Determinants of Irrigation Technology Choice

Donald H. Negri and Douglas H. Brooks

Two discrete choice models relate the probability of choosing two water-saving irrigation technologies—sprinkler and tailwater recovery pits—to the underlying physical and economic attributes of the farm using a national cross section of farm-level data. The results show that small farm size, high water or labor costs, and soils with low water-holding capacity increase the likelihood of adopting sprinkler irrigation. For gravity irrigators, large farms, high water costs, and soils with high water-holding capacity increase the probability of recirculating field runoff. In both models soil characteristics and, to a lesser extent, climate dominate the selection probabilities.

Key words: irrigation, sprinkler irrigation, water conservation, water demand.

In recent years dwindling opportunities to develop new surface water supplies, spiraling government budget deficits, and increasing concern for environmental and in-stream values of water have stifled water supply development. The Bureau of Reclamation, which in 1987 revised its mission from water development to water management, provides dramatic evidence that the era of large-scale water development has ended (U.S. Department of the Interior). Concurrently, groundwater users in many parts of the nation are facing declining groundwater tables, reduced well yields, and higher energy costs. Expanding irrigation in the southern High Plains has resulted in water table declines of 40 feet or more in the past decade while energy costs have increased over 200% (Sloggett and Dickason; Sloggett; Mapp). With little or no surface supply development and declining groundwater tables, increasing competition for the nation's water resources must be resolved through more efficient allocation and conservation. Water-saving irrigation technology is playing an increasingly important role in reducing both energy costs and water use.

Improved irrigation technology, in which the plant uses a greater fraction of applied water, has the potential to conserve water with little or no loss in yields. Sprinkler irrigation, for example, saves from 10–35% of the applied water through increased application efficiency, compared with more traditional gravity systems (Caswell and Zilberman 1985; Sloggett; Benami). We investigate econometrically the extent to which water costs, labor costs, topography, soil characteristics, and climate influence the choice of irrigation technology. Quantitative estimates of determinants of irrigation technology choice are essential for evaluating policies aimed at increasing water-use efficiency and predicting the effects of rising water costs on irrigated agriculture.

Caswell and Zilberman (1986) present a theoretical framework for analyzing irrigation technology adoption. This framework incorporates agronomic relationships between crop yield and water availability into an economic model of technology adoption. The authors

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argue that technology is used to augment the water-holding capacity of the soil—hence, irrigation technology is "land quality augmenting."

Previous empirical studies of irrigation technology adoption generally have been normative and based on engineering studies using experimental data (e.g., Benson, Everson, and Sharp), while positive econometric estimates are rare. Three recent studies have estimated the substitutability of water-saving capital for water, based on observed behavior with actual data. Caswell and Zilberman (1985), using regional data on California fruit growers, estimate adoption probabilities of sprinkler, gravity, and drip irrigation technologies. Nieswiadomy, in a study of cotton and sorghum irrigators in the Texas High Plains, estimates the elasticity of substitution between water and three irrigation technologies—center pivot, gravity, and wheel roll. Lichtenberg examines the adoption of center-pivot irrigation in Nebraska. These empirical studies support the theoretical arguments advanced by Caswell and Zilberman (1986) and substantiate a priori economic and engineering predictions that farmers adopt more efficient irrigation technology in response to higher water costs. However, these studies are limited by geographic coverage, the number of crops considered, adequate measures of land quality, and the level of data aggregation.

We employ a discrete choice model to estimate determinants of irrigation technology choice using a national cross section of farm-level data on technology choice and associated county-level data on land quality including soil texture, topography, and climate. Cross-sectional variations in water cost, labor cost, climate, topography, and soil characteristics explain which irrigation technology may be more profitably employed.

This study constitutes a comprehensive investigation of irrigation technology choice in terms of geographic coverage and physical characteristics of the farm. The results are consistent with the theoretical predictions of Caswell and Zilberman (1986), confirming the importance of land quality in determining technology choice. While water cost is a statistically significant determinant of technology choice, other determinants, including the water-holding capacity of the soil and, to a lesser extent, climate, dominate the selection probabilities.

We consider two broad categories of irrigation technology, sprinkler and gravity irrigation. Sprinkler irrigation technologies save water relative to gravity-flow systems by distributing water evenly on the field, reducing percolation below the root zone, and eliminating field runoff. However, the application efficiency of an irrigation system depends not only on the attributes of the system but also on the physical characteristics of the field such as soil texture, topography, and climate. For example, traditional gravity systems applied to land with high water-holding capacity due to high clay content and level slopes can achieve application efficiencies comparable to sprinkler irrigation. Conversely, lands with porous soils or steep slopes are unsuitable for gravity irrigation because of excessive deep percolation or runoff. Sprinkler irrigation also tends to save labor relative to gravity (Benson, Everson, and Sharp) and can be used to protect crops from light frosts.

