Groundwater economics: An object-oriented foundation for integrated studies of irrigated agricultural systems

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[1] An integrated foundation is presented to study the impacts of external forcings on irrigated agricultural systems. Individually, models are presented that simulate groundwater hydrogeology and econometric farm level crop choices and irrigated water use. The natural association between groundwater wells and agricultural parcels is employed to couple these models using geographic information science technology and open modeling interface protocols. This approach is used to study the collective action problem of the common pool. Three different policies (existing, regulation, and incentive based) are studied in the semiarid grasslands overlying the Ogallala Aquifer in the central United States. Results show that while regulation using the prior appropriation doctrine and incentives using a water buy-back program may each achieve the same level of water savings across the study region, each policy has a different impact on spatial patterns of groundwater declines and farm level economic activity. This represents the first time that groundwater and econometric models of irrigated agriculture have been integrated at the well-parcel level and provides methods for scientific investigation of this coupled natural-human system. Results are useful for science to inform decision making and public policy debate.

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1. Introduction

[2] Groundwater resources provide a primary or supplemental source of irrigation water throughout much of the world, yet overpumping and subsequent aquifer depletion may pose "the single largest threat to irrigated agriculture" [*Alley et al.*, 2002, p. 1985]. Dealing with such issues involves a three-stage process [*Livingston and Garrido*, 2004], by which (1) the economic need for change arises from externalities, (2) stakeholders identify equitable management criteria, and (3) institutions implement appropriate policy change. Clearly, the interactions between groundwater and economics are important in this process, and development of spatially referenced data and modeling are important to guide researchers and policy makers [*Adriaens et al.*, 2003], and scientific knowledge and wisdom are needed to help inform societal decisions [*Lubchenco*, 1998].

[3] Economic models of groundwater quantity are largely based upon a simplified hydroeconomic model described by *Gisser and Sánchez* [1980a, 1980b]. This model assumes that groundwater is withdrawn from a common pool or "bathtub" represented by a horizontal, unconfined aquifer with infinite hydraulic conductivity. Subsequent work by *Provencher and Burt* [1994a, 1994b] subdivided an aquifer into a set of independent water cells with self-consistent properties. More recently, econometric methods have been applied to estimate demand functions for groundwater from farm level microeconomic data, as reviewed by *Scheierling et al.* [2006]. To date, econometric models of irrigated agriculture have not been linked at a high spatial resolution to hydrologic models.

[4] A geographic information system (GIS) enables organization of geospatial data for model applications, spatial analysis, and visualization. *Adriaens et al.* [2003, p. 121] identified GIS as a requirement in developing "an interactive framework for quantitative analysis of coupling between human and natural systems." Recently, *Fohrer et al.* [2005] presented a GIS method to examine sustainable land use concepts and regional water balance, although coupling models of agricultural economics, ecology and hydrology is "under development." A major difficulty faced by *Quinn et al.* [2004] in development of GIS tools for hydroclimate models was that existing models do not fit within an object-oriented framework.

[5] A GIS data model was recently developed for data related to groundwater by G. Strassberg and D. R. Maidment (Arc Hydro groundwater data model, paper presented at

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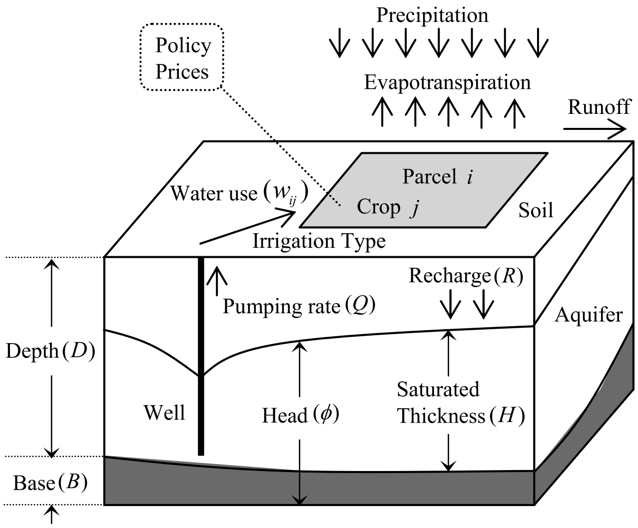

Figure 1. The groundwater and parcel attributes within a system containing the groundwater aquifer and the agricultural economy.

Geographic Information Systems in Water Resources III, American Water Resources Association, Nashville, Tennessee, 2004) and *Strassberg et al.* [2007] on the basis of the ArcHydro data model [*Maidment*, 2002]. This was extended by *Steward et al.* [2005] and E. A. Bernard et al. (A geodatabase for groundwater modeling in MLAEM and MODFLOW, paper presented at International User Conference, ESRI, San Diego, California, 25–29 July 2005), who developed modeling tools that directly access a groundwater data model. These tools are organized within an object-oriented framework whereby all data required for model development are organized as objects (points, lines, polygons and rasters) and their interactions [*Steward and Bernard*, 2006; *Steward and Ahring*, 2009; *Yang et al.*, 2009].

