Panel Estimation of Agricultural Water Demand Based on an Episode of Rate Reform

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Abstract: Agriculture is by far the dominant user of water in the western United States and in nearly all arid regions of the planet. Despite this fact and despite a growing push to rely on price mechanisms for rationalizing water allocation, there are few econometric studies of agricultural water demand that measure its responsiveness to price. Using a unique panel data set of water use at a disaggregated level, this paper estimates the parameters of an agricultural water demand function. The approach incorporates the notion of "jointness" in the farm production function, which postulates that producers choose inputs, outputs and technology simultaneously. Estimation results indicate that the own-price elasticity of water use is in the range [-0.415, -0.275], which includes the indirect effects of water price changes on output and technology choices. The estimation results also provide the first direct measurement of the conservation benefits of investment in precision irrigation technology. Water savings from technology adoption vary widely by crop but can be as high as 50 percent relative to gravity irrigation.

Keywords: Input demand estimation, water resources, conservation technology.

JEL codes: C33, Q12, Q15

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Introduction

Allocation of scarce freshwater resources is an issue of great importance in dry regions of the world (Postel, 1996; FAO). Economists and other observers have argued that policies to improve the efficiency of water allocation can help alleviate conflicts among competing users and minimize water's role as a limit to growth (Gleick, 2000; Easter, 2000; Schoengold and Zilberman, 2003). For example, marginal cost pricing or pricing based on relative productivity could give more appropriate signals to users than the quantity rationing schemes commonly used to allocate water (Burness and Quirk, 1979). Efficiency-enhancing water management strategies can also help reconcile supply and demand imbalances without resorting to costly and environmentally damaging dams and other supply augmentation measures.

Agriculture is the dominant user of water in the western United States and most other arid regions of the planet. Lacking adequate precipitation during the growing season, agriculture in these areas is dependent on large-scale diversion of surface water and groundwater pumping. In California, for example, even though large urban areas like Los Angeles, San Francisco and San Diego are almost entirely reliant on surface water diversion, agriculture in the state uses nearly 80 percent of developed surface water resources (California Department of Water Resources). In fact, considerably more water is used to grow hay in the state than is consumed by all the households and businesses in Los Angeles and San Francisco combined (National Agricultural Statistics Service).

Despite the economic and environmental significance of agricultural water use, it is surprising that there have been so few empirical studies measuring the parameters of agricultural water demand. Such information is, of course, necessary for the calculation of optimal pricing schemes and other demand management policies. This paper develops an empirical model of agricultural water demand based on the role of water in the farm production function. The paper then presents estimates of the parameters of the model based on a unique panel data set from California's San Joaquin Valley. The results shed light on the short- and long-run price elasticity of farm water demand, and also illustrate how water use is conditioned by capital investments, choice of output, and other factors.

The data used in this analysis come from the Arvin Edison Water Storage District (AEWSD), a utility serving over 130,000 acres and roughly 150 farming operations located 90 miles north of Los Angeles. In 1994, AEWSD began collection of data on technology and output choice at the field level. Combining this with records on water deliveries by field, it is possible to piece together a fairly complete picture of water use decisions at the micro level. Also important is the fact that in 1995, the District enacted a major water rate reform that facilitates identification of the demand function. Like many water authorities, AEWSD prices water according to a two-part tariff. In 1995, it decreased the fixed component and increased the variable one; a change intended to encourage water conservation by increasing its marginal price. By comparing water use before and after the rate reform, we can capture the effects of the price change controlling for factors such as environmental conditions and changes in output prices.

The demand framework used in this paper reflects the role of water and other factors in agricultural production. An important property of the farm production function is that of *jointness* (Mundlak, 2003). At any point in time, producers select a production technology given the economic environment, and this choice is made together with the decision about the composition and level of outputs. This notion has important implications for the estimation of farm water demand. Water use per unit of land is determined in part by the choice of outputs since crops vary widely in their water requirements and growth response to irrigation. Water use is also influenced by capital investments in irrigation technologies. Traditional technologies like flood irrigation result in more runoff and wasted water than modern, precision irrigation systems such as drip and microsprinkler. The jointness property implies that irrigation technology and output choice (i.e., land allocation among crops) should be modeled simultaneously with the level of water application. We accomplish this objective by conditioning water use on the choice of a variety of possible output/technology pairs. Further, to account for the endogeneity of technology and output choice in the water demand equation, we employ simultaneous equation estimation methods using instrumental variables to estimate the parameters of the water demand function.

One benefit of this approach is that it permits direct estimation of water conserved by the adoption of conservation technology. To date, there is little if any field evidence of how much water is actually saved by the use of precision irrigation systems, even though adoption is actively encouraged by governments in the western United States.[1] Our results show that there can be substantial savings from investment in precision irrigation technology, with reductions in water use per acre exceeding 40% in a few instances.

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[1] Examples of this type of program include the U.S. Farm Bill funded Environmental Quality Incentives Program (EQIP), and the Central Valley Project Improvement Act (CVPIA).

Due to the interest in using price reforms and other incentives to manage water demand, a main objective of our analysis is to measure the price elasticity of farm water use. To our knowledge, this paper is the first attempt to measure this important parameter using micro data. Our econometric model allows us to distinguish between short- and long-run elasticities of demand. Choices of outputs and production technologies are assumed to adjust over time, and thus a water price shock will have long-run effects through its influence on output and technology choice that will be distinct from the short-run effects that incorporate mainly management changes. Estimation results are used to model a counter-factual scenario in which the district's water rates remained unchanged. The results of this analysis indicate the magnitude of water savings from the rate change.

One of the main reasons for the paucity of studies examining farm water use at the micro level is difficulty in obtaining needed data. An area that has been researched more thoroughly is urban (i.e. residential and commercial) water demand. While agricultural and urban water demands differ in many ways, urban water demand studies nonetheless provide a framework for the water demand estimation problem. Hanemann (1998) reviews studies of urban water demand from 1972 to 1991. He finds that most assume either a linear, log-log, or semi-log demand function. With few exceptions, all studies find the own-price elasticity of water demand to be low, with the majority of estimates between 0.0 and -0.5. A study by Renwick and Green (2000) of residential water users in California finds that consumers are responsive to several types of programs designed to promote conservation, including pricing mechanisms such as increased water prices, and non-price mechanisms, such as educational campaigns.