For those irrigators who choose gravity systems we also estimate the probability of adopting tailwater recovery pits. Tailwater recovery pits capture field runoff in low lying pits and recirculate it to the top of the field for reuse. These systems can deliver water savings of 10–30% also depending on the physical properties of the field. With the exception of tailwater pits, no effort is made to differentiate various types of gravity and sprinkler technologies or to examine the use of drip systems. Although the use of drip systems is on the rise, total drip irrigated acreage is small and mostly devoted to specialty crops.

This investigation focuses on groundwater users and eliminates from the analysis those farmers who irrigate using only surface water.[1]

[1] Two common attributes of surface water allocation suggest that the price farmers pay for water is irrelevant to water use and production decisions at the margin. First, with few exceptions, water rights institutions, in which farmers receive water based on historical water rights or long-term contracts, rather than water markets govern surface water allocation. Second, legal doctrine and institutional restrictions generally stifle market activity in water rights. This institutional setting implies that farmers cannot purchase all the surface water they demand at prevailing prices because the water they receive is fixed and institutionally determined. Thus, surface water deliveries constitute a fixed input to the surface water user, not a variable input. As such, production decisions are based on the unobserved shadow price of water, not its purchase price. Moreover, changes in the water price for users who are not on their demand curves will affect the distribution of rents but not necessarily the allocation of resources. On Bureau of Reclamation lands, for example, Kanazawa presents empirical evidence that quantity ceilings are binding and that the implicit shadow value of water exceeds the Bureau's price.

The sample includes conjunctive users of both ground and surface water by assuming the marginal unit of water comes from the groundwater source. For groundwater irrigators we assume the marginal cost of water is the energy cost of pumping the water from the water table, plus negligible wear on the equipment.[2]

While the results are technically limited to groundwater users, they suggest the magnitude of the responses of irrigators who face market prices for water. Given the emergence of water marketing and market incentives in water allocation, these estimates will prove valuable in predicting the impact of market pricing on technology choice.

Theoretical Framework

Consider an intermediate-run multicrop model of agricultural production in which total land on the farm is fixed, but lands allocated to individual crops, irrigation technology, and other variable inputs are endogenous. Assuming profit-maximizing behavior, competitive input and output markets, and a well-defined production technology, the indirect profit function is well-defined when there is a fixed input such as land (Diewert; McFadden 1978; Lau). When land is a fixed allocatable input and variable inputs are continuous, the indirect, restricted profit function for a multiproduct farm can be written as a function of output and variable input prices and fixed input quantities (Chambers and Just),

(1)

$$\Pi(P, W, \omega, \bar{L}, \Psi) = \underset{X,\,Y,\,T}{\text{Max}}\ \{P'Y - W'X - \omega T : Y \in Y(X, \Psi, \bar{L}, T)\},$$

where P is a vector of output prices; Y is a vector of outputs; X is a vector of variable inputs including water quantity; W is a vector of variable input prices; ω is the cost of irrigation technology; T is an irrigation technology scalar; $\bar{L}$ is a scalar representing fixed land; Ψ is a vector of exogenous physical properties of land; and $Y(X, \Psi, \bar{L}, T)$ is the restricted production possibilities set, given fixed land quantity ($\bar{L}$) and land quality (Ψ). The variables X, T, and $\bar{L}$ are farm quantities which can be allocated to individual crops.

The irrigation technology input, however, is discrete and mutually exclusive, at least on small plots of land. Farm operators can choose from a discrete set of irrigation technologies, and typically only one technology can be applied to a field.[3] We can represent discrete choices by writing separate, technology-specific profit functions and assuming that all other inputs and outputs are optimized conditional on the technology choice. Let T_G and T_S denote discrete gravity and sprinkler irrigation technologies, respectively. The technology-specific restricted profit functions under sprinkler and gravity technologies are

(2)

$$\Pi_j(P, W, \bar{L}, \Psi) = \underset{X,\,Y}{\text{Max}}\ \{P'Y - W'X - \omega T_j : Y \in Y(X, \Psi, \bar{L}, T_j)\} \qquad j = S, G,$$

where total land ($\bar{L}$), irrigation technology (T_j, $j = S, G$), and land quality (Ψ) are fixed inputs.

The profit-maximizing farm operator compares the maximum quasi-rent available under each technology and chooses the technology yielding the greatest profit. The operator chooses sprinkler over gravity, for example, if $\Pi_S(P, W, \bar{L}, \Psi) > \Pi_G(P, W, \bar{L}, \Psi)$.