[6] This object-oriented approach is extended here to create a spatially referenced groundwater econometric model with wells and parcels, for the first time. First, the individual groundwater and economic modeling components are described, and the integrated approach using these models with GIS and spatially referenced data is presented. This framework is then applied to study a common property problem, where irrigation withdraws groundwater from the common pool of the Ogallala Aquifer, and to assess the possibility and promise of collective action in the management of water resources [*Benvenisti*, 1996]. Such interdisciplinary linkages together with new data sets and computational tools are necessary to engage scientists and decision makers and provide forecasts involving social change and decision making relevance [*Clark et al.*, 2001].

2. Methods

[7] The groundwater economic system (Figure 1) contains intrinsically interwoven natural and human components. At the surface, precipitation and irrigation pumped from the aquifer supply water to crops, which evapotranspire back to the atmosphere during crop growth. Excess water inputs are lost through runoff or deep percolation past the root zone that eventually recharges the aquifer. The decision to use or not use the water stored in groundwater reservoirs for growing crops is largely based upon economic considerations. High-value crops require irrigation that is limited by the availability of groundwater and the costs associated with pumping water to the parcel.

[8] A natural association exists between groundwater hydrology and agricultural economics through the well-parcel relationships. The methods by which the groundwater and economic processes are modeled and linked within an object-oriented framework are described next.

2.1. Groundwater Methods

[9] The model of groundwater flow is founded in two mathematical equations. Groundwater flow is assumed to satisfy Darcy's law, which provides a constitutive relationship between flow (**Q** is the discharge per unit width of the aquifer) and head (groundwater elevation), ϕ. This may be expressed as follows for Dupuit flow [*Strack*, 1981; *Strack et al.*, 2006] with piecewise uniform aquifer properties

$$\mathbf{Q} = -\nabla\Phi, \quad \Phi = \begin{cases} \frac{1}{2}k(\phi - B)^2 & (\phi - B) < D \\ kD(\phi - B) - \frac{1}{2}kD^2 & (\phi - B) \geq D \end{cases} \tag{1}$$

where $\Phi(x,y)$ is a scalar potential function, x and y represent coordinate directions, k is the hydraulic conductivity, B is the elevation of the base of the aquifer, and D is the vertical depth of the aquifer [*Strack*, 1989].

[10] The law of conservation of mass (continuity of flow), together with Darcy's law gives

$$\frac{\partial^2\Phi}{\partial x^2} + \frac{\partial^2\Phi}{\partial y^2} = -R + \frac{1}{\alpha}\frac{\partial\Phi}{\partial t} \tag{2}$$

where R is the rate of recharge and $\alpha = k\overline{H}/S_y$ is the aquifer diffusivity using the average saturated thickness, $\overline{H}$, and specific yield, S_y [*Bear*, 1972].

[11] Groundwater models are constructed here using an object-oriented approach called the analytic element method [*Strack*, 1989, 2003; *Haitjema*, 1995]. This vector-based methodology was chosen because it directly relates the aquifer features in Figure 1 to existing data models that organize hydrogeologic data [*Steward et al.*, 2005; *Steward and Bernard*, 2006; *Yang et al.*, 2009]. This structure will be used later to integrate groundwater and economics.

[12] In the analytic element method, the flow generated by individual aquifer features is modeled using analytic elements that (1) have specified geometry (point, line or polygon in two dimensions), (2) are represented using mathematical expressions that exactly satisfy equation (2), and (3) contain prescribed boundary conditions along the feature. (For example, a well lies at a point, uses the mathematical Theis solution, and has a boundary condition of a prescribed pumping schedule). The mathematical expressions for all analytic elements may be superimposed and evaluated at any point, providing the flow rate and head using equation (1).

[13] The mathematical description of analytic elements used to study the groundwater economic system are described

next. Regional recharge and uniform flow are modeled using [*Steward*, 2007, equation (31)]

$$\Phi = R\alpha t + Ax + By + C \tag{3}$$

where R is the specific discharge of recharge, and A, B and C are a priori unknown coefficients used to match observed values of head at a set of reference points. Aquifer properties (k, B and D) are assumed piecewise uniform within polygons. The conditions of continuity of flow and head are satisfied when a jump in potential occurs between adjacent polygons with different properties [*Strack*, 1989]. This jump condition is mathematically described using line doublets (double layers) composed of straight line segments located at the boundaries of polygons, with potential

$$\Phi = \Re \sum_{m=0}^{M} \mu_m \Omega_m(Z), \quad \Omega_m(Z) = \frac{\mathrm{i}}{2\pi} \int_{-1}^{1} \frac{\tilde{Z}^m}{Z - \tilde{Z}} \mathrm{d}\tilde{Z} \tag{4}$$

where Z is a local complex variable, μ_m are strength coefficients and closed form expressions for the kernel function Ω_m are fully developed by *Steward et al.* [2008]. An iterative method to solve for the coefficients, μ_m, to satisfy the continuity equations is presented by *Steward* [2007]. Wells are modeled using the *Theis* [1935] solution, which gives

$$\begin{aligned} \Phi &= -\frac{Q}{4\pi}\left[\mathrm{E}_1(u_1) - \mathrm{E}_1(u_2)\right] \\ u_1 &= \frac{r^2}{4\alpha(t - t_0)}, \quad u_2 = \frac{r^2}{4\alpha(t - t_0 - T)} \end{aligned} \tag{5}$$

where Q is the pumping rate of a well that turns on at time t_0 for a period T, r is the horizontal distance from the well, and E_1 is the exponential integral [*Abramowitz and Stegun*, 1972].

