A Stochastic-Dynamic Model of Costly Reversible Technology Adoption

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Kenneth A. Baerenklau[1]
University of California – Riverside
Department of Environmental Sciences

Keith C. Knapp[2]
University of California – Riverside
Department of Environmental Sciences

[1] Assistant Professor
Department of Environmental Sciences
420 Geology Building
University of California
Riverside, CA 92521
V: (951) 827-2628
E: ken.baerenklau@ucr.edu

[2] Professor
Department of Environmental Sciences
424B Geology Building
University of California
Riverside, CA 92521
V: (951) 827-4195
E: keith.knapp@ucr.edu

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Abstract

We develop a stochastic-dynamic model of technology adoption that imposes fewer restrictions on behavior than do previous studies of similar decision problems. Like these previous studies, our model is forward-looking and can be used to demonstrate the additional "hurdle rate" that must be met before adoption will take place when the future state of the world is uncertain. Unlike these previous studies, our approach does not impose the untenable assumptions that investment in a new technology is irreversible or that technologies have unlimited useful lifetimes. Rather, we address the more reasonable situation of costly reversibility and limited lifetimes. Our solution method utilizes Bellman's equation and standard dynamic programming techniques. Similar methods have been used previously to examine *irreversible* investment and adoption problems, but to our knowledge no application to costly reversible adoption has yet to appear in the literature. Our behavioral simulations, calibrated for irrigated cotton farming in California's San Joaquin Valley, demonstrate that the more restrictive approach can produce significant model prediction errors and can overlook important features of the adoption problem when decisions are reversible and technologies eventually become obsolete. Policy implications are discussed.

1. Introduction

The decision to adopt a new technology frequently requires substituting one durable good for another. Therefore, adopting (or not adopting) the new technology has both current period and future period implications because the decision changes the "state of the world" both now and in the future. For example, if an agricultural producer adopts a cheap but inefficient irrigation system when water prices are low, he may be very happy with this purchase in the short-run; but he could become quite unhappy if water prices rise in the long-run. Whereas if he adopts an expensive but highly efficient irrigation system when water prices are low, he may regret this decision in the short-run; but he may be thankful for it if water prices rise in the long-run. A rational individual who recognizes that a current decision affects both current and future welfare is best modeled as a dynamic "forward looking" agent; that is, as someone who considers the future implications of current actions. Of course, someone who can costlessly and instantaneously change the state of the world (i.e., switch irrigation systems) cares not about these future contingencies, but typically this is not the case for technology adoption problems.

Previous authors have recognized the forward-looking nature of technology adoption decisions and have investigated whether dynamic elements could help to explain why rates of technology diffusion frequently seem to be slower than expected. For example, Isik (2004) observes adoption of site-specific farming technologies lags despite evidence they produce economic benefits; Carey and Zilberman (2002) observe adoption of modern irrigation technologies in California's San Joaquin Valley seems to take place only when water becomes very scarce; and Purvis *et al.* (1995) observe very few Texas dairies utilized free-stall housing at the time of their study, despite the advantage of increased milk production.

A popular approach used by these and other authors is the Dixit-Pindyck option value model of investment (Dixit and Pindyck, 1994). The option value framework is mathematically convenient and can account for many determinants of the adoption decision, including various forms of uncertainty, future expectations, risk preferences, inter-temporal substitution, and fixed adoption costs. But a potential drawback of most studies that utilize this framework is the common assumption that the decision to exercise the option (i.e., to adopt the new technology) is irreversible. Although some options may be irreversible or effectively so (e.g., harvesting a resource stock such as timber), we believe most technology adoption decisions are not; rather, most adoption decisions are characterized by costly reversibility. For example, agricultural producers can and do replace their existing irrigation and cropping systems in response to input and output price fluctuations, changing agricultural policies, and other factors. Furthermore, we note most, if not all, technologies are not infinitely durable but rather *must* be replaced when their performance begins to deteriorate significantly.

These observations draw into question the suitability of the typical option value approach for a whole class of technology adoption problems, including the types of technologies often advocated by environmental agencies tasked with reducing pollution from agricultural operations (i.e., conservation technologies, also known as "best management practices"). Nonetheless, researchers continue to use this approach to analyze these types of adoption problems. Generally these studies have concluded that the combined effects of uncertainty and the opportunity to delay adoption provide a good explanation for why agents often postpone adopting a technology that appears to be immediately profitable. But we question the extent to which these results may be driven by the chosen analytical framework. For example, results from the finance literature (e.g., Asano, 2002; Kandel and Pearson, 2002; Hartman and Hendrickson, 2000; Abel and Eberly, 1996) suggest costly reversibility produces noticeably different model results than irreversibility. However, these applications address the problem of optimal capital stock accumulation which is structurally different from the problem of technology adoption.

The purpose of this paper is to examine the determinants of technology adoption under uncertainty using a stochastic-dynamic model of behavior that is more flexible than the standard option value approach. Our solution method utilizes Bellman's equation and standard dynamic programming techniques. Similar methods have been used by previous authors to examine *irreversible* investment and adoption problems (e.g., Bulte et al., 2002; Insley, 2002; Shively, 2001; Farzin, 1998; Abel and Eberly, 1998 and 1996), but we are not aware of any applications to costly reversible adoption. Our empirical results show the typical option value approach can produce significant model prediction errors and can overlook important features of the adoption problem when decisions actually are reversible and technologies eventually become obsolete.

2. Empirical Application

The specific problem we examine is adoption of water efficient irrigation technologies by San Joaquin Valley cotton growers who face stochastic water prices. Agricultural water use in California's arid and semi-arid growing regions continues to be scrutinized as more water is demanded by urban populations and for habitat protection. We focus on cotton producers for several reasons. First, in terms of acreage cotton is the second largest field crop in California and the fourth largest nationally: approximately 13 million acres were harvested nationwide in 2004, with 770,000 acres in California (California Agricultural Statistics Service, 2005). Second, cotton water requirements are relatively high: 2.4 to 4.2 feet per acre per year depending on the irrigation system (Caswell, Lichtenberg and Zilberman, 1990). Third, despite evidence that modern irrigation technologies can increase producer profits, the vast majority of cotton acreage remains irrigated with inefficient older technologies: approximately 65-70% of

California's cotton acreage used traditional furrow irrigation, while less than 5% uses modern drip systems (Burt, Howes and Mutziger, 2001; Horton, 2004).[1] And fourth, excellent economic data exist for cotton: the University of California Committee of Consultants on Drainage Water Reduction (UCCC) estimated detailed cotton production costs for several different types of irrigation systems, as well as expected irrigation system lifetimes. We adjust these costs to 2004 values using agricultural producer price indices published by the California Agricultural Statistics Service (CASS, 2005) to construct an accurate representation of current economic conditions facing producers. We present these data in more detail later.