Let ϵ_G and ϵ_S be random errors representing unobserved factors influencing the profitability of gravity and sprinkler irrigation, respectively, and assume these errors are additive. Introducing a random error into the profit maximization makes the profit function stochastic and the technology choice probabilistic. With a stochastic profit function, operators choose sprinkler over gravity when

(3)

$$\Pi_S(P, W, \bar{L}, \Psi) + \epsilon_S > \Pi_G(P, W, \bar{L}, \Psi) + \epsilon_G.$$

Then the probability of selecting sprinkler technology is

[2] Three circumstances may undermine the maintained hypothesis that groundwater pumping costs accurately reflect the marginal cost of water: (*a*) Several states have groundwater pumping laws that may impose binding constraints on pumped water. (*b*) Saturated thickness and water transmissivity of an aquifer are important determinants of well yield. Relatively shallow saturated thickness can substantially reduce well yields for a given pumping lift. Well yield constraints may dictate irrigation technology. (*c*) Water conservation in the current period reduces future pumping costs since pumping cost is positively related to well depth. The present model abstracts from any dynamic considerations and assumes that current water conservation has no value in reducing future pumping cost.

[3] It may be possible to achieve a level of irrigation efficiency by mixing discrete irrigation technologies on multiple fields.

$$(4) \quad P_S = \text{Prob}[\Pi_S(P, W, \bar{L}, \Psi) - \Pi_G(P, W, \bar{L}, \Psi) > \epsilon_G - \epsilon_S].$$

Estimating the probability of adopting sprinkler technology requires choosing functional forms for the profit functions and a distribution for ϵ_G and ϵ_S. For the purposes of estimation, assume that the profit functions can be approximated by first-order Taylor-series expansions,

$$(5) \quad \Pi_j(P, W, \bar{L}, \Psi) + \epsilon_j = \beta_j' Z + \epsilon_j = \beta_{j0}' + \beta_{j1}' P + \beta_{j2}' W + \beta_{j3}' \bar{L} + \beta_{j4}' \Psi + \epsilon_j \qquad j = G, S.$$

Then the probability of selecting sprinkler technology is

$$(6) \quad P_S = \text{Prob}[(\beta_S - \beta_G)' Z > \epsilon_G - \epsilon_S],$$

where $(\beta_S - \beta_G)$ is a vector of parameters to be estimated.

Let F be the cumulative distribution function of the difference $\epsilon_G - \epsilon_S$, so that $P_S = F[(\beta_S - \beta_G)' Z]$. Weibull and normal are two common distributions employed in discrete choice models. If ϵ_G and ϵ_S are independent random variables distributed as Weibulls, then the cumulative distribution function, F, generates the binomial logit model (McFadden 1974).[4] For the ith operator the probability of choosing sprinkler is

$$(7) \quad P_{Si} = \frac{\exp(\beta_S' Z_i)}{\exp(\beta_G' Z_i) + \exp(\beta_S' Z_i)}.$$

The log of the odds of choosing sprinkler over gravity is then

$$(8) \quad \ln\left(\frac{P_{Si}}{P_{Gi}}\right) = (\beta_S - \beta_G)' Z_i.$$

The binomial logit model is useful for investigating the influences of farm attributes on technology choice. The logit model relates the probability of choosing sprinkler to the underlying characteristics of the farm.[5] The dependent variable is the logarithm of the odds in favor of one alternative over the other, and the parameters are interpreted as the partial derivatives of this logarithm with respect to the independent variables. The estimated coefficients then can be used, given a set of characteristics for a hypothetical farm, to predict the selection probabilities for each technology.

A binomial logit model also is applied to the dichotomous decision to adopt, or not to adopt, tailwater recovery pits. The model and estimation procedure is essentially the same as the sprinkler model and has been applied to a sample of gravity irrigators.[6]

Estimation

In this model irrigation technology and tailwater recovery pit choices depend on output and variable input prices, total land, and land quality characteristics.[7] Farm-level data for acres of sprinkler and gravity irrigation, well pump fuel type, water source, well depth, and the existence of tailwater recovery pits are from the *1984 Farm and Ranch Irrigation Survey* (*FRIS*) conducted by the U. S. Department of Commerce, Bureau of the Census. The *FRIS* is a national survey of irrigated farms providing detailed data relating to on-farm irrigation practices.[8] The farm-level survey data are combined with county-level data for soil and climate variables and state-level farm labor wages. Climate and soil variables serve as proxies for on-farm physical conditions. For cross-sectional analysis, the observed on-farm resource allocation and irrigation technology choice are assumed to be in equilibrium with respect to the independent variables.