2.2. Economic Methods

[14] The microeconomic decisions in irrigated agriculture can be viewed as a two-stage process repeated annually, where land allocations are chosen at the beginning of each growing season, and water allocations are chosen as each season progresses [*Chambers and Just*, 1989; *Moore et al.*, 1994; *Antle and Capalbo*, 2001]. The economic component of the current model is based on work by *Hendricks* [2007], who specified and estimated a two-stage model of crop choice and water use from data in the study region.

[15] This estimation technique uses the polychotomous choice selectivity model introduced by *Lee* [1983]. Letting i and j index parcels of land and crops, respectively, c_i is a discrete variable indicating the farmer's crop choice; $c_i = j$ if and only if crop j is chosen on parcel i. Within the study region discussed later, growing conditions vary little within each parcel and the entire parcel/production area is commonly planted to one crop. A farmer's anticipated utility from growing crop j on parcel i is

$$u_{ij} = h_j\left(\mathbf{x_i}, \gamma_\mathbf{j}\right) + \epsilon_\mathbf{ij} \tag{6}$$

where $\mathbf{x_i}$ is a vector of observable variables on parcel i, $\gamma_\mathbf{j}$ is a vector of parameters to be estimated, and ϵ_{ij} is a random disturbance term, which captures unobservable factors affecting utility such as the farmer's managerial ability and experience levels with the different crops. Although known to the farmer, these factors are unobserved and thus random to the researcher. Thus, $h_j(\mathbf{x_i}, \gamma_\mathbf{j})$ is known as the "nonrandom" part of utility and ϵ_{ij} is the "random" portion.

[16] Each decision maker is assumed to select the crop that maximizes utility: $c_i = j \iff u_{ij} = \max(u_{i1}, \cdots, u_{iJ})$. Because of the unobserved factors embodied in ϵ_{ij}, a model cannot perfectly predict these choices and only $P_{ij} = \Pr(c_i = j)$ can be estimated. Assuming that ϵ_{ij} follows an extreme value type 1 distribution, this probability is [*Maddala*, 1983]

$$P_{ij} = \frac{e^{h_j\left(\mathbf{x_i}, \gamma_\mathbf{j}\right)}}{\sum_{j=1}^{J} e^{h_j\left(\mathbf{x_i}, \gamma_\mathbf{j}\right)}} \tag{7}$$

These equations comprise the multinomial logit model, which has been widely applied to study land use decisions [*Hardie and Parks*, 1997; *Lichtenberg*, 1989; *Wu et al.*, 2004].

[17] After a crop has been selected, the second decision is how much irrigation water to apply on the basis of seasonal economic and growing conditions. It is assumed that the water application level, w_{ij}, is selected by maximizing utility conditional on the crop selected in stage one. The result of this decision process is a water demand function

$$w_{ij} = g_j\left(\mathbf{z_{ij}}, \beta_\mathbf{j}\right) + \eta_\mathbf{ij} \tag{8}$$

where $\mathbf{z_{ij}}$ is a vector of observed variables during the growing season, $\beta_\mathbf{j}$ is a vector of parameters to be estimated, and η_{ij} is a random error.

[18] The polychotomous choice selectivity model estimates the parameters $\gamma_\mathbf{j}$ and $\beta_\mathbf{j}$ in a two-stage regression related to the two decision stages [*Hendricks*, 2007]. Stage 1 of the procedure is to estimate the parameters $\gamma_\mathbf{j}$ by maximizing the likelihood function formed by the probabilities in equation (7). Estimation of $\beta_\mathbf{j}$ in stage 2 is complicated by a sample selection problem. Applying ordinary least squares (OLS) directly to (8) would yield biased estimates of $\beta_\mathbf{j}$ if ϵ_{ij} and η_{ij} are correlated. *Lee* [1983] showed that the bias can be corrected by constructing the variable

$$\lambda_{ij} = f\left(F^{-1}\left(\hat{P}_{ij}\right)\right)/\hat{P}_{ij} \tag{9}$$

where f is the standard normal density function, F is the normal cumulative distribution function, and $\hat{P}_{ij}$ is the predicted probability from the estimated version of (7). The new variable is then appended to equation (8) and OLS is applied to the modified equation

$$w_{ij} = g_j\left(\mathbf{z_{ij}}, \beta_\mathbf{j}\right) + \kappa_\mathbf{j}\lambda_\mathbf{ij} + \mu_\mathbf{ij} \tag{10}$$

where $\mathrm{E}[\mu_{ij}] = 0$ and the estimate of κ_j indicates the degree of sample selection bias. If the hypothesis that $\kappa_j = 0$ cannot be rejected then sample selection does not pose a problem for crop j and the stage 2 model for that crop can be estimated by applying OLS to equation (8).

