The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
http://ageconsearch.umn.edu
aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

Estimating the Spatial Distribution of Groundwater Demand In the Texas High Plains

Shiliang Zhao
Chenggang Wang
Department of Agricultural and Applied Economics
Texas Tech University

James P. Bordovsky
Zhuping Sheng
Jesus R. Gastelum
Texas AgriLife Research and Extension
Texas A&M University

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2011 AAEA & NAREA Joint Annual Meeting, Pittsburgh, Pennsylvania, July 24-26, 2011

Copyright 2011 by Shiliang zhao, Chenggang Wang, James P. Bordovsky, Zhuping Sheng and Jesus R. Gastelum. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

Estimating the Spatial Distribution of Groundwater Demand In the Texas High Plains

Shiliang Zhao, Chenggang Wang, James P. Bordovsky, Zhuping Sheng, Jesus R. Gastelum

Abstract

Developing groundwater management plans requires a good understanding of the interdependence of groundwater hydrology and producer water use behavior. While state-of-the-art groundwater models require water demand data at highly disaggregated levels, the lack of producer water use data has held up the progress to meet that need. This paper proposes an econometric framework that links county-level crop acreage data to well-level hydrologic data to produce heterogeneous patterns of crop choice and irrigation practices within a county. Together with agronomic data on irrigation water requirements of various crops and irrigation practices, this model permits estimation of the water demand distribution within a county. We apply this model to a panel of 16 counties in the Southern Texas High Plains from 1972 to 2000. The results obtained not only are consistent with those from the traditional multinomial logit land use model, but also indicate the presence of large intra- and inter-county heterogeneity in producer water use behavior.

Keywords: Discrete Choice Model, Random-coefficients Discrete Choice Model, Crop Choice, BLP, Groundwater, Texas High Plains, Ogallala Aquifer

Introduction

The Ogallala Aquifer is the largest freshwater aquifer system in the world. The massive underground water in the Ogallala Aquifer is the lifeblood for irrigated agriculture in the Texas High Plains, where agriculture accounts for more than 90% of annual groundwater withdrawals (Jensen 2004; Stewart 2003). The region's groundwater table has declined rapidly since intensive irrigation became widespread in the 1930s. It is widely accepted that this nonrenewable aquifer resource will be exhausted in near future. The Texas state legislature in 2005 passed a bill of water conservation planning which requires Groundwater Management Areas to define desired future conditions for their respective groundwater resources. Accordingly, the High Plains Water District has established a management goal of 50/50, meaning that the district will have 50 percent of the current volume of groundwater available for use in 50 years.

After center pivot irrigation technology was introduced into this region, the low pumping cost has made Ogallala Aquifer became available for large-scale agriculture. Irrigated farmland increased substantially from 1950 to 1978, especially from 1964 to 1978 when farmers adjusted to more water-intensive crops. Irrigation and water-intensive crop acreage have remained at these higher levels (Hornbeck and Keskin 2011). Current irrigation methods within the region include conventional furrow irrigation, center pivot irrigation, Low Energy Precision Application (LEPA) and subsurface drip irrigation (SDI). In order to sustain the Ogallala Aquifer, policy makers have tried to reduce the acreage of high water use crops and rates of extraction through incentive-based measures that encourage conversion to more efficient irrigation technology.

The adoption of more efficient irrigation technology does not necessarily reduce groundwater withdrawal. Pfeiffer and Lin (2010) evaluate the effect on groundwater extraction of a widespread conversion from traditional center pivot irrigation systems to higher efficiency dropped-nozzle center pivot systems. They find that the shift to more efficient irrigation technology has not decreased the amount of water applied to a given crop, and has actually increased groundwater extraction through changing cropping patterns. Warda and Pulido-Velazquez (2008) also suggest that more efficient irrigation technology can actually lead to increased water use, because farmers may adjust their crop mix toward more water intensive crops, expand their irrigated acreage and apply more water to the crops they plant.

Because groundwater is mainly used for irrigated agriculture, water conservation must come from the reduction of water use in agriculture, through changing crop mix or improving irrigation efficiency . Understanding the farmer's choice over crops and irrigation technologies is essential to anticipating future conditions of the groundwater resources and developing effective groundwater conservation policies. The existing tool for predict the future conditions of underground water in the Texas High Plains is a groundwater simulation model for the Ogallala Aquifer, Groundwater Availability Model (GAM), developed by Texas Water Development Board. The model requires as inputs estimates of site-specific groundwater demands. Accurate estimates of irrigation water demands are essential for assessing management plans aimed to achieve the 50/50 goal. Currently, county-level water demands in GAM are estimated using an aggregation procedure that multiplies crop acreage by crop water requirement, then adds up the resulting water demands across all planted crops. When applied to the high-resolution GAM model, the county level aggregate water demand can lead to substantial information loss. Another drawback of the current GAM model is that it cannot predict future irrigation water demands.