Many studies of irrigation water demand rely on simulated data. One recent study by Bontemps and Couture (2002) uses a dynamic framework to estimate irrigation water demand in southwestern France. Bontemps and Couture simulate water demand data and analyze demand for a single crop. Their analysis supports a non-linear demand for irrigation water. In arid regions, water demand is inelastic, and as the quantity of water increases, water demand becomes more elastic. This result is because at a particular price for water, farmers in arid regions demand greater quantities of irrigation water than those in wet regions. Using a dynamic programming analysis, they predict the inflexion point where demand becomes elastic. Ogg and Gollehon (1989) use a cross-section of farms in the western U.S. to estimate agricultural water demand and estimate price elasticities in the range of [-0.26, -0.07], with differences between regions and different demand specifications. Results of a simulation by Hooker and Alexander (1998) find that demand is inelastic across a large range of prices, but becomes elastic beyond some threshold level. Their analysis uses parameter estimates based on water use in the San Joaquin Valley.

There is a body of literature that looks at the diffusion of efficient irrigation technologies, and considers the role of water price in the adoption decision. Previous studies beginning with Caswell and Zilberman (1985, 1986) have shown that an increase in water price leads to the adoption of water-conserving precision irrigation systems by farmers. Caswell and Zilberman use data from California to estimate how the rate of adoption of precision technology responds to an increase in the price of water. Their analysis underscores the importance of land quality in the technology adoption decision, as the adoption response to price changes varies with soil characteristics. A main result from Caswell and Zilberman is that an owner of low-quality land will adopt efficient irrigation technology at a lower water price than the owner of high quality land, since higher quality land is relatively more water efficient with gravity irrigation systems. One important component that is omitted from their model is the effect of management. The work assumes that conditional on land characteristics and irrigation technology, observed water use efficiency is unaffected by the amount of labor employed in the production function.

Most studies of how farmers respond to a change in water price (including the Caswell and Zilberman study just mentioned) ignore the possibility that they can adjust both crop and technology over time, and assume instead that the choice of crop is exogenous. In fact, as the jointness concept suggests, technology and output choice problems are highly correlated in agriculture (Moreno and Sunding, 2002). Moreno and Sunding estimate a bivariate probit model of output and irrigation technology choice using a cross-section of field level data. They find a correlation coefficient of 0.6 between the crop and technology equations, providing evidence that the two choices are not independent.

While treating crop choice as exogenous may be an acceptable assumption in parts of the United States such as the grain belt, where a single crop accounts for the majority of planted acreage, it is an oversimplification for more diverse production regions. One paper that does use a time-series data set with multiple crop choices is Kanazawa (1992). He uses data on pumping costs for groundwater users in California's San Joaquin Valley to estimate a demand relationship for irrigation water users. His analysis allows substitution between crops and includes land quality characteristics, but includes only annual crops. Therefore, the crop decision each year is independent of decision in previous years. Kanazawa also works at a level of aggregation greater than that used in this study, resulting in less precise estimates of the influence of environmental conditions, among other variables.

Data

Most of the data used in the estimation comes from Arvin Edison Water and Storage District (AEWSD). The data set includes an 8-year panel (1994-2001) of 125 sections (predetermined, time-invariant 640-acre blocks of land) in AEWSD. Annual data is collected at the field level on both the crop and irrigation system used in a field. Of the 125 sections, 118 have data for all the years in the study period, while the other 7 have several years missing. Most of the missing data is cropland left fallow, which is part of normal crop rotation. Available cropland per section ranges from 78 to 808 acres. Total production acreage in the surface water service area averages 44,200 acres in the sample years, with minor variations from year to year are explained by normal fallowing.

AEWSD also provided water price and water delivery data. A water year runs from March until the following February, a time period that parallels the growing season in the district. The district sets the water price at the beginning of each water year, and measures monthly deliveries at each turnout. We aggregate the water delivery data by year and turnout to obtain total water deliveries by section.

Data on crop prices comes from the annual Kern County Agricultural Commissioner's Crop Report. Data on the price of investment into various irrigation technologies is not included since these remained constant over the sample period

(Sanden, 2003). The environmental variables are chosen to reflect soil and topography characteristics relevant to farming and irrigation. These variables (slope, elevation, permeability, number of frost-free days per year, average rainfall, and average temperature) are long run averages and do not change over time.[2] Yearly temperature averages for the area were obtained from the Western Regional Climate Center. The use of the two temperature variables addresses two sources of variation in temperatures – cross-sectional variation among microclimates within the District and variation across years.

Table 1 gives historical water prices to surface users during the study period. Before 1995, AEWSD assessed a fixed per acre fee of $136.3, and a variable charge of $45.3 per acre foot of water delivered. In 1995, the District reduced the fixed fee by over 30% to $94, and increased the variable fee by over 40% to $65.3. In 1999, the variable charge decreased slightly because AEWSD found it was over collecting revenue after the 1994 price change.

Table 2 gives a summary of the land allocation over time, and Figure 1 gives the maximum and minimum values of acreage in each crop/technology pair over the sample period. The feasible technology/crop pairs are citrus/drip, citrus/gravity, grape/drip, grape/gravity, deciduous/drip, deciduous/gravity, deciduous/sprinkler, truck/gravity, truck/sprinkler, and field/sprinkler. The main citrus crop in the region is oranges; deciduous crops include mostly almonds, along with some peaches and apples. Truck crops include potatoes, carrots, and onions, while field crops include cotton and some hay. Interestingly, permanent crop acreage has increased in recent years despite

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[2] This data is collected by the USDA Natural Resource Conservation Service office in Kern County. For a complete description this data, refer to Green et al. (1997).

overarching concerns about agricultural water supply reliability. In 1994, permanent crops were planted on 49% of total acreage. By 1998, this had increased to 63% of total acreage.

Table 3 summarizes prices for those crops with significant acreage in AEWSD. During the study period crop prices exhibit the volatility commonly observed in agricultural output markets. This volatility makes it difficult for a farmer to predict future prices, and may explain why many farmers diversify land allocation.

Table 4 summarizes observed values for the variables included in the estimation. These include water use, water price, land allocation, and the various indicators of environmental quality.

Theoretical Motivation

The motivation for the empirical method used is given by a dynamic adaptation of the static model developed in Caswell and Zilberman (1986) to account for investments in irrigation technology and other specialized capital inputs. The importance of existing investment in current crop/irrigation decisions necessitates the use of a dynamic framework in modeling a farmer's decision-making process. In addition, we account for the importance of management decisions, or labor inputs, into water input demand.