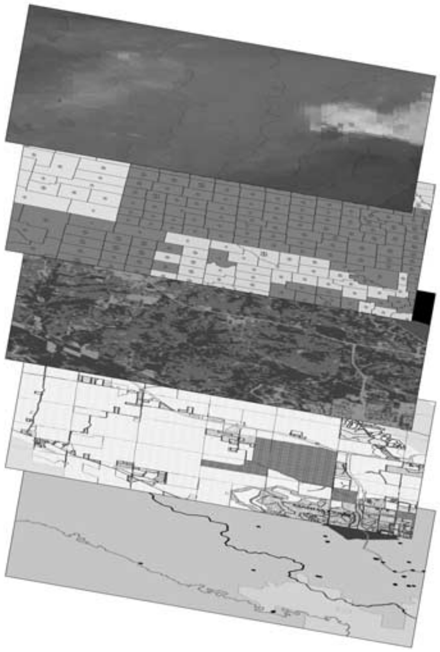

Figure 2. Thematic layers, organizing collections of common geographic data [*von Meyer*, 2004; *Yang et al.*, 2009; O. Wilhelmi et al., ArcGIS atmospheric data model, paper presented at International User Conference, San Diego, California, ESRI, 25–29 July 2005; M. Crandall, An ArcGIS datamodel for agriculture—Draft, 2003, available at http://support. esri.com/index.cfm?fa=downloads.dataModels. filteredGateway&dmid=35].

[19] The estimated equations serve as the economic component of the coupled model. Paralleling the estimation procedure, this model executes in two stages. In the first stage, the data for parcel i and year t of the simulation (or site year (i,t)) are inserted into the estimated version of (7), yielding the predicted probabilities $\hat{P}_{ij}$. While logit models are often simulated by assigning the choice with the highest predicted probability, this procedure contradicts the very definition of probability because it fixes the outcome of a random event. We adopt a simulation method that allows for any of the crops to be assigned to each site year but restricts the probability of occurrence on the basis of the logit estimates. In particular, one of the four crops is randomly assigned to site year (i,t), where crop j is selected with probability $\hat{P}_{ij}$. In the second stage, predicted water use, $\hat{w}_{it}$, is computed by inserting the data for site year (i,t) and the crop assigned in stage 1 into the estimated version of equation (8).

2.3. Integrated Groundwater Economics

[20] The groundwater model and the economic model, previously described, are each organized within a self-consistent object-oriented framework. The groundwater model contains aquifer, recharge, and well objects; the economic model contains crop production and parcel objects. This property is utilized here to circumvent problems associated with previous attempts to integrate cross-disciplinary models that were not organized around objects [*Quinn et al.*, 2004].

[21] *Arctur and Zeiler* [2004] documented a set of "best practices" in GIS data model design, with the first recommendation being to organize data in a set of thematic layers important to the system. The groundwater economic system is organized here around the themes of groundwater, parcel, agriculture, economy and atmosphere as illustrated in Figure 2. The sources of existing data model designs for each layer are also shown; data organization for the economy is presented here for the first time.

[22] These thematic layers contain objects illustrated using the data model in Figure 3. Each object has a common spatial representation of either a point or polygon, or else it

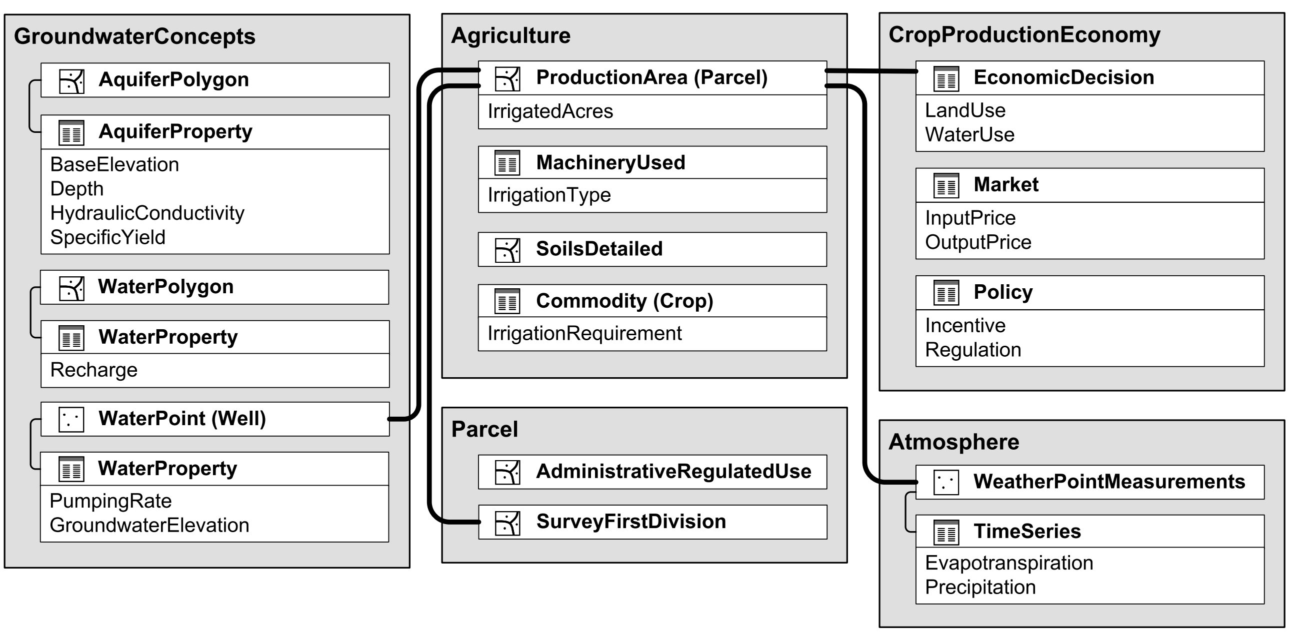

Figure 3. Data model of groundwater economics, illustrating important data attributes within thematic layers and the key relationships linking data across groundwater and economic objects.

