont Basin (ft)	Moment State Average Depth to Groundwater (ft) All Wells
Appropriators				
Beaumont-Cherry Valley Water District		-495.4***	-1,671***	-17.17
City of Banning		-1,219***	-10,465***	17.21
South Mesa Water Company		-7,366***	-9,645***	322.6
Yucaipa Valley Water District		-286.3	-32,190***	5.458
All Appropriators Pooled		375,695***	-252,649***	37,830***
Farmers				
Dowling	-50.36***			0.00
Illy	-165.6***			0.00
Murray	-66.46***			0.00
Riedman	-217.1***			0.00
Summit	-25.85***			0.00
All Farmers Pooled	-20.26			0.00
Golf Course/Housing Developments				
California Oak Valley Golf and Resort	-338.4***			81.86***
Coscan Stewart Partnership	-7.522***			0.594***
Oak Valley Partners	-324.7***			66.37***
Plantation on the Lake	-111.2***			21.06***
Sharondale Mesa Owners Association	-72.93***			26.85***
All Golf Course/Housing Developments Pooled	899.0***			39.34

Notes: Table reports regression results from an ordinary least squares (OLS) regressions for each player of the value function for that player in 1993 on the discretized state and moment state for that player in 1993. Each row reports the results of a separate regression of the value function for the respective player (or players in the respective player group) in 1993 on the discretized state and moment state for that player (or players in the respective player group) in 1993. For each player, the value function in 1993 is the present discounted value of the entire stream of expected per-period payoffs expected to be earned by the player from 1993 onwards. The value of the value function at a particular state and moment state is the present discounted value of the entire stream of expected per-period payoffs expected to be earned by the player from 1993 onwards upon reaching the state and moment state in 1993. Value functions and policy functions are solved for by solving the dynamic game using backwards induction using the estimated structural parameters and state transition densities. Intercept coefficients are not included in the table. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.7: Value Function Regression Results: Value Function, 1994

	Player's own private state			
	Depth to Groundwater (ft)	Depth to Groundwater Wells in Beaumont Basin (ft)	Depth to Groundwater Wells outside Beaumont Basin (ft)	Moment State Average Depth to Groundwater (ft) All Wells
Appropriators				
Beaumont-Cherry Valley Water District		-354.5***	-1,598***	-4.870
City of Banning		-1,030***	-8,376***	63.45
South Mesa Water Company		-6,552***	-7,255***	512.1***
Yucaipa Valley Water District		-833.6**	-24,886***	-27.00
All Appropriators Pooled		297,146***	-198,862***	30,103***
Farmers				
Dowling	-39.43***			0.00
Illy	-122.0***			0.00
Murray	-50.88***			0.00
Riedman	-207.1***			0.00
Summit	-24.50***			0.00
All Farmers Pooled	-13.80			0.00
Golf Course/Housing Developments				
California Oak Valley Golf and Resort	-304.4***			54.64***
Coscan Stewart Partnership	-5.242***			0
Oak Valley Partners	-358.2***			52.17***
Plantation on the Lake	-108.3***			19.19***
Sharondale Mesa Owners Association	-75.02***			23.02***
All Golf Course/Housing Developments Pooled	729.3***			29.81

Notes: Table reports regression results from an ordinary least squares (OLS) regressions for each player of the value function for that player in 1994 on the discretized state and moment state for that player in 1994. Each row reports the results of a separate regression of the value function for the respective player (or players in the respective player group) in 1994 on the discretized state and moment state for that player (or players in the respective player group) in 1994. For each player, the value function in 1994 is the present discounted value of the entire stream of expected per-period payoffs expected to be earned by the player from 1994 onwards. The value of the value function at a particular state and moment state is the present discounted value of the entire stream of expected per-period payoffs expected to be earned by the player from 1994 onwards upon reaching the state and moment state in 1994. Value functions and policy functions are solved for by solving the dynamic game using backwards induction using the estimated structural parameters and state transition densities. Intercept coefficients are not included in the table. Significance codes: * p <0.05, ** p<0.01, *** p< 0.001