We model the relatively simple two-technology adoption problem with one source of uncertainty. The old technology is ¼-mile surge-gated pipe furrow irrigation (furrow) and the new technology is subsurface drip irrigation (drip). We choose this type of furrow irrigation because it represents one of the most efficient furrow irrigation techniques which, presumably, producers who choose not to adopt subsurface drip irrigation might implement when faced with increased water scarcity. Our decision framework therefore characterizes the well-defined "jump" from furrow to drip that takes place after a producer has achieved maximum efficiency with a furrow system.[2] We limit our attention to water price uncertainty because we are concerned primarily with the effects of decision model structure on prediction, and because prices received by San Joaquin Valley cotton producers are much less variable than the prices they must pay for inputs such as water (Carey and Zilberman, 2002).[3]

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[1] Carey and Zilberman (2002) provide a detailed discussion of the recent history of California drought cycles and adoption of modern irrigation technologies on various crops.

[2] A useful extension of our model would be to include sprinkler irrigation as a third possible technology choice. We choose not to do this here so we may focus our attention on decision model characteristics. The qualitative nature of our results would not be affected by the inclusion of additional technologies.

[3] There may be other important stochastic components of the adoption problem, including: input constraints, policy variables, and/or subjective uncertainty about key parameter values (particularly those describing the performance of the new technology). Other authors have examined these factors (e.g., Carey and Zilberman, 2002; Isik, 2004; Baerenklau, 2005) and have found they can have significant effects on behavior in certain situations. We forego

Model Specification

Specification of a decision framework for our empirical application first requires an assumption about agricultural production. Following Carey and Zilberman (2002), we assume a von Liebig production function that establishes a piece-wise linear relationship between applied water and crop yield:

$$y_i = \begin{cases} h_i w_i, & \forall w_i < w_i^* \\ y^*, & \forall w_i \geq w_i^* \end{cases}, \quad i = 1, 2. \tag{1}$$

Here, i=1 represents furrow and i=2 represents drip; y_i is output per acre, h_i accounts for differences in irrigation efficiency; w_i is applied water; and $h_2 > h_1$. According to equation (1), output increases linearly with applied water at low application rates, up to an upper limit y^*.[4] Because $h_2 > h_1$, this upper limit is reached with less applied water when drip irrigation is used than when furrow is used.[5] Because returns to scale are constant at low application rates, if a producer finds it profitable to apply even a small amount of water, he necessarily will find it profitable to apply the full amount of water, w_i^*. Therefore each producer will grow either a full crop or no crop with this production function.

Assuming producers are risk neutral and the price of cotton remains high enough to satisfy the total profit condition, our problem can be expressed using a cost-minimization framework in which, during each decision period, a producer must decide whether to retain his

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detailed investigations of these factors here in order to examine a model that we believe produces more general insights. However, all of these represent useful extensions of this work.

4 Some studies (e.g., Hanson, Fipps and Martin, 2005) have found "yield enhancing" effects associated with using more efficient irrigation systems. This would imply $y_2^* > y_1^*$. As in Carey and Zilberman (2002), we assume any such effects are negligible.

5 We make the common simplifying assumption that each h_i is independent of technology age. That is, the irrigation efficiency of an installed technology does not gradually decline through time.

existing irrigation system or to replace it with either a new furrow or a new drip system.[6] Formally, a producer's objective at each time (t) is to make the irrigation technology decision that minimizes the expected present value of current and future production costs:

$$E_t\left[\sum_{\tau=t}^{\infty}\beta^{(\tau-t)}C\left(p_\tau,\mathbf{\Gamma}_\tau,s_\tau\right)\right], \tag{2}$$

subject to a constraint set we present below. Here, the subscript τ tracks the time period; the expectation at time (t) is taken over all future water prices, p_τ; $\mathbf{\Gamma}_\tau$ is a (2x1) vector that tracks the type of irrigation system installed (Γ^{tech}) and its age (Γ^{age}) at time τ; s_τ is a scalar that represents the adoption decision made at time τ; β is the discount factor; and $C(\cdot)$ is the cost incurred at time τ. We suppress the additional cost function parameters for the sake of notational simplicity.

The constraint set for equation (2) includes restrictions on the decision variable s_τ as well as equations of motion specifying how p_τ and $\mathbf{\Gamma}_\tau$ evolve through time. Because we have a two-technology problem, each s_τ can take one of at most three values at time τ: $s_\tau = 0$ corresponds to the decision to keep the existing irrigation system; $s_\tau = 1$ corresponds to the decision to adopt a new furrow system; $s_\tau = 2$ corresponds to the decision to adopt a new drip system. Because we assume each technology has a finite useful lifetime and because we plan to examine both costly reversibility and irreversibility, each producer's choice set is constrained further according to Table 1. For notation convenience, we denote the constraints defined in Table 1 as: $s_\tau \in \Psi$.

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[6] Berck and Helfand (1990) have shown that a continuously differentiable and concave technology may be more appropriate than equation (1) at the field level when production is characterized by significantly heterogeneous inputs. Adopting this functional specification necessitates the use of a profit-maximization framework, in which case we would need to model output as well as input prices. We believe this would complicate our model unnecessarily and detract from our main focus. However, this would be a useful extension of our framework.

The water price (p_τ) is assumed to follow an exogenous random process that cannot be predicted with certainty. This process can be expressed by a stochastic state equation that relates the future water price to the current water price. For our empirical application, we use a first-order auto-regressive process with constant θ and correlation ρ:

$$p_{\tau+1} = \theta + \rho \cdot p_\tau + \varepsilon_{\tau+1}, \tag{3}$$

where the ε_τ are assumed to be independently and identically distributed $N\left(0,\sigma^2\right)$ random variables.[7] Another assumption we make regarding the price process is the only relevant price for irrigation technology decisions is a seasonal average price expectation that is realized between growing seasons. Actual water prices fluctuate significantly during the growing season and previous authors have modeled these fluctuations. If water prices became high enough during a growing season, a producer might choose to stop irrigating and produce a limited crop; but the possibility that a producer would change his irrigation system in mid-season due to water price fluctuations is unrealistic because doing so would destroy his crop entirely. Therefore, we measure time in years and implicitly model a series of price *expectations* with equation (3) rather than a series of price *realizations*.