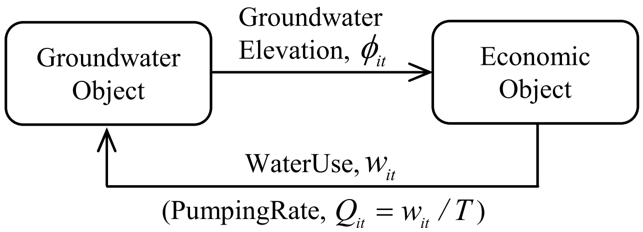

Figure 4. Data requested between the groundwater and economic objects using the OpenMI GetValues function [*Moore and Tindall*, 2005; *Gregersen et al.*, 2007].

contains tabular data. The data attributes of each object that are used in this study are also shown. For example, the well, equation (5), requires information about the pumping rate and location of the well, while the water use decision, equation (8), requires market information related to expected commodity prices and energy costs. Thus, the data model contains all data used here to model groundwater and economics.

[23] The data model also illustrates the key relationships that associate groundwater and economic data. The well is related to the parcel at which water use is authorized, and each parcel utilizes this water in agriculture production practices for a particular land use and crop choice dictated primarily by economic considerations. The relationship between well and parcel objects is used to integrate the groundwater and economic models as illustrated in Figure 4, and models are exercised iteratively as follows:

[24] 1. The groundwater model predicts the head ϕ_{it} (equation (1)), at the start of growing season t for the well that supplies water to parcel i.

[25] 2. The economic model predicts the water use w_{it} (equation (8)), at each parcel i using the estimated regression equations, with ϕ_{it} impacting regressors associated with saturated thickness.

[26] 3. The predicted net water use is divided by the period T during which the well operates to give the pumping rate $Q_{it} = w_{it}/T$ in (5) for each well. The groundwater model then predicts the head at the beginning of the next growing season at each well $\phi_{i(t+1)}$.

[27] Enabling the model programs to exchange this information as they execute is not a trivial task because of differences between the programs' data input files and conceptual differences in the models such as temporal and spatial representations. An emerging standard for the integration of models called the open modeling interface (OpenMI) [*Moore and Tindall*, 2005; *Gregersen et al.*, 2007] describes a common way for models to interact. The OpenMI Association Technical Committee (OATC) has developed software tools based on OpenMI and the results presented in this paper were obtained using a coupling based on these tools. The OATC software currently runs only on desktop computers, so a modified coupling was used on a high-performance computing cluster for the initial trials [*Bulatewicz et al.*, 2009], because of the considerable runtime of the coupled simulation.

3. Study: The Collective Action Problem

[28] The groundwater economic model is applied next to the collective action problem whereby common pool water users each have an interest in getting more out of the resource, and these interests conflict with each other [*Emel and Roberts*, 1995]. *Benvenisti* [1996] outlined two policy mechanisms by which this problem may be resolved.

[29] 1. Design rules on the use of the freshwater resource (regulation-based policy).

[30] 2. Provide individual property rights instead of treating it as a common pool resource (incentive-based policy).

[31] This retrospective study examines the impacts of regulation and incentive policies on the economic costs associated with overpumping an aquifer [*Cash et al.*, 2003], and how groundwater economic conditions would be different today if these policies had been enacted in the past.

3.1. Study Region: Semiarid Grasslands of the Central Plains and the Ogallala Aquifer

[32] The study region lies over the Ogallala Aquifer in the Central Plains of the United States of America. This aquifer was identified by *Custodio* [2002] as a case study of aquifer overexploitation, and has locally seen groundwater declines of up to 30 m over 40 years. It is also reflective of other aquifers across the world whereby most consumptive use of pumped groundwater is by irrigated agriculture with both physical and economic consequences associated with overdraft mining of aquifer storage reserves [*Foster and Chilton*, 2003]. The size of the study region (county level) was chosen as it represents the standard level of aggregation for reporting economic data (prices, crop revenue, yields, costs, etc.)

[33] Each model was first individually calibrated to reproduce historical data over the period of 1991–2004 (data for this study are summarized in Appendix A). The groundwater model was calibrated to match the groundwater elevation at observation wells summarized by *Steward et al.* [2009]. A buffer of 20 km was applied around the study region where wells were included along with their historical pumping schedules. A region of this size was found by *Steward et al.* [2009] to properly incorporate the transient effects of these wells in the study region over the time frame of this study. This model very closely matches observed changes in groundwater elevation; the residual difference between the simulated groundwater elevation and 50 observation wells in Sheridan County is 3.95 m (average absolute difference over all observations for all years).