The sample includes 5,145 farms that pump groundwater for irrigation. Fifty-four percent (2,783 observations) irrigate using gravity sys-

[4] If ϵ_G and ϵ_S are normally distributed, the probit model results. Since the two dichotomous choice models generally give similar results in practice, we apply the logit model. Maddala presents a comprehensive presentation of these and related models, including estimation techniques and comparability of results.

[5] Logit models can be used to estimate the effects of irrigation technology characteristics or farm characteristics or both. This analysis focuses on the effects of farm characteristics on choice probabilities.

[6] A polytomous choice model including three alternatives, sprinkler irrigation, gravity without tailwater reuse pits, and gravity with tailwater reuse pits, was estimated but failed to achieve convergence.

[7] Crop choice is omitted as an explanatory variable since the annual cropping pattern decision generally follows the longer-term irrigation technology choice. Hence, crop allocation would be endogenous in a structural model.

[8] The Bureau of the Census publishes aggregations of the survey data to the state level and describes in detail the sample design. The authors were granted access to individual observations under special arrangement with the Agricultural Division. Because the survey sample is stratified by state and farm size, the estimation procedure employs Census expansion weights so that the results reflect the national population of groundwater irrigators.

tems. Forty-five percent of the acreage in the sample is irrigated with sprinkler systems and 66% of the sprinkler acreage is covered by center-pivot systems. Twenty-one percent of gravity irrigators in the sample use tailwater pits.

Twenty-two percent of the sample use a mixture of sprinkler and gravity irrigation—presumably on different fields. Each field is considered a distinct technology choice. Because all fields on the farm have the same observed characteristics, they also have the same selection probabilities. Under the assumption that farm operators allocate sprinkler irrigation to that share of land where sprinkling yields greater expected profits, the observed share of sprinkler-irrigated land is an unbiased estimate of the true selection probability. The estimation uses all available information by employing the logit model using "grouped data" where the underlying framework is discrete but the dependent variable is the share of irrigated acreage using sprinkler irrigation.[9]

A grouped data approach, however, introduces heteroskedastic errors because farms have unequal numbers of fields. The variance around the on-farm selection probability may be smaller for large farms with multiple fields than for small farms with few fields. The estimation procedure corrects for heteroskedasticity by weighting the logit estimation by the total irrigated acres on the farm which is a proxy for the number of fields.

Variable input prices include water pumping cost and labor wages. The price of water is assumed to be the energy cost associated with pumping groundwater to the surface. The energy cost of water depends on the pumping lift, the fuel price and type, and the energy efficiency of the pumping unit. The cost includes only the lift cost and not any pressurization cost associated with the technology choice since pressurization is endogenous to the system choice.[10] Using a set of engineering formulae, pumping costs are calculated from well depth, fuel type observed at the farm level, and statewide energy prices.[11] The average cost per acre-foot of water for the sample is $15.80, including both gravity and sprinkler irrigators (table 1). Variation in fuel prices by state and on-farm variation in pumping lift and fuel type generate substantial variation in water costs across farms.

Insufficient cross-sectional variation in output prices precludes estimating output price parameters. However, no omitted variable bias results since omitted prices are presumably uncorrelated with the remaining independent variables.

Farm labor wages and energy prices by state for 1984 are from *Agricultural Prices, 1984 Summary* (USDA 1985).

Physical characteristics include three climatic variables, two soil texture dummies, two land capability classification dummies, and a topography variable. The physical variables reflect the average conditions in the county and proxy for farm characteristics. Climate variables are derived from a monthly summary of climatological observations from the National Oceanic and Atmospheric Administration cooperative weather stations. County climate is obtained by matching the counties represented on the *FRIS* with the nearest cooperative weather station. The topography and soil characteristics are derived from the National Resource Inventory (NRI) (USDA 1982). For each county in the U.S. the NRI sampled the physical characteristics of all nonfederal rural land at several randomly selected sites within the county. Nearly one million locations were sampled in the United States. Variables for soil texture, soil slope, and land capability classification within a county were quantified and averaged over only cropland observations.

Three climatic variables proxy evapotranspiration. Since expected weather conditions (i.e., climate) during the growing season determine technology choice, the weather variables are historical averages for the length of the growing season, rainfall, and the cumulative energy available for plant growth. Because

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[9] Defining the dependent variable to be the share of sprinkler-irrigated acreage permits efficient estimation by using all available information on technology choice. Restricting the sample to those observations that choose either sprinkler or gravity would eliminate valuable information on farms that mix irrigation technologies. Similarly, ad hoc procedures that use threshold values of the technology share to designate one technology or another would squander information.