Unlike the water price, the state variables in $\mathbf{\Gamma}$ are deterministic. Assuming "1" represents furrow irrigation and "2" represents drip, the evolution of the installed technology (Γ^{tech}) can be expressed as:

[7] Many previous studies that utilize the option value framework assume prices can be represented by geometric Brownian motion with positive drift. It is straightforward to incorporate price drift into our model by specifying an additional state variable (time) and appending a linear time trend to equation (3), but doing so is not necessary to establish our main results. Furthermore, it is not obvious that positive price drift is necessarily justified in this case or in similar earlier studies which have lacked supporting data (e.g., Carey and Zilberman, 2002). Positive input price drift seems intuitively appealing but also would seem to depend on a number of assumptions about market imperfections, output demand and input supply. Given the complexity of agricultural markets and the myriad of policies that affect them, we choose to use a simpler price process that allows us to focus our attention specifically on the role of uncertainty, rather than on the combined effects of uncertainty and temporal trends.

$$\Gamma_{\tau+1}^{tech} = \begin{cases} \Gamma_{\tau}^{tech} & \text{if } s_\tau = 0 \\ s_\tau & \text{if } s_\tau \neq 0 \end{cases}. \quad (4)$$

The evolution of the technology age (Γ^{age}) can be expressed as:

$$\Gamma_{\tau+1}^{age} = \begin{cases} \Gamma_{\tau}^{age} + 1 & \text{if } s_\tau = 0 \\ 1 & \text{if } s_\tau \neq 0 \end{cases}. \quad (5)$$

Cost Data

Our cost and technology data is drawn primarily from the University of California Committee of Consultants report on irrigation drainage water reduction (1988). As in the UCCC report, we assume a standard field size of 129.5 hectares (ha) with 125.5 ha of cropped area. We assume the field is in continuous cotton production and the cost to produce winter cover crops is negligible. Table 2 summarizes the key data we use to calibrate our model.

We assume 20% of the Capital Cost in Table 2 is labor cost and we depreciate the remaining 80% linearly over the irrigation System Life to obtain salvage values. The Variable Energy Cost for pumping and pressurization is estimated to be \$0.000907/(ha-cm^2), assuming a 60% pumping efficiency (Knapp et al., 1990) and an agricultural energy price of \$0.20/kWh in the San Joaquin Valley (California Energy Commission, 2004). The Fixed Energy Cost depends on pump size and irrigation system type but not on water volume or energy prices. Amounts of Applied Water are assumed to be at the lower ends of the ranges estimated by Caswell, Lichtenberg and Zilberman (1990) to reflect irrigation efficiency improvements achieved since that study was conducted. Given these data, the cost function $C(\cdot)$ in equation (2) is determined by summing the Capital Cost (if any), O&M Cost, Fixed Energy Cost, Non-Water Production Cost, Variable Energy Cost, water cost (water price multiplied by the amount of Applied Water), and subtracting any salvage value. All other production costs are assumed to be invariant across irrigation technologies and, as stated previously, output prices are assumed to remain high enough to satisfy the total profit condition.

3. Solution Method

Unlike the water price, equations (4) and (5) show the evolution of $\mathbf{\Gamma}$ is endogenous. That is, selection of s_τ at time τ changes the state of the world at time $(\tau+1)$. Therefore, the pay-off at time τ is a function of decisions made prior to time τ. Recognition of these linkages across time periods would lead a rational agent to perform forward-looking calculations when determining the optimal decision in any period. Therefore our constrained cost-minimization problem, defined by equations (2) – (5) and the constraints represented by $s_\tau \in \Psi$, should be cast as a discrete stochastic-dynamic optimization problem and solved accordingly.

Inspection if equations (2) – (5) reveals our decision problem is stationary because we assume an infinite time horizon and because all temporal aspects are accounted for by the water price and technology state variables.[8] That is, the problem faced by a producer in time period (t) is identical to the problem faced in any other time period. The solution therefore can be expressed as a time-autonomous rule or function of the state variables: $s^*(p,\mathbf{\Gamma})$. Substituting this rule into equation (2) defines the optimized objective function, or value function:

$$V^*(p_t,\mathbf{\Gamma}_t) \equiv E_t\left[\sum_{\tau=t}^{\infty}\beta^{(\tau-t)}C^*(p_\tau,\mathbf{\Gamma}_\tau)\right], \tag{6}$$

where $C^*(\cdot)$ represents the cost incurred during period τ conditional on the optimal decision rule $s^*(p,\mathbf{\Gamma})$ being applied in each period. Because the decision problem is stationary, it

[8] Incorporating a finite terminal time (or any other feature that makes the problem non-stationary) is straightforward but requires additional assumptions about boundary conditions and also requires economic justification. On the contrary, we believe the agricultural producers in our empirical example face planning horizons of sufficient length to make the actual problem indistinguishable from the infinite horizon problem (a common assumption in dynamic optimization). However, producers who plan to exit farming in the near future (perhaps those planning to sell their land to suburban developers) should, of course, be modeled in a finite time horizon framework.

follows that the value function defined by equation (6) also is time-autonomous.

The optimal decision rule $s^*(p,\mathbf{\Gamma})$ can be found using standard methods of dynamic programming. To do so it is convenient to rewrite equation (6) in Bellman's form, using the time-autonomy of the value function:

$$V^*(p_t,\mathbf{\Gamma}_t) \equiv E_t\left[C^*(p_t,\mathbf{\Gamma}_t) + \beta\sum_{\tau=t+1}^{\infty}\beta^{(\tau-t+1)}C^*(p_\tau,\mathbf{\Gamma}_\tau)\right], \text{ or:} \tag{7}$$

$$V^*(p_t,\mathbf{\Gamma}_t) \equiv C^*(p_t,\mathbf{\Gamma}_t) + \beta E_t V^*(p_{t+1},\mathbf{\Gamma}_{t+1}). \tag{8}$$