[34] The econometric model is presented in full in Appendix A. Stage 1 estimates the choices among the four most common irrigated crops in the region (alfalfa, corn, sorghum and soybean). The stage 1 regressors, $\mathbf{x_i}$, included measures of expected crop prices, expected pumping costs, soil attributes, aquifer saturated thickness, the type of irrigation system, and a time trend to capture other factors like improved crop varieties. Price variables reflect expectations formed at the time of planting. The utility functions $h_j(\mathbf{x_i}, \gamma_\mathbf{j})$ were linear in all variables except prices, which entered quadratically. The stage 2 regressors, $\mathbf{z_{ij}}$, were defined similarly except prices reflected expectations during the growing season, and the net irrigation requirement also was included to capture seasonal weather conditions. The water demand functions, $g_j(\mathbf{z_{ij}}, \beta_\mathbf{j})$, were specified linearly except for a quadratic time trend and interaction terms between energy prices and irrigation system indicator var-

Table 1. Estimated Elasticities by Crop and Irrigation System

Irrigation System	Crop				Weighted Average[b]
	Alfalfa	Corn	Sorghum	Soybean	
High-efficiency center pivot	0.074[a]	−0.012	−1.395	−0.740	−0.078
Standard center pivot	−0.849	−0.089	−0.599	−0.678	−0.164
Flood		−0.231	−1.008	−0.651	−0.368
Weighted average[b]	−0.590	−0.072	−0.875	−0.722	−0.155

[a]Not statistically different from zero.
[b]Weighted by number of observations.

iables; the latter control for differences in pumping costs across systems [*Rogers and Alam*, 2006].

[35] The estimated elasticities of water use with respect to the pumping cost variable are reported in Table 1. The estimates vary by crop and irrigation and system but are all in the inelastic range, as supported by previous studies [*Scheierling et al.*, 2006]. Water demand for corn is more inelastic than that of other crops, while more efficient irrigation systems also lead to more inelastic demand. The overall weighted average estimate of the demand elasticity is −0.155. The stage 1 regression had a pseudo R^2 of 0.224 and the stage 2 regressions had adjusted R^2 ranging from 0.13 to 0.53 depending on the crop.

[36] These measures of fit are typical of cross-sectional econometric models, and imply that water use is impacted by several unobserved factors, such as individual farmers' managerial practices and operational constraints, which our model does not capture. The two-stage model has a mean absolute prediction error of 3.71 acre inches/acre (9.5 cm) for the sample data and 4.55 acre inches/acre (11.7 cm) for nonsample data.

[37] The calibrated groundwater and economic models were then exercised over the same time period, using the integrated approach described in section 2.3: the groundwater model calculated head, which was used as a regressor in the economic model to predict crop choice and water use, which was then used by the groundwater model to predict the groundwater elevation in the following year. Results are presented in Figure 5a using the existing water policies. The net change in saturated thickness is shown between the predevelopment groundwater table and the end of the simulation period, and the size of wells are scaled on the basis of pumping rate in the last year. Note that the 829 irrigation wells that were included in the economic model are black, and the 77 nonirrigation wells (e.g., municipal, feedlots, or industry) in the study region are gray. The parcels over which irrigation occurred are also shown, along with the crop choice for the last year of simulation. The code "multicrop" indicates more than one well-parcel/production area pair resided within the legal PLSS land unit.

[38] These results illustrate the largest groundwater declines occurring beneath the wells with the highest water use, and their close association with the irrigated parcels. In the long term such water use cannot be sustained with current rates of recharge, and the questions naturally arise: How long will the water last, and how can we plan for future economic activity? These questions have implications across scales from individual farms to regional, and the impact of two different policies is studied next.

3.2. Regulation Policy: Enforcing Prior Appropriation Doctrine

[39] Policy mechanisms exist within the study region to regulate the use of groundwater. Specifically, the Kansas Groundwater Management District Act contains provision K.S.A. 82a-1036, which allows the chief engineer to designate an intensive groundwater use control area (IGUCA) to implement corrective control provisions. A number of mechanisms are put forth in K.S.A. 82a-1038 from closing an IGUCA to further appropriations to reducing the permissible groundwater withdrawal on the basis of either relative dates of priority of such rights or a rotating schedule. The specific policy examined here is strict enforcement of the prior appropriation doctrine to reduce groundwater consumption to match average natural recharge rates within an area under consideration as a high-priority aquifer subunit by the northwest Kansas groundwater management district (GMD) 4.

[40] A number of sources document the average annual recharge rate (R) in the study region: 0.006 m (0.25 inches) [*Bayne*, 1956], 0.0074 m (0.29 inches) [*Kansas Water Resources Board*, 1967], 0−0.013 m (0−0.5 inches) [*Sophocleous and Schloss*, 2000], 0.013 m (0.5 inches) GMD 4 Rules and Regulations 5-24-1, and 0.02 m (spatial average 0.5−1.0 inches) [*Hansen*, 1991]. In this scenario, we adopted the largest published value of R = 0.02 m/a, which gives a natural recharge of 5.1×10^6 m^3/a over the 255 km^2 high-priority area illustrated in Figure 5b. The water use by individual wells was computed using rules established within the Lower Smoky Hill IGUCA and Walnut Creek IGUCA, which determine the amount of allowable water use on the basis of the average water use during the previous 5 years. This 5 year average water use by the 196 points of diversion in the high-priority area is 5.16×10^7 m^3/a, necessitating a 90% reduction to match natural recharge. Preferentially allocating water using prior appropriation results in removing 173 wells from production and allowing irrigation by the 23 wells with senior water rights.