[10] Caswell and Zilberman (1985) include the cost of pressurization in the water-cost variable. In their model water cost is an attribute of the irrigation system. This analysis focuses on how farm characteristics affect choice probabilities. Hence, we exclude pressurization cost from the water-cost variable.

[11] The general form of the pumping cost calculation is (Gollehon, p. 54) $PC = FP(1.3716(L + 2.31OP))/FE$, where PC is the pumping cost ($/acre-foot), FP is the fuel price ($/unit fuel), L is the total pumping lift (feet), OP is the system operating pressure in pounds per square inch (PSI), and FE is the "Nebraska Standard" water horsepower-hours per unit fuel. We assume a 5 PSI operating pressure since sprinkler pressurization is excluded.

actual weather may differ from climate, the technology choices are optimal, *ex ante.* The climatic variables are: (*a*) the average number of frost-free days during the year, (*b*) the total precipitation (in inches) for the growing season, May through September, and (*c*) the cumulative growing degree days for the growing season, May through September, using a base of 60 degrees Fahrenheit. Growing degree days are defined for each day as the mean daily temperature minus 60 degrees, if the mean exceeds 60, and zero otherwise.

County observations of soil texture on cropland are classified on a five-point scale where the numbers 1 through 5 indicate progressively clay-like textures (i.e., 1 = sand, 2 = sandy loam, 3 = loam, 4 = clay loam, 5 = clay).[12] The average for the county then is partitioned into three dummy variables representing sand (texture $\leq$ 2.3), loam (2.3 < texture < 3.6), and clay (texture $\geq$ 3.6) soils. Sand and clay dummies appear in the logit equations and measure the log of the technology choice odds relative to loam.

The land capability classification system used by the NRI groups soils based on their ability to produce commonly cultivated crops (USDA 1973). The land capability classes, identified numerically 1 through 8, indicate progressively greater limitations that restrict the use of the land for agriculture. Limitations include soils that are erosive, saline, shallow, stony, or wet. As with the soil texture variables, county observations of cropland capability are averaged and then classified into dummy variables. The average of county observations on land capability is a continuous variable on the interval 1 to 8. Dummies for "high productivity" soils (land classification less than 2.5) and "low productivity" soils (land classification greater than 3.5) enter the equations as proxies for soil quality.[13]

[12] The NRI classified soil textures into 21 separate categories. Based on a conversation with Swane Scott, an irrigation engineer with the Soil Conservation Service, USDA, these 21 categories were reduced to five categories that have approximately the same water-intake rates.

[13] There may be some overlap between the soil productivity dummies and the other soil and climate variables since the land capability classification system uses soil and climate characteristics to define soil limitations (USDA 1973). Overlap may introduce some collinearity among the physical characteristics. However, overlap with the climate is minimized because "Whenever the moisture limitation is removed [by irrigation], the soil is classified according to the effects of other permanent features and hazards that limit its use and permanence . . ." (USDA 1973, p. 15). In other words, when irrigation eliminates climate limitations, the classification system reverts to other limiting features.

The topographical slope variable is the average slope on cropland in the county measured as percent slope.

Four regional dummies, Southwest (CO, OK, TX, NM, AZ, CA, NV, UT), Northwest (WA, OR, ID, MT, WY), Northern Plains (ND, SD, NE, KS), and South (FL, GA, AL, SC, AR, LA, MS, TN, NC, VA, WV, KY, MD, DE) are included as independent variables to account for unobserved regional factors influencing technology choice. These may include soil and climate differences not captured by the soil and climate variables, education, transportation and processing infrastructure, and marketing. All regional dummies reflect the log of the odds relative to the Northeast, the omitted region. The means of the regional dummies show the geographic distribution of the observations (table 1).

Total irrigated acres from the survey measures total land availability and captures any farm scale effects. Finally, explanatory variables also include a dummy variable indicating the use of surface water since conjunctive users may behave differently than exclusive users of groundwater.

Results

Table 1 reports maximum likelihood estimates of the irrigation technology and tailwater recovery choice parameters. The log-likelihood ratio tests, distributed Chi-square, for testing the models against an alternative in which all parameters are zero also are reported in table 1. Of the 16 parameters estimated in the sprinkler choice model, 12 are statistically significant at the 10% level or better. In the tailwater model 11 of the 16 parameters are significant at the 10% level. For both models the test rejects the hypothesis that all parameters are zero at less than the 1% level of significance. Table 1 also reports the value for the likelihood ratio index (*LRI*) or McFadden's R^2, a statistic closely related to the likelihood ratio test and a measure for the "goodness of fit." The statistic is defined as $LRI = 1 - [L(\omega)/L(\Omega)]$, where $L(\Omega)$ is the value of the log-likelihood function when maximized with respect to the parameters, and $L(\omega)$ is the maximum value of the log-likelihood function under the constraint that all parameters are zero. The *LRI* is .22 for the sprinkler choice model and .14 for the recovery pit model.