The purpose of this paper is to overcome the limitation of the current GAM model. We develop a model by which future irrigation water demands can be predicated for the Texas High Plains, and which can be incorporated into the existing GAM model to assess the management plans proposed to achieve the 50/50 goal. Because GAM divides the whole region into a large number of cells that are much smaller than an individual county's area, we strive to estimate the spatial distributions of water demands within each county, rather than the aggregate water demand at the county level. This effort is expected to improve significantly the predicting power of GAM because intra-county water demand variability is likely large in the study area as indicated by the observed heterogeneity in such hydrological variables as water table and saturated thickness.

Econometric Framework

The multinomial logit model has been widely adopted in analysis of crop choices and irrigation technology adoption (Negri and Brooks 1990; Green et al. 1986). Most of the multinomial logit land use models use county-level data, which cannot produce site-specific estimate of water demand within a county. We use a random-coefficients discrete choice model to link the county-level data to hydrological data at the pumping well level. The dependent variables are acreage shares for crop-irrigation technology combinations and the independent variables are the prices of crop, the seed cost for crop and irrigation installation costs. Hydrological data are introduced into the model by affecting the coefficients on the price and cost variables.

We estimate our model using the BLP technique (Berry, Levinsohn, and Pakes 1995), Berry and his coauthors developed this technique to aggregate a distribution of consumer preferences over products into a market-level demand system in order to produce more efficient estimates of price elasticities of demands. We employ this technique to aggregate well-level hydrological data into our county-level land use model, so as to produce within-county distributions of price elasticities of land shares. Nevo (2000) deveoped a computer program in Matlab to execute the BLP technique, which we adopt in our analysis.

Suppose we observe the production data of $i = 1,...,I_t$ producers in $t = 1,...,T$ county-year combinations. In each county-year, farmers choose a crop to grow and an irrigation technology among j crop-irrigation technology choices. The conditional indirect utility of farmer i choosing crop-irrigation system combination j at county-year t is

$$\begin{aligned} u_{ijt} &= x_j \beta_i^* + \xi_j + \varepsilon_{ijt} \\ i &= 1,\ldots,I_t; \quad j = 1,\ldots,J; \quad t = 1,\ldots,T, \end{aligned} \tag{1}$$

where x_j is a K-dimensional row vector of observable crop and irrigation system characteristics, including crop price, seed price and installation cost of the irrigation system. ξ_j is the unobserved (by the econometrician) crop-irrigation system characteristics including the productivity of a given crop-irrigation system, ε_{ijt} is a mean-zero stochastic term, β_i^* are $K+1$ individual-specific coefficients depending on hydrological conditions individual farmers face. Let the average value of parameter β_i across farmers as β, and assume the following specification for β_i:

$$(2) \qquad \beta_i^* \;=\; \beta + \Pi G_i + \Sigma \upsilon_i, \qquad \upsilon_i \sim N(0, I_K)$$

where K is the dimension of the observed characteristics vector, G_i is a two by one vector of groundwater variables including pumping lift and well yield, Π is a $(K+1)\times 2$ matrix of coefficients. υ_i is a $K\times 1$ vector of unobservable farmer characteristics and is assumed to have a standard normal distribution, and Σ is a scaling matrix on υ_i. The coefficients on crop-irrigation system characteristics, β_i, therefore, consists of a constant term β and a random term ΠG_i whose distribution depends on coefficient Π and the spatial distribution of pumping lift and well yield.

Data

As show in the map in figure (1), the study region includes 16 counties in the Southern Texas High Plains: Bailey, Castro, Cochran, Crosby, Dawson, Floyd, Gaines, Hale, Hockley, Lamb, Lubbock, Lynn, Parmer, Swisher, Terry, and Yoakum. The study region covers most of the Southern Texas High Plains. Our dataset is a panel covering these 16 counties from 1972 to 2000. Each county's land is assumed to be allocated to corn, cotton, sorghum, wheat and "other" crops, including peanut, hay, oats, soybean, etc. The crop acreage data are taken from the farm survey conducted annually by USDA's National Agricultural Statistical Service (NASS). For each crop, the planted acreage is divided further into dry land and irrigated by furrow, sprinkler, center pivot, LEPA and SDI. The classification system results in 24 land use types.