[41] The impact of the regulation policy is modeled assuming it was implemented in 1991 but all other factors remained the same. This retrospective study illustrates how conditions would be different today if this policy had been implemented in 1991. The coupled groundwater economic model illustrates that this policy addresses the issue of sustained groundwater declines in the high-priority area (maximum groundwater declines since predevelopment at

Figure 5. Groundwater economic results for three water use policies from 1991 to 2004 in a study region of approximately 50 km × 50 km in the Ogallala Aquifer region of Sheridan County, Kansas. The change in saturated thickness from predevelopment to the end of simulation (shown in meters) is shown along with the water use for wells and crop choices for parcels in the last year of simulation. (a) Existing policy: wells/parcels with crop choice and water use estimated using historical information. (b) Regulation policy: wells/parcels removed in a high-priority subunit on the basis of the prior appropriation doctrine. (c) Incentive policy: wells/parcels removed throughout study region on the basis of a voluntary water retirement program.

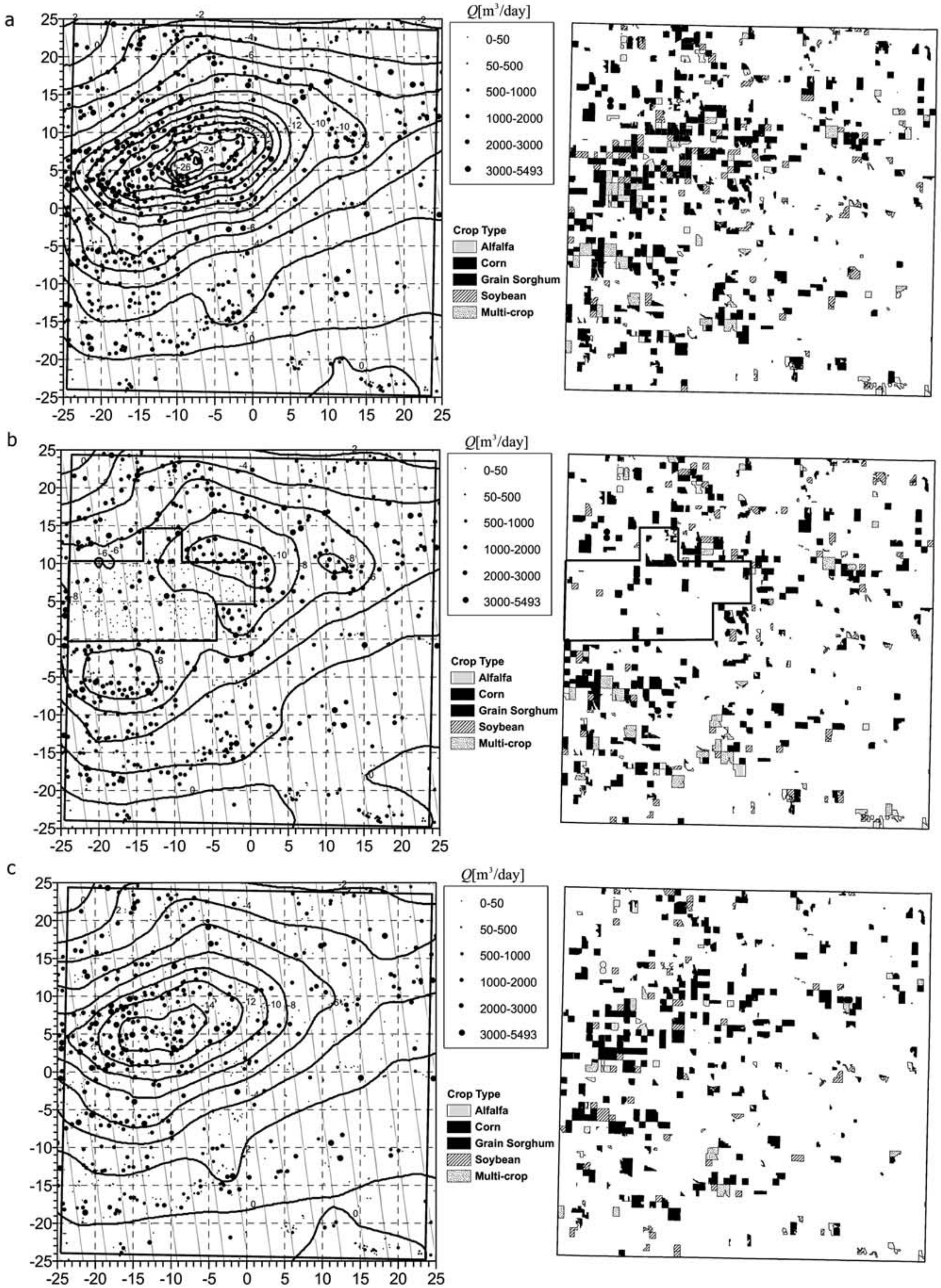
a
Q[m³/day]
0-50
50-500
500-1000
1000-2000
2000-3000
3000-5493
Crop Type
Alfalfa
Corn
Grain Sorghum
Soybean
Multi-crop
b
Q[m³/day]
0-50
50-500
500-1000
1000-2000
2000-3000
3000-5493
Crop Type
Alfalfa
Corn
Grain Sorghum
Soybean
Multi-crop
c
Q[m³/day]
0-50
50-500
500-1000
1000-2000
2000-3000
3000-5493
Crop Type
Alfalfa
Corn
Grain Sorghum
Soybean
Multi-crop