The parameter estimates are consistent with theoretical predictions (Caswell and Zilberman 1986), other empirical studies of irrigation technology (Caswell and Zilberman 1985; Lichtenberg; Nieswiadomy), and agronomic guides to choosing irrigation technology (Finkel and Nir).

Sprinkler Technology Model Results

Coefficients for all variables except for two land capability, one climate, and one regional dummy are significantly different from zero at the 5% level (table 1). The price of water has the expected sign—the probability of adopting water-saving technology increases with the cost of water.

Sign predictions based on water-holding capacity of the soil are borne out by the estimated coefficients. The coefficients on sand, clay, and soil slope confirm the expected effect of topography and soil texture—farms consisting of soils with low water-holding capacity are more likely to adopt sprinkler irrigation. Similarly, the coefficient on low productivity soils is positive, although only marginally significant. Together these coefficients support the hypothesis that sprinklers are land quality augmenting.

The water source or delivery system often favors a method of water distribution to the field. The results show that farms with access to surface water sources are more likely to choose a gravity system. This result is not surprising since "... surface water is supplied by water districts that, in most cases, have geared their water distribution system to the traditional technology" (Caswell and Zilberman 1985, p. 229).

The coefficient on labor can be explained by the comparative labor intensity of the two irrigation systems. Gravity irrigation systems tend to be more labor intensive than sprinkler (Benson, Everson, and Sharp). The positive coefficient indicates a shift to labor-saving sprinkler irrigation in the presence of scarce labor.[14]

The coefficient on total irrigated acres suggests a negative farm scale effect on sprinkler adoption—farms with larger irrigated acreage tend to use gravity irrigation systems. Finkel and Nir offer one explanation for the result: "Large fields are equally suitable for all types of irrigation, but smaller fields are more suitable to pressure irrigation if the dimensions are less than the efficient length of run for the specific soil type . . ." (p. 38). On small farms with gravity distribution systems, the water loss through the conveyance ditches can constitute a large share of total water losses which makes small farms more likely candidates for sprinkler systems.

Climate plays an important role in technology choice. The probability of adopting sprinkler relative to gravity technology varies positively with total rainfall and inversely with growing degree days and growing season length. In regions with more rainfall, irrigation is primarily supplemental. Since crop damage may result from unexpected rainfall following a heavy irrigation, "... supplementary irrigation generally favors sprinkler methods with portable equipment by which light, frequent application can be made as needed . . ." (Finkel and Nir, p. 39). Consequently, operators in regions with higher rainfall are more likely to adopt sprinkler systems because sprinkling permits greater control over the quantity applied.

In hot and windy regions a larger fraction of water applied through sprinkler systems evaporates. In extreme conditions the losses can approach 15%, making sprinklers an inappropriate technology (Finkel and Nir). The coefficient on growing degree days substantiates the influence of higher temperatures on evaporation and technology choice.

Longer growing seasons increase the probability of adopting gravity irrigation. Short growing seasons correspond to colder climates where sprinklers can be used for frost protection.

Finally, the coefficients on the regional dummies indicate that unobserved factors correlated with region are affecting choice probabilities. The negative coefficients indicate that the omitted Northeast region has unobserved characteristics more conducive to sprinkler irrigation compared to the four included regions.

Tables 2 and 3 are useful for evaluating the relative contribution of the explanatory variables to the selection probabilities. Table 2 shows the change in the predicted probabilities

[14] There is substantial variation in the labor requirement of the sprinkler systems included under the broad heading of sprinkler irrigation. Sprinkling with pipes that must be moved manually usually requires more labor hours than traditional gravity systems. On the other hand, center pivot and other more permanent sprinkler systems can substantially reduce the labor cost of irrigation. Hand-move irrigation systems account for only 12% of the sprinkler irrigated acreage in the sample.

Table 1. Maximum Likelihood Estimates of Irrigation Technology and Tailwater Pit Discrete Choice Parameters