Table A.8: Value Function Regression Results: Value Function, 1995

	Player's own private state			
	Depth to Groundwater (ft)	Depth to Groundwater Wells in Beaumont Basin (ft)	Depth to Groundwater Wells outside Beaumont Basin (ft)	Moment State Average Depth to Groundwater (ft) All Wells
Appropriators				
Beaumont-Cherry Valley Water District		-224.8***	-1,311***	1.134
City of Banning		-722.5***	-6,104***	40.42**
South Mesa Water Company		-4,757***	-6,808***	256.3*
Yucaipa Valley Water District		-386.0*	-16,796***	170.9*
All Appropriators Pooled		210,363***	-140,546***	22,434***
Farmers				
Dowling	-30.43***			0.00
Illy	-96.24***			0.00
Murray	-40.08***			0.00
Riedman	-164.7***			0.00
Summit	-18.84***			0.00
All Farmers Pooled	-11.00			0.00
Golf Course/Housing Developments				
California Oak Valley Golf and Resort	-231.1***			5.696***
Coscan Stewart Partnership	0			0
Oak Valley Partners	-155.8***			24.27***
Plantation on the Lake	-85.77***			8.329***
Sharondale Mesa Owners Association	-64.69***			10.47***
All Golf Course/Housing Developments Pooled	518.7***			9.755

Notes: Table reports regression results from an ordinary least squares (OLS) regressions for each player of the value function for that player in 1995 on the discretized state and moment state for that player in 1995. Each row reports the results of a separate regression of the value function for the respective player (or players in the respective player group) in 1995 on the discretized state and moment state for that player (or players in the respective player group) in 1995. For each player, the value function in 1995 is the present discounted value of the entire stream of expected per-period payoffs expected to be earned by the player from 1995 onwards. The value of the value function at a particular state and moment state is the present discounted value of the entire stream of expected per-period payoffs expected to be earned by the player from 1995 onwards upon reaching the state and moment state in 1995. Value functions and policy functions are solved for by solving the dynamic game using backwards induction using the estimated structural parameters and state transition densities. Intercept coefficients are not included in the table. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.9: Value Function Regression Results: Value Function, 1996

	Player's own private state			
	Depth to Groundwater (ft)	Depth to Groundwater Wells in Beaumont Basin (ft)	Depth to Groundwater Wells outside Beaumont Basin (ft)	Moment State Average Depth to Groundwater (ft) All Wells
Appropriators				
Beaumont-Cherry Valley Water District		-140.6***	-703.4***	1.902
City of Banning		-446.9***	-3,002***	33.15***
South Mesa Water Company		-3,046***	-3,366***	167.1**
Yucaipa Valley Water District		-259.6*	-8,097***	83.95
All Appropriators Pooled		111,273***	-73,943***	11,967***
Farmers				
Dowling	-15.41***			0.00
Illy	-53.53***			0.00
Murray	-20.25***			0.00
Riedman	-81.22***			0.00
Summit	-10.21***			0.00
All Farmers Pooled	-4.244			0.00
Golf Course/Housing Developments				
California Oak Valley Golf and Resort	-119.8***			0.00
Coscan Stewart Partnership	0			0.00
Oak Valley Partners	-85.04***			0.00
Plantation on the Lake	-48.15***			0.00
Sharondale Mesa Owners Association	-41.19***			0.00
All Golf Course/Housing Developments Pooled	297.1***			0.00

Notes: Table reports regression results from an ordinary least squares (OLS) regressions for each player of the value function for that player in 1996 on the discretized state and moment state for that player in 1996. Each row reports the results of a separate regression of the value function for the respective player (or players in the respective player group) in 1996 on the discretized state and moment state for that player (or players in the respective player group) in 1996. For each player, the value function in 1996 is the present discounted value of the entire stream of expected per-period payoffs expected to be earned by the player from 1996 onwards. The value of the value function at a particular state and moment state is the present discounted value of the entire stream of expected per-period payoffs expected to be earned by the player from 1996 onwards upon reaching the state and moment state in 1996. Value functions and policy functions are solved for by solving the dynamic game using backwards induction using the estimated structural parameters and state transition densities. Intercept coefficients are not included in the table. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.10: Long-Term Robustness – Structural Parameter Estimates