The choice at a particular location *i* at time *t* is independent of the choices at other locations, so to limit notation we remove the location subscript from the following model. Letting j denote the crop/irrigation technology pair, we assume that output is given by a production function, $y = f_j(e_{jt})$, where y denotes the yield per acre, and e the effective water per acre, or water available to the plant. The effective water per acre is a function of the applied water per acre (a_{jt}), crop/irrigation technology choice (j), environmental conditions (Z), weather shocks (X_t), and management level or labor inputs (m_{jt}), and this ratio is considered fixed conditional on the variables mentioned. To develop the model, we further define the following other variables:

p_{jt} = output price for crop j at time t.

$\overline{A}$ = total available land.

WP_t = the relative price of water to management inputs at time t.

$h_j(Z, X_t, m_{jt})$ = input use efficiency of water with crop/technology j, land quality conditions Z, current weather X_t, and management level m_{jt}. This input use efficiency parameter must be in the (0, 1) interval, and is larger for modern irrigation technology than for traditional flood irrigation.

A_{jt} = total acreage in crop/technology j at time t.

x_{jt} = change in total acreage in crop/technology j between $t-1$ and t.

Using this notation, the dynamic programming problem facing the farmer at time t is to maximize profit

(1)
$$V(\{A_t\}) = \max_{\{a_t\},\{m_t\},\{x_t\}} \sum_j p_{jt} f_j(e_{jt}) A_{jt} - WP_t \sum_j a_{jt} A_{jt} - \sum_j m_{jt} A_{jt} - \sum_j C_j(x_{jt}) + \frac{1}{1+r} V(\{A_{t+1}\})$$

subject to J equations of motion,

(2)
$$A_{jt} = A_{jt-1} + x_{jt}$$

a restriction on land area available,

(3)
$$\sum_j A_{jt} \le \overline{A}$$

and *J* water-use efficiency identities

$$(4) \qquad e_{jt} = h_j(Z, X_t, m_{jt}) \cdot a_{jt} .$$

While we are unable to observe labor or management inputs from our data, the effect of a change in management on water use will be observed from the coefficient on the ratio of water price to the price of management inputs. Water and labor are the only two variable inputs in a particular period, since the capital investment is fixed in the short term.

Empirical Model

In our econometric analysis we estimate a reduced form model of water demand reflecting equations (1) – (4), explaining water use at a particular location as a function of output and technology choices, relative prices, and other factors such as environmental characteristics. Our estimation strategy assumes that each joint choice of irrigation technology and crop has a fixed input/output ratio in the short run, and this ratio is a function of environmental conditions, management inputs, crop choice, and irrigation technology. We note that our approach is consistent with the commonly used putty-clay production framework. This approach assumes that the durability of physical capital fixes the input/output ratio in the short run, but that the choice of technology will adjust over time to changes in the relative prices of inputs and outputs (Wei, 2003; Gilchrist and Williams, 2000). Irrigation systems can be modeled using this framework, since they are comprised of pipes, valves, heads, and other types of equipment. The choice of crop can also be viewed as a particular type of capital investment, as all crops require a significant investment in specialized farm equipment and human capital, while perennial crops also require capital investment in plant stock.

One potential problem is the endogeneity of certain explanatory variables, particularly the land allocation variables, as they are functions of both land quality characteristics and water price. Using the regression version of the Hausman test of endogeneity of the land allocation variables, we are able to reject the null hypothesis that all land allocation variables are exogenous with a significance level of 99%. Therefore, we use instruments for all of these variables to eliminate any potential problems with endogeneity. The estimation method chosen is 2SLS estimation with system estimation in the first stage (estimating acreage in each crop/technology pair) instead of a single equation. Several alternative specifications are used to estimate second stage water demand equation.

Stage 1 Estimation:

In the following formulation, we let *A* denote the total available acreage at location *i*, Z_i the vector of section specific variables, X_t the time specific variables, and WP_t the water price in period *t*. Letting *j* denote the crop/technology pair, we estimate a system of *J* equations of the following form:

$$A_{ijt} = \alpha_{0j} + \alpha_{1j} Z_i + \alpha_{2j} X_t + \alpha_{3j} A_{ijt-1} + \alpha_{4j} WP_t + \varepsilon_j \,, \tag{5}$$

where $\varepsilon_j \sim \eta(0, \sigma_j^2)$.

Variables in Stage 1:

Time specific variables: Time specific variables included in the regression include *output prices* and *water price*. We adopt a rational expectations approach and use current prices as the best indicator of expected future prices.[3]

Location specific variables: The variables specific to each section included in these regressions are *slope*, *permeability*, *average section temperature*, and *frost-free days*. Each of these variables affects what type of crop can be grown at a particular location. For example, crops with a low frost tolerance are less likely to be planted in areas with a low number of frost-free days.

Lagged acreage variables: The lagged value of acreage in each crop/technology pair is used as an explanatory variable in the current acreage allocation. This variable is included to measure the effect of adjustment costs and the durable nature of technology and output choices. Obviously, perennial crops are durable since they require an established stand of trees or vines. Other sources of adjustment costs in the cropping decision are that growing a crop takes specific human capital (i.e. knowing how to grow grapes does not imply that one knows how to grow lettuce), and also that the long-term relationship between a farmer and a distributor of a crop influences the price farmers receive for their output (Hueth and Ligon, 1999).

Estimating the crop/technology pair equations jointly with a SUR model allows consideration of the case where $Cov(\varepsilon_k, \varepsilon_j) \neq 0$ if $k \neq j$, and results in more efficient parameter estimates than is the case when the equations are estimated separately. The results of the SUR estimation are in Table 5. Generally, we find that lagged acreage (a

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[3] We tried various other measures of output prices, including using past trends in output prices to predict current prices. However, the results of the analysis are robust to the choice of the method used to determine expectations, and we therefore decide to use the simpler rational expectations approach.

proxy for existing investment in the land and an attempt to capture the role of adjustment costs) in each crop and technology pair is important in explaining current land allocation choices. We also find that while this is a significant variable in all crop and technology choices, the magnitude of the estimated coefficients is lower with annual crops than with permanent crops. This shows that altering acreage in annual crops is relatively less expensive than altering permanent crop acreage. A Breusch-Pagan test rejects the null hypothesis that the error terms are independent and validates the use of a SUR. This estimation provides predicted values for land allocation, values that are used in the second stage estimation.

Stage 2 Estimation:

The main equation to be estimated is the water demand equation, where water demand is a function of water price, section specific variables, and time specific variables as shown below.

$$W_{it}^{D} = q_{itn}(Z_i, X_t, WP_t, \{\hat{A}_{it}\}) \tag{6}$$

W_{it}^{D} = water used at location *i* in time period *t*.

X_t = time dependent factors.

Z_i = location-specific variables.

$\hat{A}_{ijt}$ = the fitted value for acreage in crop/irrigation pair *j* at location *i* at time *t*.