The independent variables include crop price, seed price, installation cost of the irrigation system, a given locations' pumping lift and well yield. The irrigation equipment installation cost was estimated by interviewing local irrigation system dealers and expressed as the annual cost per acre of irrigated land. We obtained crop price data from USDA's Agricultural Statistics Board. The seed price data are taken from crop budgets compiled by Texas AgriLife Extension Service. Price and cost data are all adjusted by CPI. The pumping lift and well yield data are generated from the GAM model. GAM divides each county into hundreds of cells, for which the pumping lift and well yield data are generated. We then aggregated the data into 49 observations as representative of the empirical joint distribution of pumping lift and well yield. Table (1) presents of the summary statistics of the variables above. Cotton is the main crop in this region with an average share of more than 30%, followed by sorghum and wheat with each having a 10% acreage share. The installation cost varies widely across different irrigation systems: furrow only costs about \$1.7 per acre per year, while SDI costs over \$100 per acre per year; the cost for center pivot and LEPA are less than the cost of SDI but significantly higher than that of sprinkler and furrow. The average pumping lift in this area is 150 feet but it varies across counties and over time. In some places the pumping lift is zero (indicating a location with surface water), while in other places the pumping lift is near 800 feet. The well yield is not distributed evenly across the whole region as well, ranging from zero to 4 ac-ft per hour.

Results and Discussion

Table (2) presents the results from a logit regression, where the independent variables are crop price, seed price, installation cost, lagged shares, the county average values of pumping lift and well yield, and 24 crop-irrigation system dummies. All parameters but those on seed price and installation cost are statistically significant.

Table (3) presents a sample of estimated own- and cross-price elasticities of crop acreage shares from the logit model. Each entry i, j gives the elasticity of crop i with respect to a change in the price of crop j. Cotton has an higher own price elasticity than other crops have. When cotton price increases, land planted to corn, sorghum and wheat will be converted to cotton. The cross elasticities on the three crops are of similar size, indicating an increase in cotton price will reduce their acreage shares in equal proportions. An increase in corn price, however, will draw more land from cotton than from sorghum and wheat. A similar result applies to the situation when sorghum and wheat prices rise. These results are reasonable because the soil and climate in the study region are generally suitable for growing cotton, while corn, sorghum, and wheat acreage are more clustered and therefore less likely to change.

The results from the BLP model are presented in table (4). The first column contains the means of the random coefficients, β. They are very similar to those from the table (2) logit model. The coefficients for seed price and installation cost are statistically insignificant. The coefficients for crop price and lagged share are statistically significant and of the expected sign. The crop-irrigation system dummy variables are all significant.

Parameter estimates of pumping lift and well yield are presented in the next two columns. The significant constant terms suggest that the farmer's unity is higher if the pumping lift is lower and well yield is greater. This makes sense because lower pumping lift implies lower pumping cost and higher well yield implies higher irrigation water supplies, both of which can boost the producer's profit and therefore utility. This confirms hydrological conditions are important factors affecting the producer's crop and technology choice.

Pumping lift has a significant negative interactive effect on crop price. This implies that the marginal utility of crop price will decrease as pumping lift increases. In other words, farmers with lower groundwater table are less sensitive to crop price changes. This is because crop yield is lower if groundwater table is lower (pumping cost is higher), and a given amount of price change will have a greater effect on profit for a producer with higher yield.

Figures (2) and (3) respectively show Parmer and Lynn counties' groundwater pumping lift and well yield contour map in 1973, and the corresponding crop price coefficient distributions. Parmer county is located at the northwest corner and Lynn county is at the southeast corner in our study region. Their hydrological conditions are in stark contrast. The 1973 mean pumping lifts in Parmer and Lynn are are 320 and 50 foot, respectively. The two figures show the farmer in these two counties have different responses to crop price change. The mean value of the crop price coefficient is lower in Parmer than in Lynn, because the former has a higher pumping lift than does the latter. Additionally, Parmer's price coefficient distribution is skewed towards the left, while Lynn's is skewed towards the right, consistent with the fact that more farmers in Parmer has a higher pumping lift, while more farmers in Lynn has a lower pumping lift.

The figure (4) plots compare the own price elasticity distributions of the various irrigation systems and crops. The first plot, for example, compares the own price elasticity distributions of the dryland cotton and irrigated cotton by five irrigation systems. The other three plots are for corn, sorghum, and wheat. It is clear from all these four plots that the range of the price elasticity distribution is larger for more efficient irrigation systems. This is because improving irrigation efficiency amounts to increasing the water supply, which in turn expands the crop choice set of the producer.

Conclusions

Developing groundwater management plans requires a good understanding of the interdependence of groundwater hydrology and producer water use behavior. While state-of-the-art groundwater models require water demand data at highly disaggregated levels, the lack of producer water use data has held up the progress to meet that need. This paper proposes an econometric framework that links county-level crop acreage data to well-level hydrologic data to produce heterogeneous patterns of crop choice and irrigation practices within a county. Together with agronomic data on irrigation water requirements of various crops and irrigation practices, this model permits estimation of the water demand distribution within a county. We apply this model to a panel of 16 counties in the Southern Texas High Plains from 1972 to 2000. The results obtained not only are consistent with those from the traditional multinomial logit land use model, but also indicate the presence of large intra- and inter-county heterogeneity in producer water use behavior. Future research will incorporate the model into an existing hydrologic model to offer a planning tool for groundwater management in the Southern Texas High Plains.