Player Group	Parameter Estimates	
	Base Case	Robustness
	(1)	(2)
Appropriators		
Consumer surplus	2.21***	2.22***
Consumer surplus, squared	-3.98E-08***	-3.99E-08***
Extraction inside Beaumont Basin (acre-ft) × Depth to groundwater ×:		
Beaumont or Banning dummy ×:		
Log(Population)	1.91***	1.91***
Regional price untreated water imports	-0.08***	-0.08***
Yucaipa Valley Water District	-75.65***	-75.65
Extraction outside Beaumont Basin (acre-ft) × Depth to groundwater ×:		
Beaumont Cherry Valley Water District dummy × 1/Number of wells	-60.36***	-60.36 ***
City of Banning dummy × 1/Number of wells	-384.00***	-384.00***
Yucaipa Valley Water District dummy	-164.03***	-164.03***
All extraction (acre-ft) × Depth to groundwater ×:		
South Mesa Water Company dummy	-323.41***	-323.41***
Coefficients in Continuation Value in Year 1996 on:		
Own depth to groundwater inside Beaumont Basin in 1996		0.00
Own depth to groundwater outside Beaumont Basin in 1996		0.00
Mean depth to groundwater over all players in 1996		0.00
Farmers		
Extraction (acre-ft) ×:		
Average crop price	0.23	0.23
Average crop price ×:		
Number of days with high temperature ≥ 90 degrees F	-0.01	-0.01
Precipitation, inches (April-October)	-0.34	-0.34
Precipitation, inches (April-October) × Number of degree days	0.01	0.01
Precipitation, inches (April-October)	24.63***	24.63***
Total number of wells in Beaumont Basin	18.81***	18.81
Total number of wells in all locations	12.10***	12.10
Location in Beaumont Basin dummy	18.82***	18.82
Extraction per well, squared	-0.03	-0.03
Coefficients in Continuation Value in Year 1996 on:		
Own depth to groundwater in 1996		0.00
Mean depth to groundwater over all players in 1996		0.00
Golf Course/Housing Development		
Extraction (acre-ft) ×:		
Number of wells	-134.42***	-134.42***
Number of wells ×:		
Golf course dummy	-67.73***	-67.73***
Saturated hydraulic conductivity (ft/day)	1.68***	1.69***
Retirement home dummy	-64.22***	-64.22
CA Real GDP per capita	8.09***	8.11***
Planned construction dummy	230.36***	230.36***
Population, City of Beaumont	4.36***	4.37***
Extraction per well, squared	-0.12***	0.12***
Coefficients in Continuation Value in Year 1996 on:		
Own depth to groundwater in 1996		0.00
Mean depth to groundwater over all players in 1996		0.00

Notes: Table reports the structural parameter estimates for the player group payoff functions for the base case (Specification (1)) and the long-term robustness (Specification (2)). The parameter estimates for the base-case Specification (1) are the same as those reported in Table 5. Each player group's payoff function is a linear function of the state variables. Standard errors are computed using 100 bootstrapped estimates of the structural parameters. Bootstrap estimates are computed using counterfactual sets of players chosen by random draws from the group of players in the dataset. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B Additional Discussion of Empirical Approach

B.1 Residential Water Demand

As part of the estimation procedure, we estimate the residential household water demand function in the following equation, which is then used to estimate consumer surplus and water sales revenue for water districts. The following discussion is taken from Sears et al. (2023).

Our observational unit here is a water district in a given year. Our regression model is given by:

$$lnq_i = \alpha_0 + \alpha_1 ln[P_i] + \alpha_2 ln[f_i] + X_i'\alpha_3 + \epsilon_i, \tag{B.1}$$

where q_i is the quantity of household monthly water consumption in water district i; P_i is the residential water price in water district i; f_i is the average household size in district i; and X_i is a vector of controls, which include median per capita income, state-wide unemployment, precipitation, and rate structure design.

Since residential water price is endogenously determined by both supply and demand for water, we employ an instrumental variables approach, as is common in the literature on residential water demand (Worthington and Hoffman, 2008). Here we instrument for the price of water with supply shifters. Specifically, our instruments for price are the annual equivalent unit price charged by the State Water Project (SWP) for water delivery to the water district's nearest State Water Project contractor, and the product of the average depth to groundwater in the district and the price of electricity. These supply shifters are correlated with price because water district costs are generally included in the pricing formula for the district. Since water districts draw on groundwater, surface water, and water imports to meet their supply needs, these instruments clearly affect the cost of the water district's supply.