WP_t = variable water fee at time *t*.

Variables in Stage 2:

Time dependent variables: *Average yearly temperature* is included in the water demand regression. It is expected to have a positive coefficient, since more water is needed when temperatures are warmer. *Variable water fee* is perhaps the variable of most interest in this study. We expect the coefficient on water price to be negative since farmers will be more careful with water application at a higher water price. Only small changes in labor prices over the sample period were observed, so defining water price as the price of water relative to labor yields almost identical results to the ones presented here.[4]

The first stage of the estimation includes output prices, which are expected to influence the choice of crop. The reason that these variables aren't included in the water demand estimation is that once the choice is made to grow a particular crop, output prices will not affect the amount of water used. The only exception to this is if output prices are so low that farmers choose to let a crop die in the field instead of harvesting.

Section specific variables: *Average slope* is expected to have a positive coefficient. A greater slope increases the amount of water that runs off the land, resulting in a lower amount of applied water reaching the roots of the plant. *Average permeability* is also expected to have a positive coefficient. Permeability refers to how easily water moves through the soil. With a high permeability, water will quickly move away from the root zone of the plant, and increase requirement for applied water. *Average section temperature* measures the long run average temperature at the section. This measures

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[4] We do not include prices of other non-water and non-labor farm inputs such as fertilizers and pesticides. While labor in the form of better management can be a substitute for applied water, previous results in both economics and agronomy show that there are very few substitutes for water in crop production (see, for example, Hanks et al. (1969), Power et al. (1973)).

variability within the sample at each point in time. A higher average temperature should increase water use, for the same reasons as average yearly use.

Fitted land allocation variables: The variables are the fitted values of acreage in each of the land allocation variables. The expected sign on all of these variables is positive, since a greater quantity of land in production requires more applied water. However, one can develop interesting hypotheses about the relative magnitudes of these coefficients. We expect that the coefficient on a particular crop in drip irrigation is smaller than the coefficient on the same crop in gravity irrigation. These relationships have often been tested using experimental data, but farmers are exposed to conditions that don't mimic the idealized conditions of a field test experiment.

Specification Issues in Stage 2:

The estimation of the water demand equation uses panel data which raises several potential issues. One potential problem is heteroscedasticity. One method of solving this problem is to use a generalized least squares (GLS) model. If the variation in errors is due to unobserved characteristics at the section level, another possible method is to use either fixed or random effects. Random effects models assume that the error term can be divided into the 'true' error and another term unique to a specific group in the sample. However, for random effects to be valid, the error terms must be uncorrelated with the explanatory variables. A test of our data shows that this assumption does not hold. Fixed effects allow correlation between the error terms and the explanatory variables, but it limits the choice of variables. Because a fixed effects model examines the differences within a group over time, the impact of individual specific variables (such as land quality characteristics) that remain constant cannot be identified.

There are two reasons that we decide against the use of a fixed effects regression. First, the data contains many of the micro variables that determine crop and irrigation choice at a section level. Since these are some of the factors that would be included and not identifiable in a fixed effects regression, we would be unable to observe the importance of these characteristics. The second reason to not use fixed effects is the lack of a direct link between a section and a single landowner. If a section was owned by a single individual, there could also be individual characteristics that influence behavior. However, multiple farmers can own land in the same section, and a single farmer can own land in multiple sections. Also, land could have been sold during the period from one farmer to another, something we have no information on. For these reasons, attempting to use fixed effects to account for individual variation is inaccurate.

As the demand estimation uses predicted values of land acreage instead of actual values, the error terms and the standard errors from the second stage regression are biased. These need to be corrected before any tests are done for potential problems such as autocorrelation and heteroscedasticity in the data. Using the Durbin-Watson test on the corrected errors, we reject the null hypothesis of no autocorrelation. Another concern is heteroscedasticity of the error terms in the water demand regression. Using White’s test for heteroscedasticity, we reject the null hypothesis of homoscedastic error terms. Using these results, we estimate the following model:

$$(7) \qquad W_{it}^{D} = \gamma_0 + \gamma_1 X_t + \gamma_2 Z_i + \sum_{j=1}^{J} \gamma_{3j} \hat{A}_{ijt} + \gamma_4 WP_t + \varepsilon_{it}$$

Where $\varepsilon_{it} = \varphi \varepsilon_{it-1} + \mu_{it}$ and $\mu_{it} \sim \eta(0, \sigma_{it}^2)$

The results of the water demand estimation are in table 6. For comparison, we present the results of the OLS estimation, IV estimation, and the GLS estimation with AR(1) errors. The results are very similar across econometric specifications.

At a qualitative level, the estimation results invite a couple of observations. One regards the difference in the coefficients on precision (drip or sprinkler) and traditional (gravity) irrigation methods. This comparison provides direct evidence that even under non-experimental conditions, there is a reduction in water use achieved by the adoption of modern irrigation systems. To our knowledge, this is the first time such a benefit from investment in agricultural water conservation technology has been demonstrated and measured under field conditions. Another interesting result is the importance of water price in the second-stage water use equation – this coefficient is negative and significant. This finding demonstrates that marginal price can influence farm water demand – even controlling for other factors such as output choice and capital investments in production technology. The significance of water price in this equation suggests that better management alone can result in a significant amount of conservation, and can do so in the short run. We discuss both these points in more detail below.

Water Savings from Investment in Precision Technology

An interesting and useful result of this analysis is that it allows measurement of the water savings resulting from investment in precision irrigation technology. By comparing the coefficients of the same crop under different irrigation technologies in the water demand estimation, we can estimate the reduction in water application per acre from a change in technology. The results of the tests on the equivalence of the coefficients are presented in Table 7. With the exception of the difference between water use by deciduous crops in gravity and in sprinkler irrigation, all of the coefficient pairs are found to be significantly different in several of the regression results. In some cases, adoption of precision technology can cut water use per acre by half.

Another important result is that precision technology appears to result in different amounts of conservation when used on different crops. For example, the coefficient on citrus in drip irrigation is only half of the coefficient on citrus in gravity in both the OLS and the IV regressions. Therefore, the gain in moving from gravity to drip in citrus is very high. In grapes, drip irrigation still uses less water then gravity, but the difference is much smaller. This comparison provides at least a partial explanation for the fact that there are many more acres in the grapes/gravity pair than in citrus/gravity. The differential gains of the switch to efficient technology make sense from an agronomic or physical point of view as well. With citrus crops, the trees are planted far away from each other, leaving a lot of land between the trees where water is not used by the plant. Applying water directly to the root zone, as is the case with drip irrigation, will accordingly result in more water savings. Grapevines are planted much closer to each other, resulting in less wasted water from gravity applied irrigation water.