References

Albrecht, D.E. 1990. "The adaptations of farmers in an era of declining groundwater supplies." Southern Rural Sociology 7:46–62.

Arriagada, L.E.S. 2005. "Optimal Crop Choice: Farmer Adaptation to Climate Change." Unpublished, http://www.aeaweb.org/annual_mtg_papers/2006/0108_1300_0403.pdf.

Berry, S., J. Levinsohn, and A. Pakes. 1995. "Automobile Prices in Market Equilibrium." Econometrica 63:841–890.

Berry, S.T. 1994. "Estimating Discrete-Choice Models of Product Differentiation." The RAND Journal of Economics 25:242–262.

Brouwer, R., and M. Hofkes. 2008. "Integrated hydro-economic modelling: Approaches, key issues and future research directions." Ecological Economics 66:16–22.

Carpentier, A., and E. Letort. 2008. "Modelling acreage decisions within the multinomial logit framework : profit functions and discrete choice models." In American Agricultural Economics Association 2008 Annual Meeting, Orlando, Florida.

Caswell, M.F., and D. Zilberman. 1986. "The Effects of Well Depth and Land Quality on the Choice of Irrigation Technology." American Journal of Agricultural Economics 68:798–811.

Colaizzi, P., P.H.Gowda, T.H. Marek, and D.O. Porter. 2009. "Irrigation In The Texas High Plains: A Brief History And Potential Reductions In Demand." Irrigation and Drainage 58:257–274.

Green, G., D. Sunding, D. Zilberman, and D. Parker. 1986. "Explaining Irrigation Technology Choices: A Microparameter Approach." American Journal of Agricultural Economics 78:1064–1072.

Harou, J.J., M. Pulido-Velazquez, D.E. Rosenberg, J. Medellin-Azuara, J.R. Lund, and R.E. Howitt. 2009. "Hydro-economic models: Concepts, design, applications, and future prospects." Journal of Hydrology 375:627–643.

Hornbeck, R., and P. Keskin. 2011. “Farming the Ogallala Aquifer:Short-run and Long-run Impacts of Groundwater Access.” Unpublished, http://cbey.research.yale.edu/uploads/Ogallala_Feb2011.pdf.

Jensen, R. 2004. “Ogallala Aquifer: Using Improved Irrigation Technology and Water Conservation to Meet Future Needs.” Texas Water Resources Institute August:1.

McFadden, D. 1980. “Econometric Models for Probabilistic Choice Among Products.” The Journal of Business, 53:s13–s29.

Moore, M.R., N.R. Gollehon, and M.B. Carey. 1994. “Multicrop Production Decisions in Western Irrigated Agriculture: The Role of Water Price.” American Journal of Agricultural Economics 76:859–874.

Moreno, G., and D.L. Sunding. 2005. “Joint Estimation of Technology Adoption and Land Allocation with Implications for the Design of Conservation Policy.” American Journal of Agricultural Economics 87:1009–1019.

Negri, D.H., and D.H. Brooks. 1990. “Determinants of Irrigation Technology Choice.” American Journal of Agricultural Economics 15:213–223.

Nevo, A. 2001. “Measuring Market Power in the Ready-to-Eat Cereal Industry.” Econometrica 69:307–342.

—. 2000. “A Practitioner’s Guide to Estimation of Random-Coefficients Logit Models of Demand.” Journal of Economics & Management Strategy 9:513-548.

Pfeiffer, L., and C.Y.C. Lin. 2010. “Does Efficient Irrigation Technology Lead to Reduced Groundwater Extraction?: Empirical Evidence.” In Agricultural and Applied Economics Association 2010 Annual Meeting,Denver, Colorado.

Segarra, E., and Y. Feng. 1984. “Irrigation Technology Adoption in the Texas High Plains.” Texas Journal of Agriculture and Natural Resources 7:71–83.

Seo, S., E. Segarra, P.D. Mitchell, and D.J. Leatham. 2008. “Irrigation technology adoption and its implication for water conservation in the Texas High Plains: a real options approach.” Agricultural Economics 38:47–55.

Stewart, B.A. 2003. Aquifers, Ogallala. Encyclopedia of Water Science, S. W. Trimble, B. A. Stewart, and T. A. Howell, eds. Taylor & Francis.

Terrell, B.L., and P.N. Johnson. 1999. "Economic Impact Of The Depletion Of The Ogallala Aquifer: A Case Study Of The Southern High Plains Of Texas." In American Agricultural Economics Association annual meeting in Nashville, TN.