Rather than attempting to find an analytical solution for $s^*(p,\mathbf{\Gamma})$, we solve our problem numerically. We first discretize the state space into a finite set of possible state variable combinations (we use \$1 increments for the water price; $\mathbf{\Gamma}$ is discrete by definition) and then use value function iteration – a standard dynamic programming technique – implemented with original computer code to find the solution. To accomplish this we first initialize $V(p,\mathbf{\Gamma})$. Then, for each possible combination of state and decision variables $(p_t,\mathbf{\Gamma}_t,s_t)$, we use equations (3) – (5) and the constraints in Table 1 to determine $E_t V(p_{t+1},\mathbf{\Gamma}_{t+1})$. We then find the unique $s_t \in \Psi$ that minimizes $\left(C(p_t,\mathbf{\Gamma}_t,s_t) + \beta E_t V(p_{t+1},\mathbf{\Gamma}_{t+1})\right)$, we set $s(p_t,\mathbf{\Gamma}_t) = s_t$, and we update $V(p_t,\mathbf{\Gamma}_t)$ according to equation (8). We continue iteratively updating $V(p,\mathbf{\Gamma})$ and $s(p,\mathbf{\Gamma})$ until we satisfy a convergence tolerance for both functions. By the contraction mapping property of Bellman's form, $V(p,\mathbf{\Gamma}) \rightarrow V^*(p,\mathbf{\Gamma})$ and $s(p,\mathbf{\Gamma}) \rightarrow s^*(p,\mathbf{\Gamma})$ both asymptotically.

4. Results and Discussion

Baseline cases

In addition to the cost data in Table 2, we must specify some additional values before conducting our simulations: the price process parameters (θ, ρ, σ^2), the initial price (p_0), the discount factor (β), and an indicator for reversible investment: $R \in \{0,1\}$. Our first simulation establishes the deterministic decision rule, therefore $\sigma^2 = 0$. For the remaining parameters:

- We set $R = 1$ (i.e., investment in the new technology is reversible).[9]
- We set $\theta = 7.5$ and $\rho = 0.9$, implying a corresponding long-run expected water price of $\theta/(1-\rho) = \$75$ per acre-foot (af).[10]
- We set $p_0 = \$75$, the long-run expected water price.
- We set $\beta = 1/1.08 = 0.926$, implying a discount rate of 8%. We use a relatively high discount rate because in subsequent simulations the value function is stochastic and therefore should be discounted at a rate higher than the risk-free rate.

Figure 1 presents two separate optimal investment rules – one for furrow system users and one for drip system users – for the deterministic case. According to the figure, a furrow system user will chose to adopt a new drip system only if the (age, price) state variable pair falls in the upper shaded regions;[11] otherwise, she will retain her existing furrow system (or replace it with a new one if it has reached its replacement age of 12 years). A drip system user will chose to adopt a new furrow system only if the (age, price) pair falls in the lower cross-hatched regions of Figure 1; otherwise, he will retain his existing drip system (or replace it with a new one if it has reached its replacement age of 8 years). Note that the control rule is the same for both technologies at their respective replacement ages of 8 and 12 years: invest in a new drip system

[9] We are not aware of any empirical data suggesting producers are switching from drip systems to furrow systems in significant numbers. However, this does not imply adoption is irreversible and our results demonstrate the importance of accounting for the *possibility* that adoption may be reversed even if producers choose not to do so.

[10] There exists very limited data on water prices, but Carey and Zilberman (2002) report water sales by the San Joaquin Valley Districts in the range of \$70 - \$80/af from 1993 - 1994. Our long-run 95% confidence interval includes all but the single highest water price reported by Carey and Zilberman from 1988 - 1995.

[11] Note that the upper shaded regions continue above \$150, but have been truncated for presentation.

if the water price is at least \$85; otherwise invest in a new furrow system.

Figure 1 provides some initial insights into the adoption problem. First, the figure shows reverting from a drip to a furrow system is optimal for a non-trivial set of (age, price) pairs. This suggests prohibiting divestiture of the new technology – as do many previous applications of the option value model – may have a substantial impact on behavioral predictions. Second, system age appears to significantly affect the technology switching price. For a furrow user with a relatively new system, the water price must be at least in the range of \$94 - \$104 to trigger investment in a drip system; but for a furrow (or drip) user with an old system that has reached its replacement age, the water price can be as low as \$85.

To establish a more realistic baseline case, we retain the previous parameter values but we introduce uncertainty into the price path by setting $\sigma^2 = 100$. Figure 2 shows a possible realization of our water price process, as well as the 95% confidence bounds an agent would place on the process during the initial period. Figure 3 shows the optimal investment rule for this baseline case. Incorporating uncertainty not only makes the simulations more realistic, but also has a noticeable effect on the optimal investment rules. The replacement age switching price is now \$89, approximately 4.7% higher than in the deterministic case (\$85). The furrow-to-drip switching prices for newer furrow systems also are noticeably higher than in the deterministic case (by about 10%, on average), and the drip-to-furrow switching prices are significantly lower (by about 20%, on average). These observations confirm the results of many previous studies as well as economic intuition, namely the combined effects of uncertainty and the opportunity to postpone investment introduces an additional “hurdle rate” that must be met before investment will take place. That is, relative to the deterministic case, prices must be even higher to encourage adoption of the new technology and they must be even lower to encourage adoption of the old technology, even when adoption is reversible.

Figure 3 also reveals that system age still has a noticeable effect on the technology switching prices for the case of a stochastic water price. This suggests if the water price fluctuates such that it happens to be relatively low when the replacement age of a furrow system is reached, adoption of a drip system would not occur even if water prices tend to be relatively high – high enough to justify adoption in a model that neglects system age – at most other times. Even if water prices are relatively constant, the figure also suggests a group of otherwise identical farms with differing technology ages will chose to adopt at different times. These observations present a new candidate explanation for delayed adoption of modern technologies with limited useful lifetimes that previous studies have not been able to address. Our results demonstrate adoption of a finitely durable technology depends not only on the realization of a high input price, but also on the timing of that realization in relation to the age of the installed technology. If these cycles are not, in a sense, "synchronized," adoption can be postponed. We examine the effects of system age and expected system life in more detail later.