Derivation of Direct and Indirect Water Price Elasticity

The estimation method chosen accounts for the potential endogeneity of investment in perennial crops and efficient irrigation. One benefit of this approach is that the microeconomic response to changes in water price can be decomposed into direct and indirect effects, where the latter include changes in capital investment and land allocation. Using the notation from equations (5) and (7), we calculate the following formula for the change in water use with respect to the price of water.

$$(8) \qquad \frac{\partial W_{it}^{D}}{\partial WP_t} = \gamma_4 + \sum_{j=1}^{J} \gamma_{3j} \frac{\partial \hat{A}_{ijt}}{\partial WP_t} = \underbrace{\gamma_4}_{\substack{\text{direct effect of}\\ \text{management}}} + \underbrace{\sum_{j=1}^{J} \gamma_{3j}\alpha_{4j}}_{\substack{\text{indirect effect of}\\ \text{land use changes}}}$$

Converting this to an elasticity measure at mean values gives the following:

$$(9) \qquad \varepsilon_p = \frac{\partial \overline{W}^{D}}{\partial \overline{WP}} \frac{\overline{WP}}{\overline{W}^{D}} = \gamma_4 \frac{\overline{WP}}{\overline{W}^{D}} + \sum_{j=1}^{J} \gamma_{3j}\alpha_{4j} \frac{\overline{WP}}{\overline{W}^{D}}$$

Since the coefficients on the water price variable are both positive and negative in the SUR regressions, it is not clear *a priori* if the total effect of a change in water price will be larger or smaller than the direct effect. Table 8 presents the estimated demand elasticities from each econometric specification. The indirect elasticities are all negative and significantly different from zero for the average section in our sample, implying that a change in the price of water induces water-conserving changes in crop and technology choices.[5] It should also be noted that the indirect effects or water price are smaller than the direct effects. This pattern is explained by the fact that, while the price of water has been shown to be a significant determinant of adoption of conservation technology in agriculture, it is by no means the only determinant (Green et al., 1996). Other factors such as weed control, a desire to save on labor costs, or a need to apply fertilizers precisely through the irrigation system can all spur investment in precision irrigation systems. Similarly, the price of water has been shown to have only a relatively small influence on crop choice since the price of water is often a small share of the cost of production.

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[5] An 'average' section refers to a section with all explanatory variables equal to the sample means.

The calculated total own-price elasticity of water use is in the range [-0.415, -0.275]. This finding implies that agricultural water demand is somewhat more elastic with respect to the price of water than indicated by previous studies. Accordingly, one implication of our research is that water rate changes can have a larger effect on water allocation than previously assumed. It is also worth noting that our panel only includes 6 years of data after the major rate change. Given the durability of capital investments in irrigation systems, which can have a useful life of ten years or more, and plant stock, which can last up to forty years for some trees and vines, we would expect indirect effects to be larger when measured over a longer time period.[6]

Some simple calculations help to illustrate the relative magnitudes of the direct and indirect effects. Using the results of the IV estimation shows that at the average values (1,064.9 acre-feet applied per section at a price of $57.3 per acre-foot); a price increase of 10% or $5.73 per acre-foot will reduce water use per section by a total of 34.5 acre-feet (30.5 acre-feet due to better management and 4.0 acre-feet due to changes in land allocation). Using the results of the GLS AR(1) estimation shows that the same price increase will reduce water use per section by a total of 44.2 acre-feet (36.7 acre-feet due to better management and 7.5 acre-feet due to changes in land allocation). With 125 sections in the sample, this translates into 4,312.5 to 5,525 acre-feet of water conserved annually for other uses.

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[6] Examination of the lagged acreage terms in the first stage regression suggests that the long-run indirect effects of water price changes may ultimately be 4-5 times greater than the measured indirect effects.

Water Rate Change and Water Use Reduction

The results of the statistical analysis allow us to compare the choices of farmers after the water rate change with the predictions of those same choices if water rates had remained at their 1994 levels. In addition, we are able to decompose the difference in water use into the direct and indirect effects of the price change.

Chart 3 compares the predicted water use under actual water prices with the predicted values under 1994 water price levels. Predicted values of water use are conditional on actual output prices, water prices, and the initial land allocations. To calculate water use if no price changes had occurred, the results of the regressions are then used to simulate farmer behavior if no price change had occurred (i.e. that the variable price of water remained at its 1994 level of $45.3 per acre-foot). Chart 4 decomposes this difference into the direct and indirect effects. We find that the direct effect of the price change is responsible for the larger portion of the water reduction, where this direct effect ranges between 52.5% and 84.9% of the reduction in water use, with an average of 72.4%.

Conclusions

Agriculture is the most important user of water in the western United States and in most arid regions of the world. As a result of rapid population growth and increasing concern about the environmental effects of surface water diversions, agricultural interests are under increasing pressure to conserve water. Financial incentives, whether embodied in water trading opportunities or increased water rates, are widely touted by economists as an effective means of reallocating water supplies and encouraging conservation in agriculture. On the other hand, it is sometimes postulated that the price of water delivered to farmers is so highly subsidized that there is no significant demand response to modest price changes (Garrido, 2003; Jones, 2003). Missing from this important policy debate are sound estimates of the price elasticity of farm water demand.

Using a unique data set along with an estimation methodology that reflects the role of water in the production function, we are able to answer this and several other important questions about farm water use. The estimated own-price elasticity of agricultural water demand is in the range [-0.275 to –0.415]. Of this total elasticity, the indirect effects of water price on output and technology choices account for roughly 17 percent of the total, while direct effects make up the balance. This finding suggests that more active management has a large influence on water use. With larger price changes, indirect effects may be a larger fraction of the total.

Another important finding concerns the conservation benefits of adoption of precision irrigation technology. Comparing coefficients in the demand equation, the savings from switching from, say, gravity irrigation to drip is measured directly. For some crops, the water savings from investment in modern technology is large – in the range of 50 percent per acre. For others, the savings are not nearly as great. These findings provide a window on the performance of programs designed to stimulate investment in modern irrigation technologies and suggest that expectations of water savings be conditioned on land allocation among crops.