Variable	Sprinkler Irrigation Mean (SD)	Sprinkler Irrigation Coefficient (*t*-statistic)[a]	Tailwater Pit Mean (SD)	Tailwater Pit Coefficient (*t*-statistic)[a]
Price of Water ($/acre-foot)	15.6 (10.3)	.011 (3.59)	16.4 (10.4)	.0289 (6.70)
Price of Labor ($/hour)	4.4 (0.51)	.232 (2.37)	4.39 (0.49)	.259 (1.45)
Irrigated Acres (100 acres)	2.9 (7.27)	−.0013 (−2.57)	3.60 (8.70)	.002 (3.86)
Surface Water (0–1)[b]	0.20 (0.40)	−0.68 (−7.98)	0.29 (0.45)	.435 (3.96)
Climate Variables				
Frost-free days (number/year)	267 (61)	−.0026 (−1.63)	268 (59.6)	−.009 (−3.60)
Total rainfall (inches May–Sept.)	13.7 (9.7)	.030 (3.84)	12.9 (9.0)	−.037 (−3.51)
Growing deg. days (100 Gdd May–Sept.)	18.9 (7.2)	−.041 (−3.51)	20.3 (6.2)	.011 (0.66)
Soil Variables				
Soil slope (percent slope)	2.2 (2.3)	0.34 (12.06)	1.60 (1.59)	−.070 (−1.65)
High Productivity	.34 (0.48)	.046 (0.57)	0.43 (0.49)	.377 (3.54)
Low Productivity	0.17 (0.37)	.156 (1.35)	0.09 (0.29)	−.834 (−3.72)
Sand	0.17 (0.38)	1.67 (16.2)	0.07 (0.26)	−.308 (−1.79)
Clay	0.10 (0.30)	−.389 (−3.45)	0.12 (0.32)	.438 (3.50)
Region				
Northwest	0.10 (0.30)	−0.03 (−0.14)	0.05 (0.22)	−1.89 (−3.86)
Southwest	0.44 (0.50)	−1.19 (−5.08)	0.51 (0.50)	−.046 (−0.09)
South	0.14 (0.35)	−1.55 (−6.92)	0.13 (0.34)	−0.69 (−1.39)
Northern Plains	0.25 (0.43)	−1.22 (−5.65)	0.29 (0.45)	.704 (1.38)
No. of Observations	5,145		2,783	
Log Likelihood	−2,769		−1,555	
Log Likelihood (slope = 0)	−3,542		−1,815	
Chi-Sq (15 d.f.)	1,546		520	
Likelihood Ratio Index	.22		.14	

[a] Asymptotic *t*-statistics.
[b] Dummy variable. Use of surface water = 1.

for a change in each continuous independent variable from one standard deviation below its mean to one standard deviation above its mean, holding all other variables at their mean values. Table 3 shows the effect of soil texture (sand versus clay) and water source (groundwater only versus conjunctive use) on the probability of observing sprinkler technology, again holding all other variables at their mean values.

Soil slope has the greatest impact on adopting sprinkling, accounting for a .37 increase in the predicted probability (table 2). Changes in predicted probability for the three climate variables are considerably smaller ranging from .08 to .146 in absolute value. While water cost,

Table 2. Influence of Explanatory Variables on Choice Probabilities[a]

Variable	Change in Predicted Probability: Sprinkler	Tailwater Pit
Price of Water	.058**	.122**
Price of Labor	.059**	.052*
Irrigated Acres	−.005**	.007**
Frost-Free Days	−.080*	−.213**
Expected Rainfall	.146**	−.138**
Growing Degree Days	−.146**	.027
Soil Slope	.370**	−.046*

[a] All changes in predicted probability are based on a change in the independent variable from one standard deviation below its mean to one standard deviation above its mean. The predicted probability at the means of the independent variables is .50 for sprinkler and .29 for tailwater pits.
Note: Double asterisk indicates the logit coefficient is statistically significant at the 5% level; single asterisk indicates the logit coefficient is statistically significant at the 10% level.

labor cost, and irrigated acreage are statistically significant determinants of technology choice, their impact on the choice probabilities appears to be relatively small. A change in the price of water from $5.30 to $25.90 per acre-foot (one standard deviation below the mean to one above) produces only a .058 increase in the predicted probability.

The importance of soil texture in determining the technology choice is illustrated in table 3. For exclusive users of groundwater sandy soil increases the probability of adopting sprinkling by .45 over clay, from .37 for clay to .82 for sandy soil. Soil texture has an equally large impact (.47) on conjunctive users of ground and surface water. Table 3 also shows that access to surface water decreases the probability of sprinkler use by .12 in the presence of sandy soils and by .14 in the presence of clay soils.

Both tables 2 and 3 underscore the dominance of land quality variables, particularly soil texture, soil slope, and, to a lesser extent, climate. Compared to the on-farm physical characteristics, the impact of water cost on the

Table 3. Predicted Probabilities of Sprinkler Adoption by Soil Texture and Water Source

	Ground Only	Ground and Surface
Sand	.82	.70
Clay	.37	.23

Table 4. Predicted Probabilities of Tailwater Recovery Pit Adoption by Soil Texture and Soil Productivity

	High Productivity	Low Productivity
Sand	.28	.10
Clay	.45	.19

choice probability, while statistically significant, is relatively small.