To assess the impact on the optimal investment rule of assuming adoption is irreversible, we re-run our baseline simulation with $R = 0$. Figure 4 shows these results.[12] Imposing this constraint on the model has the anticipated effect on predicted switching prices. The replacement age switching price is now \$101, approximately 13.5% higher than for the reversible baseline case (\$89). The furrow-to-drip switching prices for newer furrow systems also are significantly higher than before: approximately 7.2%, on average. In other words, an even larger hurdle rate must be met before adoption of the new technology will occur. The implications of our results for empirical modeling are straightforward: if, rather than simulating behavior, we were attempting to describe observed behavior with a model that assumes adoption

[12] The drip-to-furrow switching prices are not applicable because adoption of a drip system is irreversible.

is irreversible when it truly is reversible, we would produce biased parameter estimates and consequently poor out-of-sample predictions and policy recommendations.[13]

Sensitivity Analysis

To better understand the relationships between model output and the irreversibility assumption, we conduct a sensitivity analysis for three key parameters: the discount rate, the expected drip system life and the long-run expected water price. In each case we derive both the reversible and irreversible decision rules to help illuminate the types of bias we might incur when assuming adoption is irreversible. The first parameter we examine is the discount rate, an important component of any multi-period optimization model.[14] Intuitively, decreasing the discount rate would tend to decrease the furrow-to-drip switching price. This is because future costs have a higher present value with a lower discount rate (a higher value of β). And because the furrow technology incurs relatively larger future costs (for water inputs) than does the drip technology, the total cost to install and operate a furrow irrigation system increases faster than the total cost for a drip system when the discount rate declines. A low discount rate effectively "penalizes" a furrow system more than it does a drip system; therefore, the furrow-to-drip switching price should move in the same direction as the discount rate.

Figure 5 shows this intuition holds. Furthermore, the figure demonstrates a model with irreversible adoption can approximately replicate the decision rule for a model with reversible adoption if the discount rate is reduced by about 2%. These results imply estimates of discount rates derived from models of irreversible investment will be biased downward when adoption is

[13] An analytical expression for the bias would be difficult to derive given the recursive definition of the value function. However, it would be possible to generate choice data from a known model of reversible adoption and then to estimate the parameter values with a model that assumes irreversibility. We leave this for future work.

[14] One reason for the growth in popularity of the option value model is related to discounting: models that fail to incorporate the opportunity to postpone the investment decision often cannot replicate observed behavior unless unrealistically high discount rates are used.

reversible. This observation also suggests a related problem for the more typical case of a modeling exercise with a pre-specified discount rate: because one of the common motivations for using an option value model is to avoid the need to use an unreasonably high discount rate with a non-forward-looking model to mimic observed behavior (see footnote 14), this downward bias would have the unfortunate effect of promoting the selection of an option value model with a "more reasonable" discount rate when the use of such a model is not entirely warranted.

To further investigate the role of system age, our second sensitivity analysis addresses the System Life parameters in Table 2. An important improvement that tends to happen to most technologies with the passage of time is an increase in the technology's useful lifetime. Some automobile manufacturers currently advertise their engines do not require mechanical service until they reach 100,000 miles. This is a remarkable improvement over first-generation automobiles and even over automobiles manufactured only a few decades ago. A similar trend may be happening with drip irrigation systems. Rain and Foley (2001) report the life expectancy of a subsurface drip system is approximately 10 years. Neufeld, Davison and Stevenson (1997) state the "expected system life is highly dependent upon the operation, design and ongoing maintenance of the system" but "industry representatives indicate properly designed and maintained systems should last up to 15 years." (pp. 2-3) Zimet and Smith (2000) claim that some components of a drip system can last up to 20 years. As the expected useful life of a drip system increases, the furrow-to-drip switching price for all furrow system ages should decrease because the expected cost of drip irrigation will be lower when its expected lifetime is greater.

Figure 6 shows the switching price behaves as expected and suggests it is more sensitive to changes in the expected system life than to changes in the discount rate. Furthermore, the figure demonstrates the discrepancy between the reversible and irreversible decision rules varies noticeably with the expected system life parameter. For a 7-year system life, the switching prices under irreversibility are 16 – 25% higher than those under reversibility; but the discrepancy is quite small for a 9-year system life. Because system life, like the discount rate, also would be a parameter that is assumed for a modeling exercise rather than estimated from data, Figure 6 suggests it is important for the analyst to make a good assumption about this parameter; otherwise, significant amounts of bias could be introduced into the estimated parameters as the model attempts to compensate for this error. Unfortunately, making a good assumption about system lifetimes may not be straightforward because it is not the *true* system life that affects the adoption decision but rather an agent's *belief* about the system life. The same is true for other model parameters, such as those specifying the price process. Therefore, if the analyst is attempting to derive parameter estimates from observed adoption data, accounting for subjective beliefs appears to be rather important.[15]

Our third sensitivity analysis addresses the possibility that agents may hold subjective beliefs about the constant term (θ) in our price process, and thus about the long-run water price expectation. Because higher water prices favor drip systems, we should see the furrow-to-drip switching price decrease as θ increases. Figure 7 shows this appears to be true and, according to the same reasoning we used for our sensitivity analysis of the discount rate, implies the irreversibility assumption introduces an upward bias on empirical estimates of price expectations. The discrepancy between the reversible and irreversible decision rules also exhibits significant variability depending on the long-run price expectation. For the case of $\theta = 5$ (i.e., a long-run price expectation of \$50), the switching prices under irreversibility are 23 – 32% higher than those under reversibility; but there is virtually no discrepancy for the case of $\theta = 10$ (i.e., a long-run price expectation of \$100).

[15] See Baerenklau (2005) for an example.

5. Conclusions

Our flexible decision framework sheds light on the implications of using more restrictive models of behavior, including many previous applications of the option value model. Like these applications, our model is forward-looking and can be used to demonstrate the additional "hurdle rate" that must be met before investment will take place when the future state of the world is uncertain. However, our approach does not impose the untenable assumptions that investment in a new technology is irreversible or that technologies have unlimited useful lifetimes.

In cases where the decision to adopt a new technology is most appropriately modeled as reversible, we show the irreversibility assumption can lead to significant model prediction errors: measured in terms of switching prices, the discrepancies can be up to 32% of the true values, depending on model parameters. By extension, this assumption would produce biased parameter estimates derived from observed behavior. Furthermore, because our approach accounts for the fact that most technologies eventually must be replaced, we also are able to examine the relevance of technology age to the adoption problem. We find this variable has a conspicuous effect on the switching price which we illustrate graphically.

If not readily apparent, the policy-relevance of these results can be demonstrated by considering the process by which a regulator might determine the proper incentive to encourage adoption of an environmentally friendly production technology. The regulator's problem can be cast as a stochastic-dynamic optimal control problem: maximize an inter-temporal social welfare function subject to equations of motion for the relevant state variables (including indicators of market value and environmental quality) by manipulating one or more control variables (i.e., the incentive). Buried in the mathematics of this problem is an adoption rule characterizing the decisions made by the agents who face the incentive. If the adoption rule is incorrectly specified, the regulator's derived control rule will be incorrect and the outcome will be inefficient. Therefore, our results raise questions not only about the validity of a large number of previous technology adoption studies, but also about the suitability of these models for guiding development of agri-environmental policies.