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Table 1 - Summary of Water Prices, 1994-2001 [1,2]

Year	Fixed Cost	Variable Cost	Estimated Total Variable Cost	Estimated Total Cost per Acre
1994	136.3	45.3	124.6	260.9
1995	94.0	65.3	179.6	273.6
1996	94.0	65.3	179.6	273.6
1997	94.0	65.3	179.6	273.6
1998	80.0	64.8	178.2	258.2
1999	80.0	50.8	139.7	219.7
2000	80.0	50.8	139.7	219.7
2001	58.0	50.8	139.7	197.7

[1] Fixed costs are paid per acre, while the variable costs are paid per acre-foot. Both of these are expressed in nominal dollars.

[2] While these variable costs are per acre-foot, the district assumes an average application of 2.75 acre-feet per acre when it determines pricing.

Table 2 - Land Allocation Over Time by Crop and Technology Type

Crop Type	Irrigation Type	1994	1995	1996	1997	1998	1999	2000	2001
Citrus	Drip	16.9%	16.8%	16.4%	20.9%	22.0%	22.4%	22.0%	22.3%
	Gravity	1.9%	2.0%	2.2%	2.3%	2.4%	0.9%	1.4%	1.3%
	Sprinkler	0.0%	0.0%	0.0%	0.1%	0.1%	0.0%	0.0%	0.0%
Grape	Drip	9.3%	9.3%	9.4%	12.0%	12.8%	18.5%	15.6%	15.8%
	Gravity	10.1%	11.6%	10.9%	12.6%	12.4%	8.0%	9.6%	10.2%
	Sprinkler	0.0%	0.0%	0.0%	0.2%	0.2%	0.0%	0.4%	0.3%
Deciduous	Drip	3.8%	3.8%	4.5%	6.8%	7.4%	5.3%	5.6%	6.0%
	Gravity	2.9%	2.6%	3.6%	3.5%	3.8%	4.1%	4.2%	4.6%
	Sprinkler	4.5%	4.6%	1.9%	2.6%	2.1%	3.1%	1.8%	1.9%
Truck	Drip	0.6%	0.5%	0.2%	1.0%	0.3%	0.7%	1.6%	0.8%
	Gravity	4.0%	3.2%	0.0%	3.7%	3.5%	3.8%	4.2%	2.3%
	Sprinkler	27.3%	24.8%	29.7%	12.4%	16.6%	17.0%	16.0%	16.7%
Field	Drip	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	Gravity	0.5%	1.1%	0.0%	0.4%	0.1%	0.0%	0.2%	0.0%
	Sprinkler	18.3%	19.7%	21.3%	21.5%	16.2%	16.3%	17.4%	17.6%
All Permanent Crops	Drip	30.0%	29.9%	30.3%	39.7%	42.2%	46.2%	43.2%	44.2%
	Gravity	14.9%	16.2%	16.7%	18.4%	18.6%	12.9%	15.2%	16.2%
	Sprinkler	4.5%	4.6%	1.9%	2.9%	2.4%	3.1%	2.2%	2.2%
All Annual Crops	Drip	0.6%	0.6%	0.2%	1.0%	0.3%	0.7%	1.6%	0.8%
	Gravity	4.4%	4.2%	0.0%	4.1%	3.6%	3.8%	4.4%	2.3%
	Sprinkler	45.5%	44.5%	51.0%	33.9%	32.8%	33.3%	33.4%	34.3%

Chart 1 - Minimum and Maximum Acreage in Each Crop/Irrigation Pair, 1994-2001

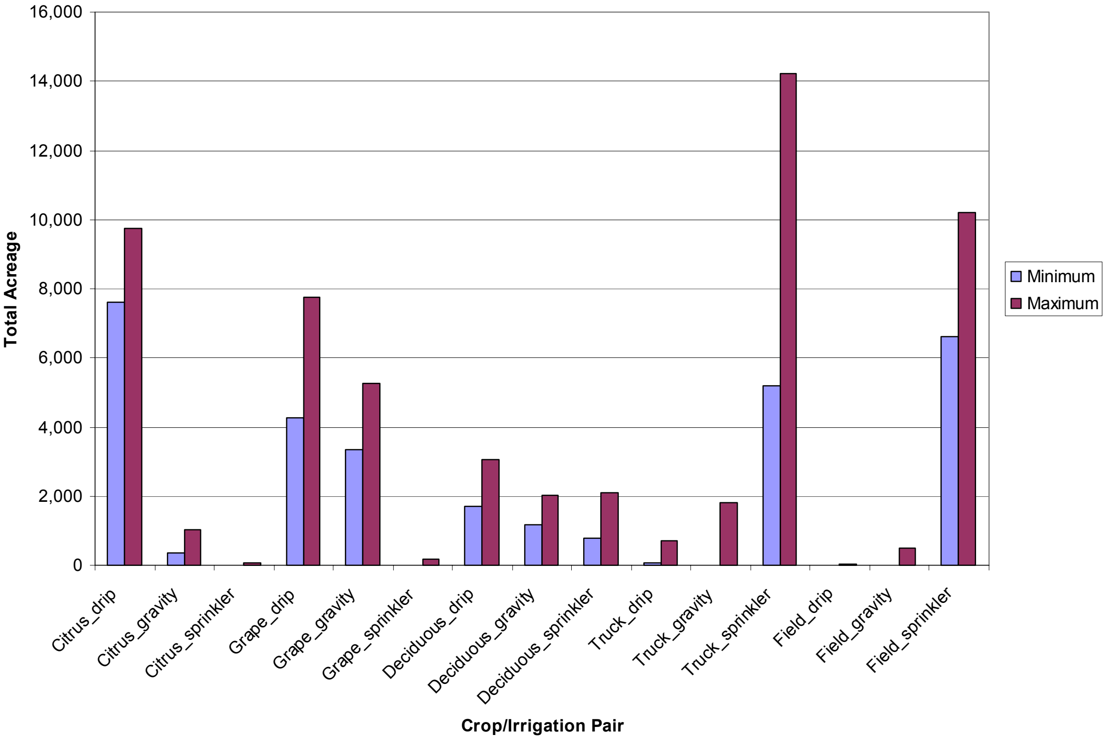

Table 3 - Summary of Crop Prices, 1993-2001 [1,2]

Crop	1993	1994	1995	1996	1997	1998	1999	2000	2001	Mean	Minimum	Maximum
Onions	205	147	267	288	244	239	177	231	280	231	147	288
Carrots	11.7	12.9	16.7	13.4	12.9	12.0	16.8	13.1	17.4	14.1	11.7	17.4
Potatoes	8.1	6.9	8.9	5.1	6.7	6.9	6.9	5.4	10.7	7.3	5.1	10.7
Cotton	243	243	216	216	226	285	305	210	214	240	210	305
Grapes	1099	1186	1225	1384	1150	1250	1210	1110	1150	1196	1099	1384
Oranges	395	437	443	370	429	455	685	410	512	460	370	685
Almonds	3860	2598	5000	4065	3060	3200	1710	2040	1780	3035	1710	5000

[1] Price information on onions, cotton, grapes, oranges, and almonds were obtained from the Kern County Agricultural Commissioner's Report. Prices are in dollars per ton.