Tailwater Recovery Model

The parameters of the tailwater recovery model are estimated using a sample of gravity irrigators. The conclusions from the model are similar to those obtained for sprinkler in that land quality characteristics have the greatest impact on the selection probabilities. Table 1 presents the parameter estimates and tables 2 and 4 illustrate the relative contributions of the explanatory variables to the selection probabilities.

In the tailwater recovery choice model soil texture, growing season length, and soil productivity have strong impacts on the decision to recirculate tailwater. In contrast to sprinkler irrigation, tailwater recovery pits are an effective water-saving practice only on soils with high water-holding capacity since high water intake rates associated with sandy soils limit or preclude water runoff. The sizable change in predicted probability (table 4) associated with the soil texture dummy variables again emphasizes the importance of soil texture in the choice of conservation technology.

Soil salinity may be the driving force behind the significance of the coefficients on soil productivity. Salinity is one of the soil characteristics in the land capability classification system limiting sustained agricultural production.[15] Where soils have high salt content, recirculating runoff water increases salt concentration. Both soil productivity dummy variables are significant and opposite in sign with high productivity favoring the adoption of tailwater pits. Table 4 shows a change from

[15] Because low soil quality may be due to a variety of limiting soil characteristics (including salinity, inadequate drainage, and erosion), it is impossible with these data to identify the exact source of the result.

low to high productivity soils increases the predicted probability of adopting recovery pits by .18 for sandy soils and by .26 for clay soils.

Compared to the sprinkler model, water cost is more effective in inducing gravity irrigators to adopt water-saving recirculation practices. A change in water cost from $6 to $26.80 per acre-foot (one standard deviation below the mean to one above) increases the probability of adopting a recovery pit by .12. The result may be explained, in part, by the disparate installation costs of the two irrigation practices. For gravity irrigation recovery pits represent a relatively inexpensive water-saving adaption to high water costs.

The probability of adopting recovery pits increases with the number of irrigated acres on the farm. Two explanations for this appear likely. First, larger farms can drain multiple fields into a single recovery pit, thus reducing the unit cost of recirculating water. Second, there may be a threshold number of irrigated acres below which recovery pits are unwarranted. Although the coefficient is statistically significant, table 2 shows that the influence of irrigated acreage on the selection probabilities is small.

Gravity irrigation systems are limited to fields with little or no slope because of the erosion potential of slopes greater than a few percent. Thus, the average slope for the subsample of gravity irrigators is only 1.6% while the average slope for the entire sample is 2.2% (table 1). Reuse pits can be used on steep slopes but pumping costs increase with the slope. The negative coefficient on slope, indicating that recovery pits tend to be used on flat terrain, may be explained by the pumping costs associated with steep slopes.

We have no prior expectations for the sign of labor costs since the incremental labor cost of operating a recovery pit is negligible. Table 2 shows that the impact of labor costs on tailwater selection probabilities is positive but relatively small.

The effect of growing degree days is not statistically different from zero suggesting that evaporation from recovery pits in hot climates is not sufficient to influence the adoption decision.

Finally, the probability of selecting a recovery pit varies inversely with both the total rainfall and the length of the growing season. More rainfall reduces the effectiveness and the necessity of tailwater pits as the quantity of irrigation water applied falls and conservation is less essential. There is no strong a priori reason to expect a negative coefficient on season length. The result might be partly explained by the high correlation between long growing seasons and regions subject to soil salinity problems.

Conclusions

Applying a discrete choice model to water-saving irrigation technology decisions reveals the importance of physical characteristics in determining technology choice. Physical characteristics, including soil slope, texture, and quality, and, to a lesser extent, climate, dominate the selection probabilities.

The decision to adopt water-saving irrigation technology also responds to the cost of pumping groundwater. High water costs increase the likelihood of adopting more efficient irrigation technologies. However, there is a marked difference between the responsiveness of the two water-saving practices—tailwater recovery pits are moderately sensitive to water costs while the impact of water cost on sprinkler choice appears to be small. The results suggest that water-pricing policies aimed at influencing the farmer's decision to adopt sprinkler systems may be ineffective if taken alone without regard to other determinants of technology choice.

Irrigated agriculture surely faces a future of higher water costs. This analysis examines only two water conservation alternatives. Other alternatives include altering cropping patterns (with the potential for switching to dryland farming), adopting more efficient water management practices (such as laser leveling or irrigation scheduling), or adopting advanced irrigation technologies (such as surge-flow; cablegation; or low-energy, precision application). Acceptance of these alternatives is already growing (Sweeten and Jordan). Future irrigation technology research should incorporate a broader range of technologies and water management practices.

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