Our model advances the literature on technology adoption but also highlights a number of issues that remain to be investigated. We show the assumption of irreversibility, often readily employed by analysts for convenience, can have a significant impact on model output. But we do not delve into the details of exactly what determines the extent of reversibility or the cost of reversing a previous investment. For example, we account for capital (installation) costs, but we do not address learning costs or other sources of aversion to change. To the extent adopting a different technology has other inherent switching costs, these should be incorporated into the analysis. We briefly examine the importance of assessing subjective beliefs about key model parameters, but we do not explore this topic in detail. Agents may have subjective beliefs about input and output prices, production efficiencies, probability distributions, and other important parameters which analysts typically assume are known with certainty but which in reality are not. We believe our model presents a realistic characterization of the technology adoption problem, but it does not explore the effects of inter-temporal substitution, risk preferences, or credit constraints on adoption behavior. Of course, given the diversity of technology adoption scenarios that can arise in practice, a general model of technology adoption that incorporates all of these features and can be applied to any situation should not be the goal of future research. But to the extent researchers can better incorporate the vital characteristics of the specific scenarios they examine into their models, improved behavioral predictions and policy recommendations will result.

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Table 1: Choice Set Constraints (Ψ)

Is adoption of the new technology reversible?	Has the new technology been adopted previously?	Has the installed technology reached its replacement age?	Applicable Choice Set:
Yes	Yes	Yes	{1,2}
Yes	Yes	No	{0,1,2}
Yes	No	Yes	{1,2}
Yes	No	No	{0,1,2}
No	Yes	Yes	{2}
No	Yes	No	{0,2}
No	No	Yes	{1,2}
No	No	No	{0,1,2}

Table 2: Cost Data used to Calibrate the Adoption Model

Variable	1/4-mile Surge-Gated Furrow	Subsurface Drip
Capital Cost ($)[a]	$131,100	$450,965
O&M Cost ($/year)[a]	$3,943	$23,164
Fixed Energy Cost ($/year)[a]	$360	$360
Non-Water Production Cost ($/year)[a]	$183,303	$132,641
Pressure Head (cm)[b]	305	1,524
System Life (years)[b]	12	8
Applied Water (ft/acre/year)[c]	3.7	2.4

[a] University of California Committee of Consultants on Drainage Water Reduction (1988), inflated to 2004 values using agricultural producer price indices published by the California Agricultural Statistics Service (2005).
[b] University of California Committee of Consultants on Drainage Water Reduction (1988).
[c] Caswell, Lichtenberg and Zilberman (1990).

Figure 1: Optimal Decision Rules for the Deterministic Case

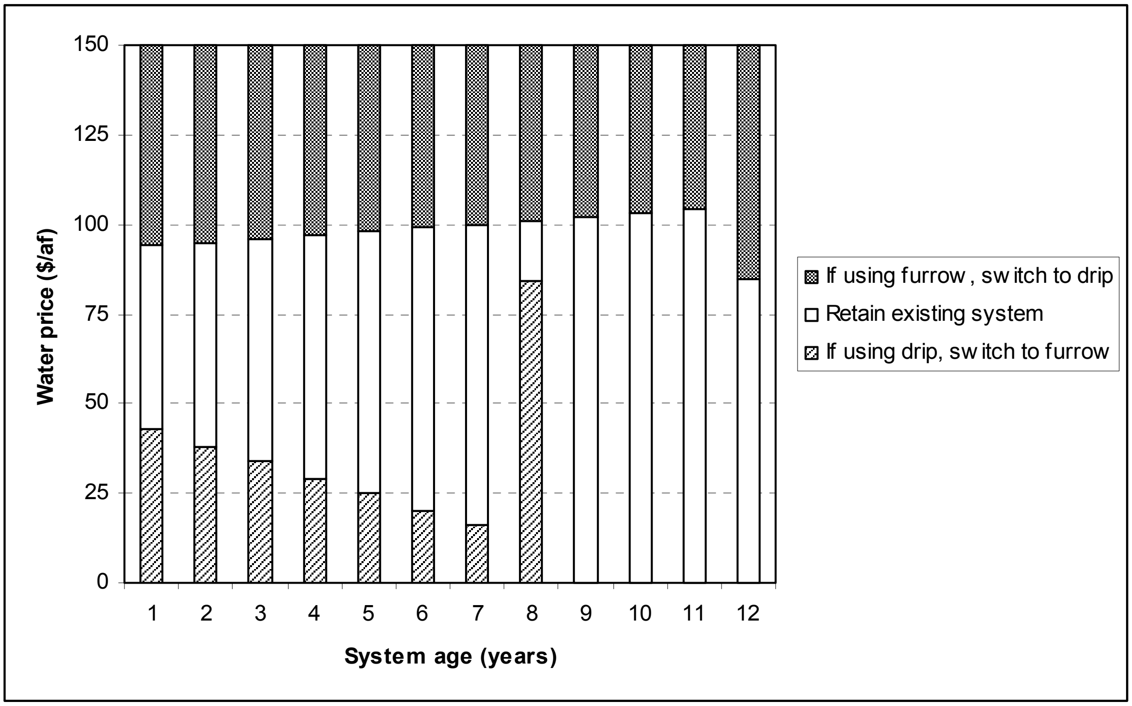

Figure 2: Price Process Confidence Bounds and a Possible Price Series for the Baseline Case