[2] Price information on carrots and potatoes were obtained from USDA, and are in dollars per container weight.

Table 4 - Summary Statistics of Variables

Number of observations: 969

Variable Description	Mean	Std. Dev.	Minimum	Maximum
Total Water Use	1064.9	67.4	1.0	4861.0
Water Price	57.3	8.0	45.3	65.3
Slope	1.6	1.2	0.5	9.4
Section Temperature	63.0	1.0	59.3	65.0
Permeability	2.7	2.9	0.1	13.0
Elevation	562.1	129.9	343.9	960.0
Frost-Free Days	270.5	10.2	198.5	275.8
Citrus_drip	71.9	130.4	0.0	630.0
Citrus_gravity	6.5	33.2	0.0	271.0
Grape_drip	46.2	90.5	0.0	415.0
Grape_gravity	38.6	89.1	0.0	529.0
Deciduous_drip	19.4	65.1	0.0	630.0
Deciduous_gravity	13.2	50.5	0.0	548.0
Deciduous_sprinkler	10.2	44.8	0.0	622.0
Truck_gravity	11.0	42.0	0.0	392.0
Truck_sprinkler	73.6	112.5	0.0	650.0
Field_sprinkler	67.3	107.3	0.0	525.0
Orange price index	118.5	22.7	94.0	173.0
Grape price index	110.0	7.2	101.0	126.0
Almond price index	75.9	28.1	44.0	130.0
Potato price index	89.1	21.2	63.0	133.0
Carrot price index	123.2	17.5	103.0	149.0
Onion price index	114.4	22.4	72.0	140.0
Cotton price index	98.5	14.1	86.0	126.0
Annual crop price index	103.6	8.6	91.0	120.0
Permanent crop price index	105.3	8.6	92.0	118.0
Yearly temperature	64.5	1.3	62.2	66.1

Table 5 - Seemingly Unrelated Regression (SUR) Results

(Dependent Variables – Acreage in Each Crop and Irrigation Type)

	Citrus Drip	Citrus Gravity	Grape Drip	Grape Gravity	Deciduous Drip	Deciduous Gravity	Deciduous Sprinkler	Truck Sprinkler	Truck Gravity	Field Sprinkler
Slope	* 1.90	-0.45	1.00	-0.38	0.93	-0.96	0.18	** -5.06	-1.29	*** -5.97
	(1.88)	(-1.11)	(1.00)	(-0.39)	(0.90)	(-1.17)	(0.24)	(-2.14)	(-1.29)	(-2.77)
Permeability	0.09	0.08	-0.04	0.10	0.18	-0.33	0.13	-0.49	* -0.79	0.64
	(0.23)	(0.47)	(-0.10)	(0.25)	(0.42)	(-0.95)	(0.41)	(-0.50)	(-1.87)	(0.71)
Section temperature	1.50	0.29	-1.20	-0.54	0.04	-0.50	0.42	-4.25	-0.89	** -8.82
	(0.92)	(0.41)	(-0.71)	(-0.32)	(0.02)	(-0.35)	(0.32)	(-1.07)	(-0.52)	(-2.41)
frost-free days	-0.11	* -0.11	0.09	0.03	-0.01	0.06	0.03	0.46	0.19	** 0.74
	(-0.72)	(-1.67)	(0.59)	(0.17)	(-0.03)	(0.49)	(0.27)	(1.26)	(1.18)	(2.19)
Acreage (lagged)	*** 0.96	*** 0.90	*** 0.95	*** 0.92	*** 0.89	*** 0.88	*** 0.79	*** 0.68	*** 0.54	*** 0.71
	(106.45)	(65.26)	(80.79)	(82.03)	(59.34)	(52.14)	(51.39)	(29.14)	(21.34)	(30.24)
Water Price	* 0.41	-0.07	0.04	-0.08	0.21	0.02	-0.22	*** -2.20	0.24	0.42
	(1.82)	(-0.72)	(0.17)	(-0.36)	(0.83)	(0.09)	(-1.21)	(-3.30)	(0.84)	(0.71)
Orange Price Index	0.03	*** -0.09	*** 0.37	*** -0.25	** -0.16	-0.03	** 0.17			
	(0.43)	(-3.27)	(5.32)	(-3.74)	(-2.18)	(-0.56)	(2.42)			
Grape Price Index	-0.13	-0.01	0.19	* -0.32	0.02	0.27	** -0.34			
	(-0.68)	(-0.11)	(0.94)	(-1.63)	(0.09)	(1.59)	(-2.22)			
Almond Price Index	-0.09	0.003	0.05	0.04	-0.08	-0.07	** 0.13			
	(-1.29)	(0.10)	(0.63)	(0.58)	(-1.05)	(-1.10)	(2.24)			
Potato Price Index								-0.02	0.18	-0.47
								(-0.05)	(1.15)	(-1.40)
Carrot Price Index								-0.43	-0.18	0.71
								(-0.87)	(-0.86)	(1.58)
Onion Price Index								** 0.60	** -0.25	** -0.40
								(2.42)	(-2.42)	(-1.77)
Cotton Price Index								** 0.74	-0.04	*** -0.88
								(2.20)	(-0.32)	(-2.96)
Annual Crop Price Index	-0.11	0.06	* -0.28	** 0.31	0.08	0.09	-0.08			
	(-0.73)	(0.90)	(-1.76)	(1.99)	(0.51)	(0.72)	(-0.66)			
Permanent Crop Price Index								1.12	0.23	-0.67
								(1.39)	(0.66)	(-0.92)
Constant	-58.35	22.20	13.59	64.37	1.90	-12.68	-0.53	94.52	16.79	*** 516.8
	(-0.69)	(0.61)	(0.15)	(0.74)	(0.02)	(-0.17)	(-0.01)	(0.45)	(0.19)	(2.68)
R-squared	0.935	0.810	0.849	0.850	0.681	0.662	0.641	0.464	0.303	0.516

Numbers in parentheses are t-statistics, * = 10% significance, ** = 5% significance, *** = 1% significance

Table 6 - Water Demand Estimation Results

(Dependent Variable – Total Water Use)