We believe that these instruments also satisfy the exclusion restriction. The State Water Project (SWP) price for water delivery to the district's nearest State Water Project contractor is determined by the State Water Project, and reflects the costs of transporting water, obtaining supplies, and maintenance (California Department of Water Resources, 2016). Since the State Water Project does not sell directly to water districts, but rather to large contractors who then sell water to the water districts, no single district can fully determine the demands of a contractor, and the pricing rule used by the SWP is not driven by the demands of any single contractor. Furthermore, differences across contractors in price are driven mainly by differences in location, and the maintenance and capital costs of the pipelines that transport water to each district. Thus, the State Water Project (SWP) price for water delivery to the district's nearest State Water Project contractor is a supply shifter that does not affect residential water demand except through its effect on the residential water price. The average depth to groundwater in the district interacted with the price of electricity is similarly a supply shifter that does not affect residential water demand except through its effect on the residential water price. We conduct several tests of both correlation and the exclusion restriction, and find evidence that is consistent with our instruments being both relevant and valid. The Sanderson-Windmeijer first-stage F-statistic (Sanderson and Windmeijer, 2016), which is a modification and improvement of the Angrist-Pischke first-stage F-statistic (Angrist and Pischke, 2009), is equal to 199, which is greater than the threshold of 10 used in current practice (Staiger and Stock, 1997; Stock and Yogo, 2005; Andrews et al., 2019), and also greater than the threshold of 104.7 for a true 5 percent test (Lee et al., 2021).

For our water demand estimation, we use pooled data from the bi-annual California/Nevada Water Rate Survey conducted by the American Water Works Association. We do not treat our data as a panel due to the infrequency of repeated observations in our data. We use data on household size by city and county from the California Department of Finance; data on median adjusted gross income by county from the California Franchise Tax Board; and data on the industrial average electricity price for California from the US EIA. Our dataset covers the years 2007-2015. Summary statistics are presented in Table A.3 in the Appendix.

Our empirical results for the residential water demand function can be found in Table B.1. We find elasticities of price and household size that fit with our prior belief that demand should be inelastic with regard to each, and fit within the bounds of prior results in the literature (Worthington and Hoffman, 2008). Since the coefficients on the variables in the vector X_i of controls are not significant at a 5% level, we do not include these variables as determinants of water demand in our structural model, but instead account for them by solving for the constant $\hat{A}$ that equates mean predicted household consumption (using only price and household size as predictors) with actual consumption.

Table B.1: Residential Water Demand

	Dependent variable is: Log Quantity of Household Monthly Water Consumption (hundred cubic feet)
Log Average price paid by the user (dollars per hundred cubic feet)	-0.321**
	(0.100)
Log Average household size in city	0.407**
	(0.137)
Log Median personal income in county (dollars)	-0.142
	(0.144)
Log Unemployment rate in state	0.00281
	(0.0573)
Log Precipitation in county, full year (inches)	0.0158
	(0.0304)
Structure = 2, Declining	-0.0284
	(0.204)
Structure = 3, Inclining	-0.0328
	(0.0609)
Structure = 5, Other	0.00915
	(0.0974)
Structure = 6, Uniform	-0.0652
	(0.0829)
Constant	3.792**
	(1.422)
Observations	210
R-squared	0.645
RMSE	0.253
Instruments for residential water price	
Charge for water supply for closest SWP contractor (dollars per acre-foot)	Y
Log Depth to groundwater (feet) X Electricity price in water district (dollars per kwh)	Y
Sanderson-Windmeijer first-stage F-statistic	199
Anderson underidentification test p-value	0.000106
Stock-Wright p-value	0.0167
Hansen J test p-value	0.449

Notes: Standard errors in parentheses. We use two supply shifters to instrument for residential water price: the annual equivalent unit price charged by the State Water Project (SWP) for water delivery to the water district's nearest State Water Project contractor; and the product of the average depth to groundwater in the district and the price of electricity. Significance codes: *** p<0.001, ** p<0.01, * p<0.05