Warda, F.A., and M. Pulido-Velazquez. 2008. "Water conservation in irrigation can increase water use." Proceedings of the National Academay of Science 105:18215–18220.

Wheeler, E., E. Segarra, P. Johnson, J. Johnson, and D. Willis. 2006. "Economic and Hydrologic Implications of Selected Water Policy Alternatives for the Southern Ogallala Aquifer." Unpublished, http://www.depts.ttu.edu/casnr/water/wheeler.pdf.

Figures

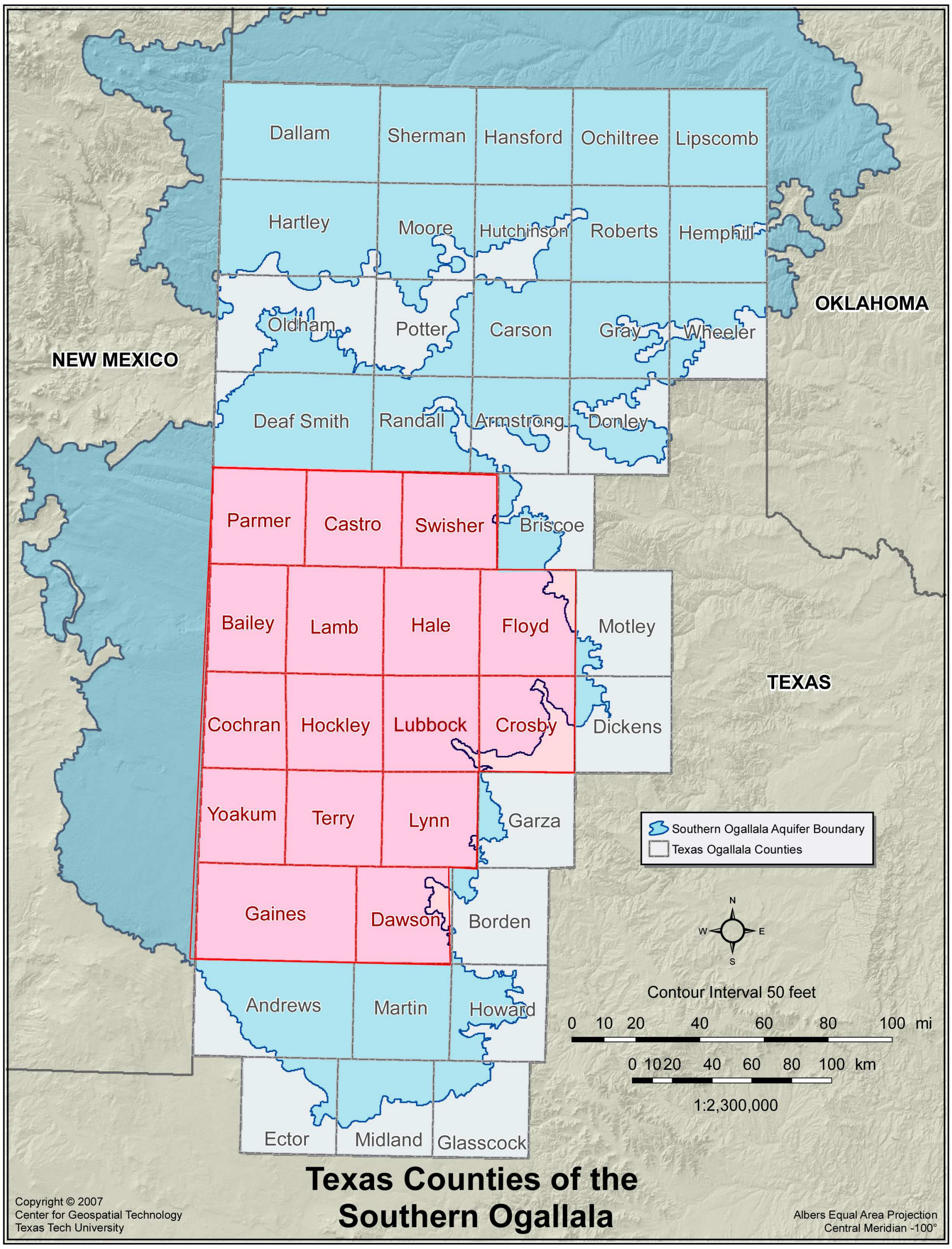

Figure 1. The Study Area

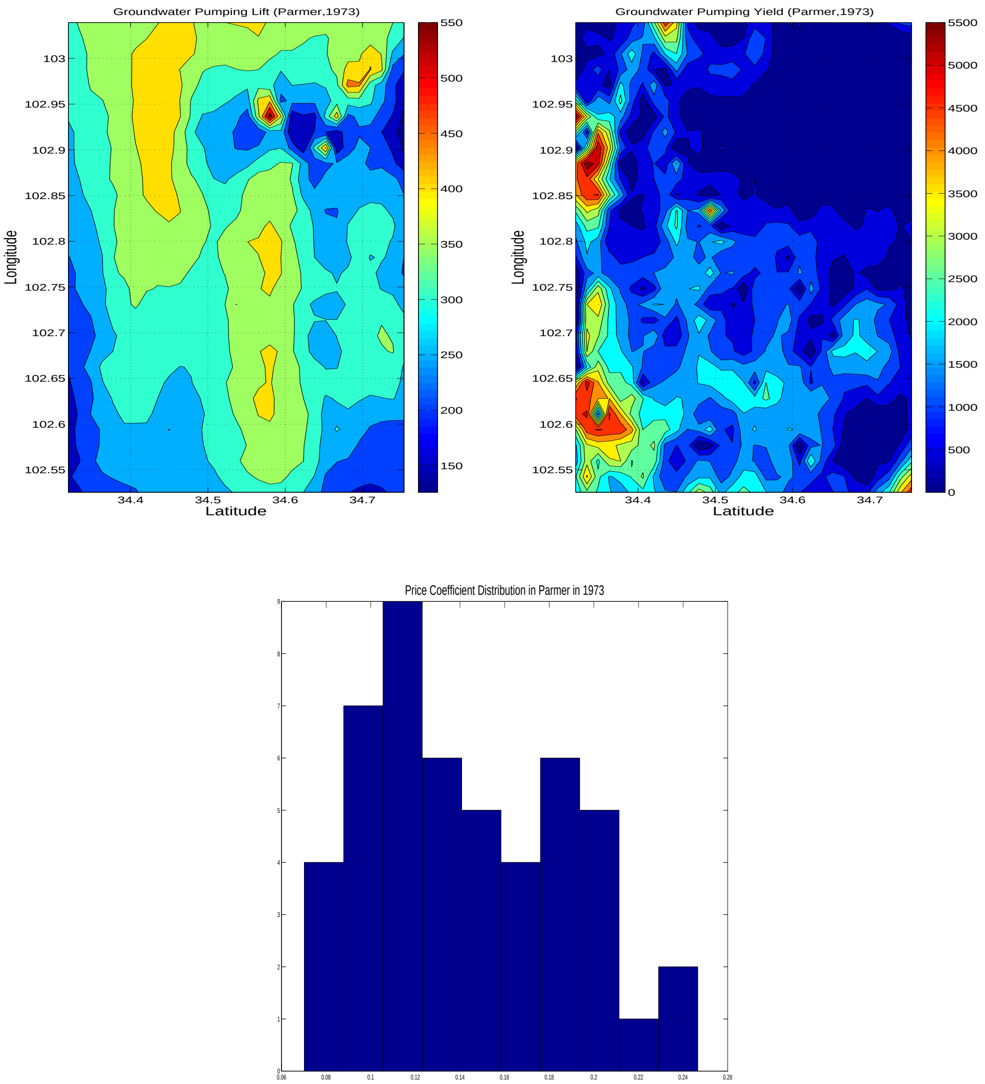

Figure 2. Price Coefficient and Groundwater Distribution(Parmer,1973)