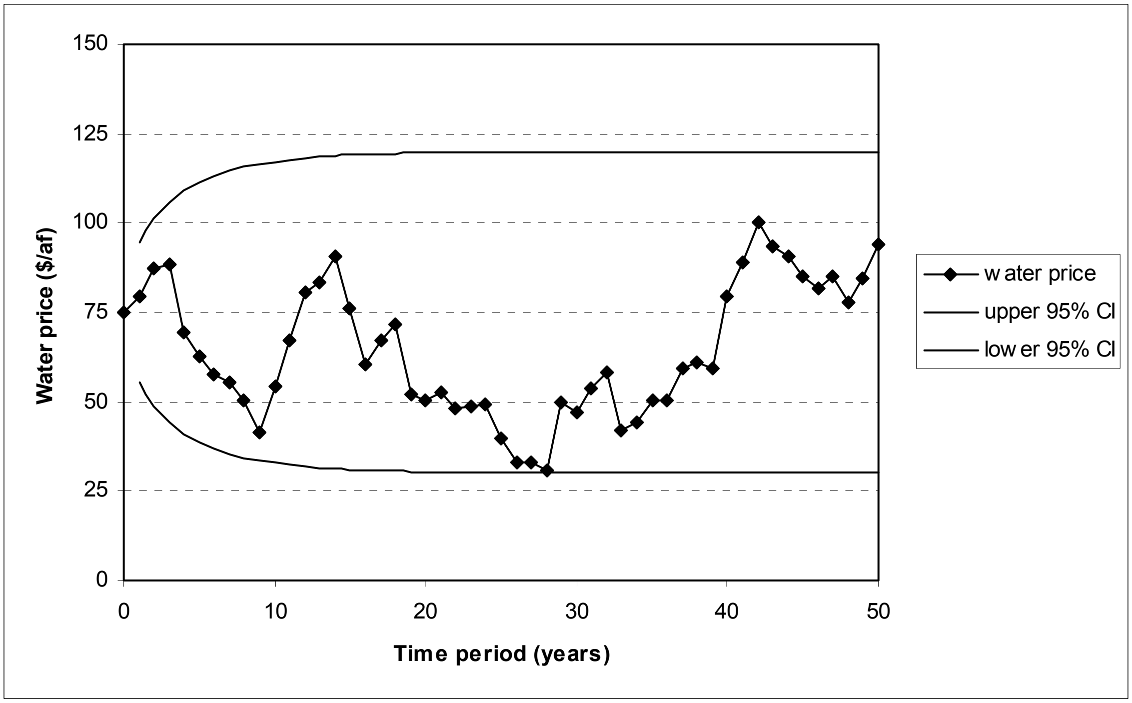

Figure 3: Optimal Decision Rules for the Baseline Case

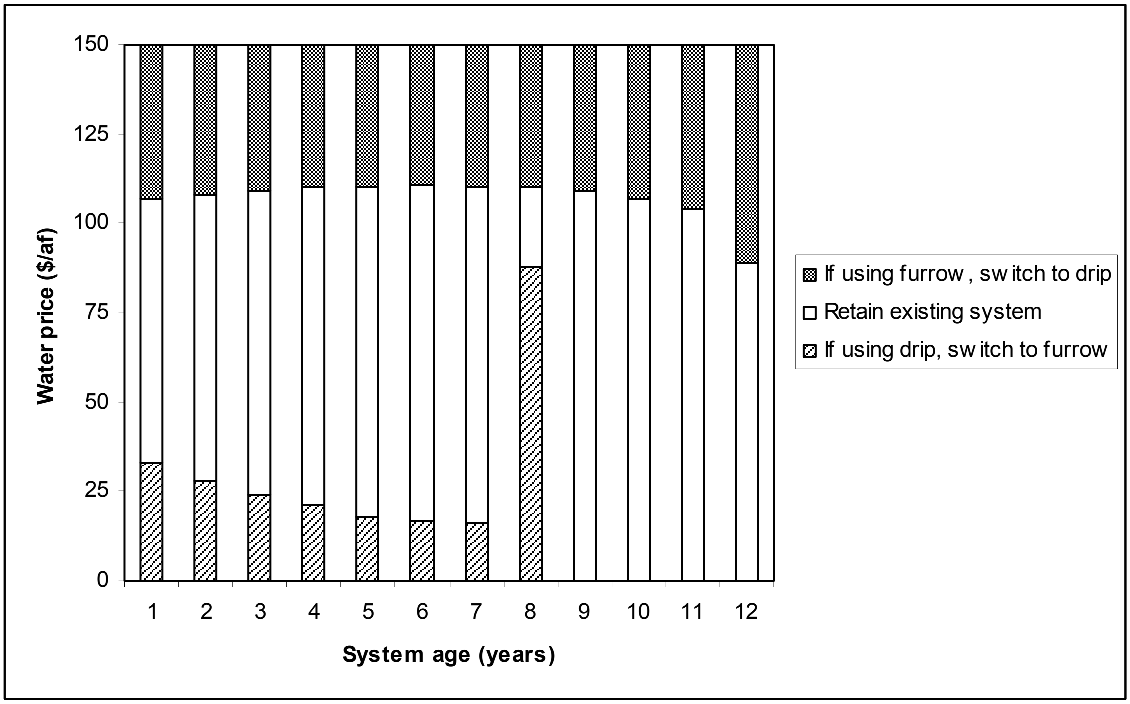

Figure 4: Optimal Decision Rule for the Baseline Case with Irreversibility

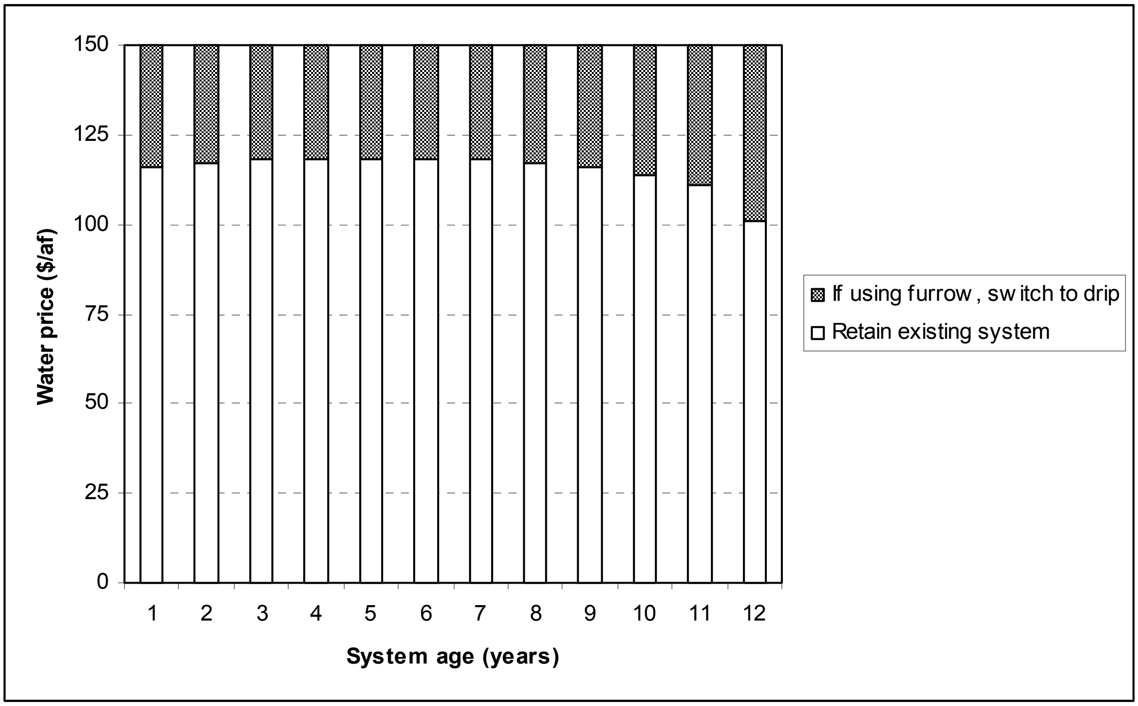

Figure 5: Comparison of Furrow-to-Drip Switching Prices for the Reversible and Irreversible Cases with Varying Discount Rates