	OLS Estimation (no correction)	IV Estimation (robust std errors)	GLS AR(1) (common rho)
Average Slope	9.63	16.43	4.15
	(0.66)	(0.90)	(0.24)
Section Average Temperature	* -27.36	-23.89	** -38.77
	(-1.61)	(-1.37)	(-2.22)
Permeability	*** 17.70	*** 18.48	*** 29.36
	(3.27)	(3.32)	(4.66)
Water Price	*** -5.30	*** -5.31	*** -6.40
	(-2.86)	(-2.78)	(-5.89)
Citrus_Drip	*** 1.73	*** 1.97	*** 1.35
	(12.64)	(13.26)	(9.42)
Citrus_Gravity	*** 3.23	*** 3.94	*** 2.35
	(7.15)	(8.44)	(4.34)
Grape_Drip	*** 1.41	*** 1.40	*** 1.47
	(8.30)	(7.94)	(7.49)
Grape_Gravity	*** 2.02	*** 2.31	*** 1.37
	(11.37)	(8.76)	(6.64)
Deciduous_Drip	*** 2.40	*** 1.88	*** 1.87
	(10.50)	(3.55)	(5.85)
Deciduous_Gravity	*** 2.86	*** 3.25	*** 3.32
	(9.54)	(7.55)	(7.05)
Deciduous_Sprinkler	*** 2.33	*** 3.67	*** 2.30
	(6.92)	(2.75)	(4.12)
Truck_Sprinkler	*** 1.25	*** 1.16	*** 1.28
	(8.59)	(4.70)	(8.01)
Truck_Gravity	*** 2.15	*** 2.77	*** 2.20
	(5.92)	(4.36)	(4.74)
Field_Sprinkler	*** 2.00	*** 2.73	*** 1.73
	(12.96)	(9.89)	(9.97)
Yearly Average Temperature	** 25.58	* 21.22	*** 37.61
	(2.21)	(1.81)	(5.27)
Constant	732.93	692.44	696.82
	(0.56)	(0.53)	(0.59)
Number of observations	965	965	965
R-sq	0.430	0.407	
(within)			
(between)			
rho estimate			0.571

Numbers in parentheses are t-statistics, * = 10% significance, ** = 5% significance, *** = 1% significance

Table 7 – Coefficients of Crop/Technology Pairs

	Type of Irrigation	Type of Crop Citrus	Grape	Deciduous	Deciduous	Truck	Field
OLS Estimation	Drip	1.73	1.41	2.40	n.a.	n.a.	n.a.
(no correction)	Gravity	3.23	2.02	2.86	2.86	2.15	n.a.
	Sprinkler	n.a.	n.a.	n.a.	2.33	1.25	2.00
Chi-squared value for difference		*** 10.79	*** 6.76	1.42	1.39	** 5.40	n.a.
IV Estimation	Drip	1.97	1.40	1.88	n.a.	n.a.	n.a.
(robust std errors)	Gravity	3.94	2.31	3.25	3.25	2.77	n.a.
	Sprinkler	n.a.	n.a.	n.a.	3.67	1.16	2.73
Chi-squared value for difference		*** 16.75	*** 8.31	* 3.78	0.08	** 4.86	n.a.
GLS AR(1)	Drip	1.35	1.47	1.87	n.a.	n.a.	n.a.
	Gravity	2.35	1.37	3.32	3.32	2.20	n.a.
	Sprinkler	n.a.	n.a.	n.a.	2.30	1.28	1.73
Chi-squared value for difference		* 3.50	0.18	*** 6.93	2.43	** 3.99	n.a.

Chi-squared values are with one degree of freedom
For 1% the critical value is 6.63
For 5% the critical value is 3.84
For 10% the critical value is 2.71

Table 8 - Water Price Elasticities

At Mean Values	Direct Elasticity	Indirect Elasticity	Total Elasticity
OLS Estimation	-0.275		-0.275
IV Estimation	-0.286	-0.038	-0.324
GLS AR(1)	-0.345	-0.070	-0.415

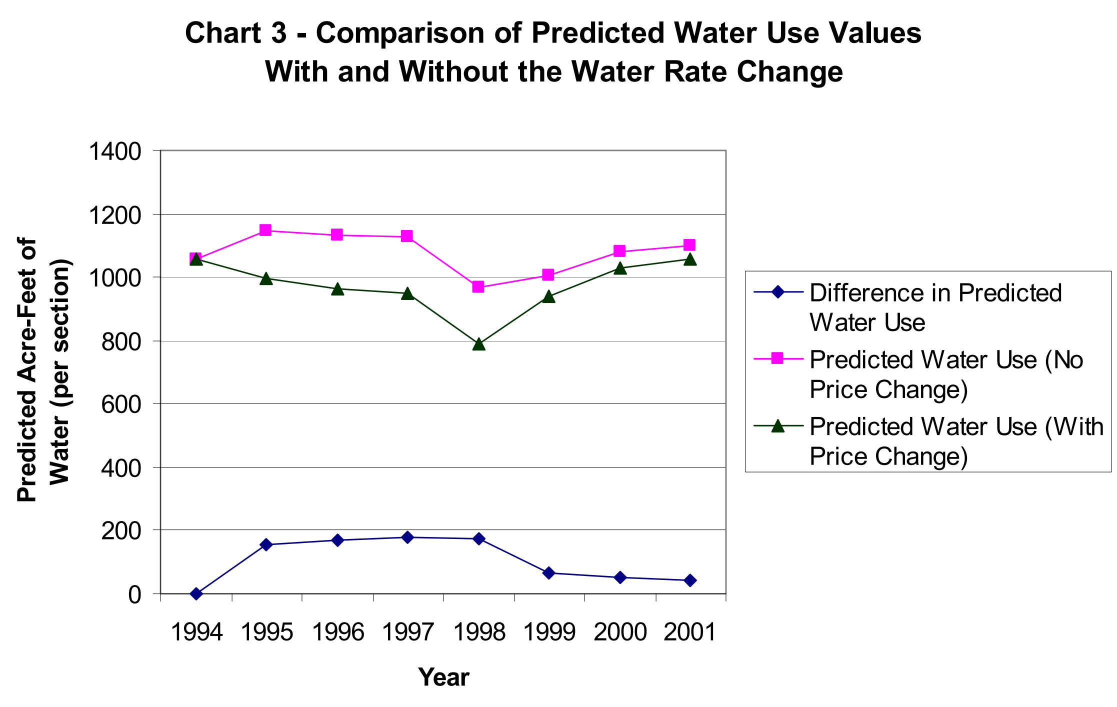

Chart 3 - Comparison of Predicted Water Use Values With and Without the Water Rate Change

Chart 4 - Comparison of the Direct and Indirect Effects of Water Use Reductions