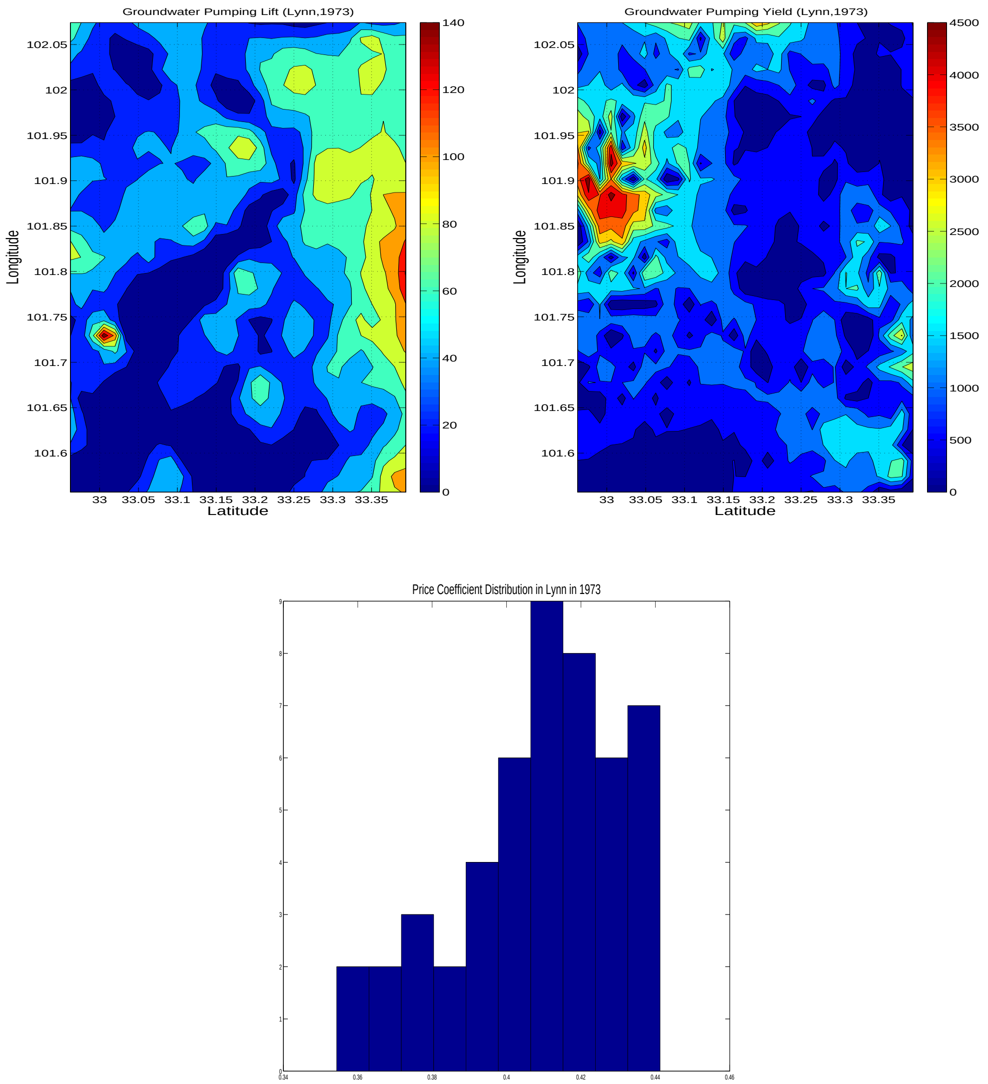

Figure 3. Price Coefficient and Groundwater Distribution(Lynn,1973)