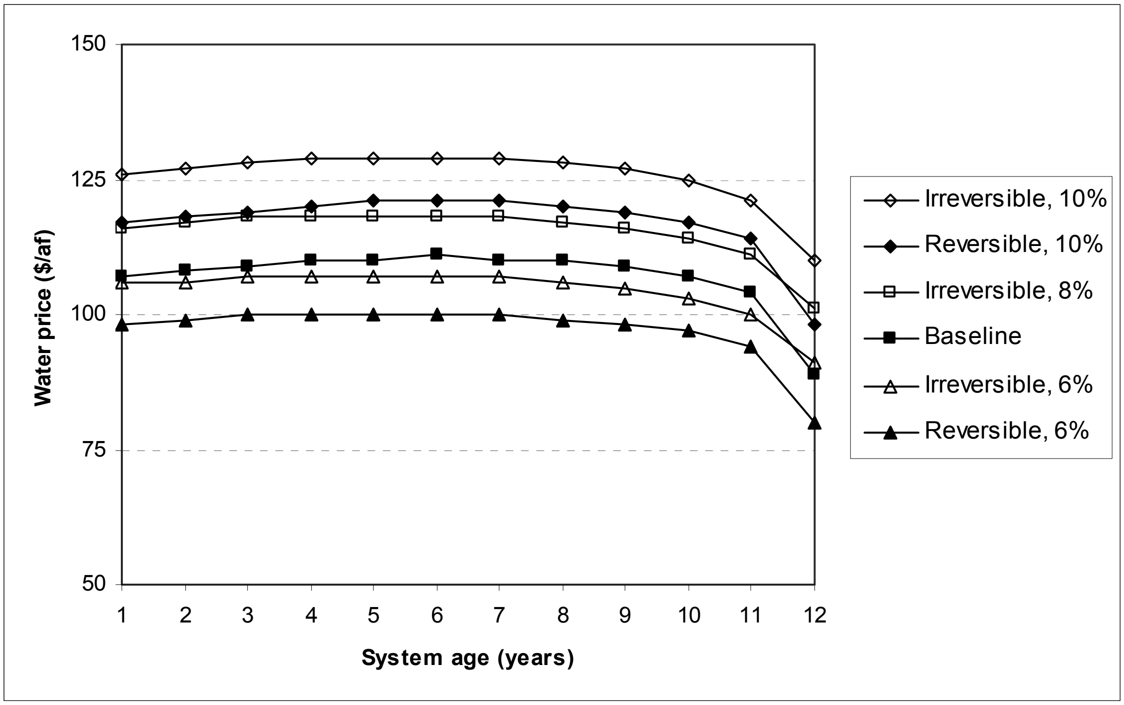

Figure 6: Comparison of Furrow-to-Drip Switching Prices for the Reversible and Irreversible Cases with Varying Drip System Lifetimes

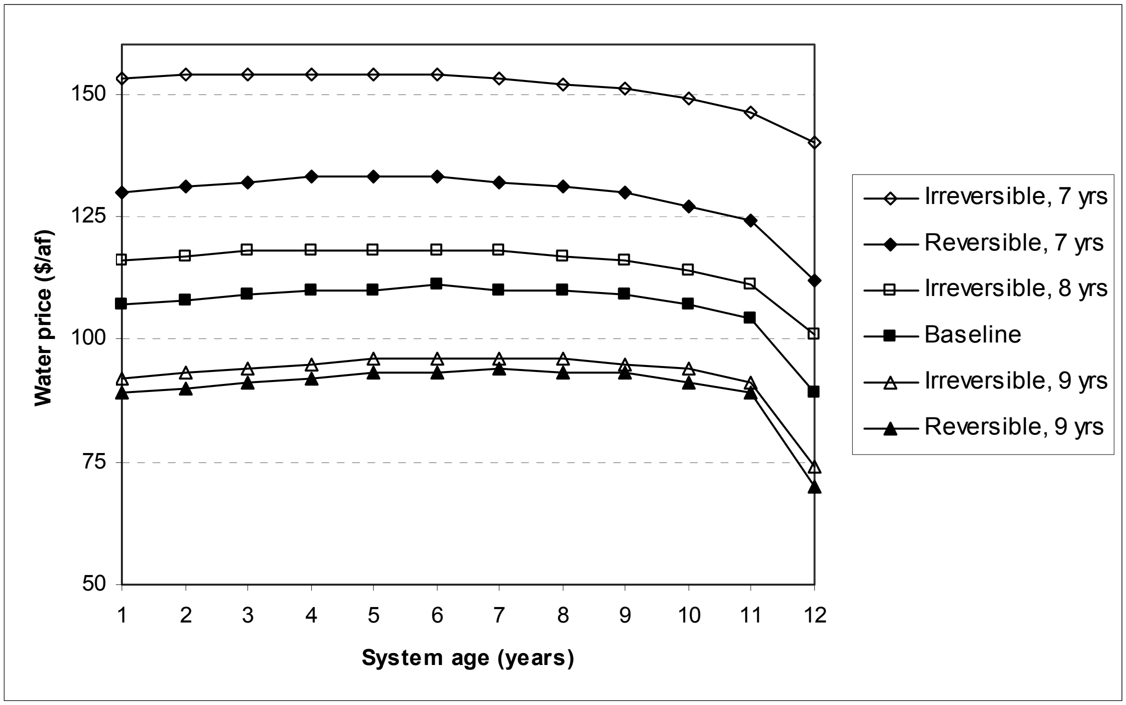

Figure 7: Comparison of Furrow-to-Drip Switching Prices for the Reversible and Irreversible Cases with Varying Long-Run Price Levels