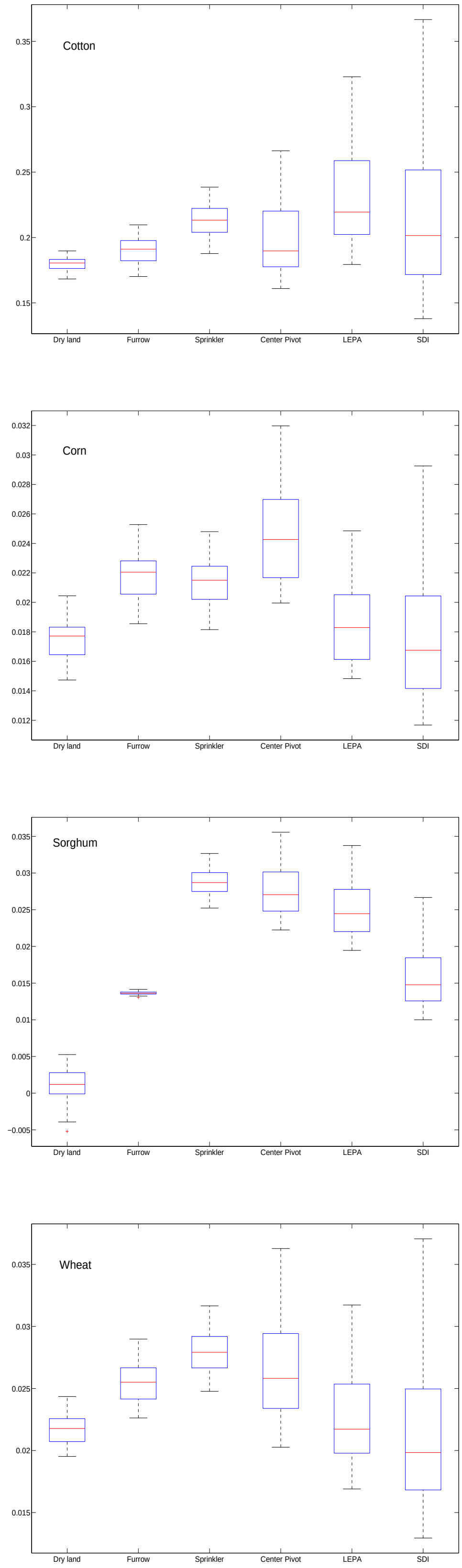

Figure 4. Crop's own price elasticity for different irrigation technology

Tables

Table 1. Descriptive Statistics of Key Variables Used in the Analysis

		Mean	Median	Std. Dev.	Min	Max
Crop Share (%)	Cotton	0.305	0.299	0.144	0.032	0.701
	Corn	0.045	0.004	0.075	0	0.525
	Sorghum	0.093	0.066	0.079	0.002	0.415
	Wheat	0.098	0.065	0.088	0	0.477
Crop Price ($/lb)	Cotton	0.574	0.485	0.205	0.277	1.054
	Corn	0.052	0.046	0.023	0.023	0.115
	Sorghum	0.045	0.040	0.020	0.019	0.103
	Wheat	0.060	0.053	0.031	0.024	0.159
Seed Price	Cotton($/lb)	0.470	0.468	0.117	0.303	0.711
	Corn($/lb)	1.147	1.078	0.260	0.688	1.884
	Sorghum($/lb)	0.629	0.613	0.097	0.462	0.813
	Wheat($/bu)	0.128	0.113	0.051	0.040	0.242
Installation cost($/ac-year)	Furrow	1.720	1.522	0.012	1.407	2.595
	Sprinkler	6.461	5.559	0.058	4.851	10.803
	Center Pivot	62.480	61.146	0.299	46.428	76.957
	LEPA	67.595	65.667	0.331	50.534	83.934
	SDI	111.073	87.546	1.661	64.049	241.743
Well Property	Lift(foot)	150.835	135.750	3.329	0	798.4
	Yield(ac-ft/hr)	0.234	0.181	0.225	0	4.121

Table 2. Result From logit Model

Variable	DF	Parameter Estimate	Standard Error	t-Value	$Pr > \|t\|$
Intercept	1	-0.395	0.045	-8.68	$<$.0001
Crop price	1	0.263	0.073	3.6	0.0003
Seed price	1	0.092	0.049	1.86	0.0625
Installation cost	1	-0.578	0.37	-1.55	0.1214
Lagged share	1	0.879	0.004	215.73	$<$.0001
Mean lift	1	0.735	0.095	7.67	$<$.0001
Mean yield	1	0.771	0.092	8.31	$<$.0001
crop-sys1	1	-0.487	0.060	-8.04	$<$.0001
crop-sys2	1	-0.699	0.060	-11.54	$<$.0001
crop-sys3	1	-0.272	0.060	-4.5	$<$.0001
crop-sys4	1	-0.600	0.061	-9.7	$<$.0001
crop-sys5	1	-0.946	0.068	-13.85	$<$.0001
crop-sys6	1	-0.248	0.061	-4.07	$<$.0001
crop-sys7	1	-0.648	0.071	-9.06	$<$.0001
crop-sys8	1	-0.887	0.073	-12.11	$<$.0001
crop-sys9	1	-0.623	0.073	-8.44	$<$.0001
crop-sys10	1	-0.822	0.075	-10.87	$<$.0001
crop-sys11	1	-0.931	0.081	-11.44	$<$.0001
crop-sys12	1	-1.014	0.074	-13.57	$<$.0001
crop-sys13	1	-0.615	0.055	-11.1	$<$.0001
crop-sys14	1	-0.817	0.056	-14.39	$<$.0001
crop-sys15	1	-0.474	0.059	-8.03	$<$.0001
crop-sys16	1	-0.758	0.062	-12.18	$<$.0001
crop-sys17	1	-0.891	0.069	-12.83	$<$.0001
crop-sys18	1	-0.310	0.054	-5.68	$<$.0001
crop-sys19	1	-0.430	0.047	-8.65	$<$.0001
crop-sys20	1	-0.678	0.051	-13.2	$<$.0001
crop-sys21	1	-0.333	0.054	-6.1	$<$.0001
crop-sys22	1	-0.684	0.057	-11.84	$<$.0001
crop-sys23	1	-0.843	0.066	-12.68	$<$.0001

Table 3. Own and Cross Price Elasticity of Crop Acreage Shares

	cotton	corn	sorghum	wheat
cotton	0.178645	-0.000865	-0.000753	-0.000994
corn	-0.001613	0.016962	-0.000125	-0.000165
sorghum	-0.003046	-0.000302	0.014623	-0.000362
wheat	-0.003178	-0.000288	-0.00025	0.019438

Table 4. Result From Random Coefficient Model

		Interaction with groundwater	
Variable	Means	Lift	Yield
Intercept	-0.3557	-0.4881	0.4228
	(0.0478)	(0.1726)	(0.1883)
Crop price	0.4456	-0.8986	-
	(0.1359)	(0.2321)	
Seed price	0.0502	-	0.1502
	(0.0318)		(0.0413)
Installation cost	-2.9195	0.9539	0.746
	(1.8473)	(2.3548)	(0.9853)
Lagged share	0.8879		
	(0.0047)		