Figure 5

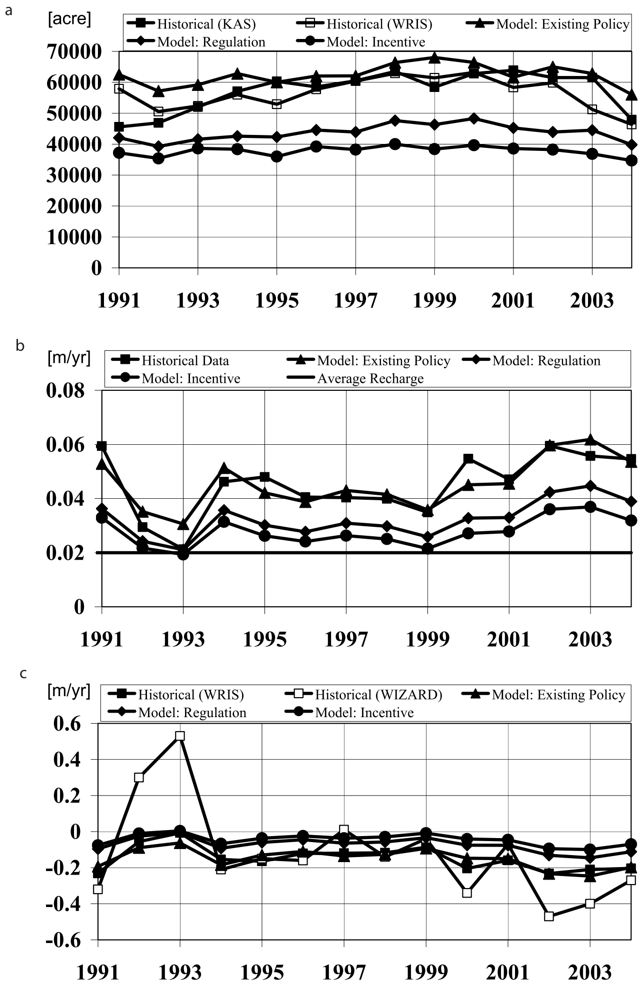

Figure 6. Historical data and results for three policies in the study region. (a) Crop choice: number of acres of irrigated corn. (b) Water use: average irrigated groundwater extraction. (c) Average change in groundwater elevation.

the 10 m contour instead of 26 m in this region with existing policy). The model also illustrates the loss of economic activity through irrigated agriculture in the high-priority area.

3.3. Incentive Policy: Water Buy-Back Program

[42] Policy mechanisms also exist within the study region to modify water use through financial incentives. The Kansas Water Appropriation Act K.S.A. 82a-701 states that a water right is a "real property right appurtenant to and severable from the land on or in connection with which the water is used." In 2006, the Kansas Legislature approved a Water Transition Assistance Program (HB2710) as a 5 year pilot project to purchase water rights in the Prairie Dog Creek in northwest Kansas and the Rattlesnake Creek in south-central Kansas. Another water buy-back example is the Kansas Upper Arkansas River Conservation Reserve Enhancement Program, which is a partnership between USDA and the State of Kansas. Pertinent goals are to reduce the amount of groundwater used for irrigation and to improve groundwater levels.

[43] In this scenario, a voluntary water retirement program is assumed to result in the same net water savings over the study region (county) as the regulation achieved in scenario 2 (4.65×10^7 m^3/a average over the 5 years before simulation). The 5 year average water use in the study region is 1.38×10^8m^3/a, which gives a water reduction of 34%. The buy-back program was simulated by assuming that every producer has equal incentive to enroll and wells were randomly removed from production until the target water reduction was achieved. This results in a reduction from the 729 points of diversions that withdraw water before the policy was implemented to 473 points of diversion after the policy is enacted. The spatial patterns of changes in groundwater elevation and irrigated crop selections is illustrated in Figure 5c.

[44] The response to change in policy over time is illustrated in Figure 6, where results from the groundwater economic model are aggregated across the study region. The historical crop choice was computed using both the Kansas Agricultural Statistics as well as the Water Resources Information System (WRIS) at the Kansas Department of Agriculture. This WRIS data set also provides the information about historical irrigated water use. The historical average change in groundwater elevation was computed by subtracting the average annual extraction from WRIS minus the average annual recharge from *Hansen* [1991] divided by the specific yield; it was also computed by geospatially averaging observation water levels from the Kansas WIZARD database [*Steward et al.*, 2009].

[45] Most of the WIZARD groundwater elevation data are collected in wells used for irrigation with yearly fluctuations in head to tens of meters. To obtain a measure of average annual change in groundwater over the county, water level was sampled between 1 December and 31 January when the head in wells were mostly recovered from pumping; this gave between 129 and 176 yearly measurements in Sheridan County and a buffer region. For each year, the average change in groundwater elevation was computed by applying the inverse distance weighting method to a 500 m grid over the study region using wells with data at the beginning and end of the year. While the data is noisy it reflects the impact of climate on irrigation water demand and scheduling, where less pumping occurred in the wet early 1990s and drought occurred in the early 2000s. In fact, preirrigation before the growing season is common practice in dry years to build water in the soil profile necessary for crop production. While the timing of water level measurements and pumping schedules may lead to a model that over or under predicts well borehole data for a given year, on average the model closely matches observation data; the net change in groundwater elevation over the period of study (historical data of −2.1 m from WRIS and −1.7 m from WIZARD) compares favorably to the model of existing policy (−2.1 m), and differs from the policies of regulation (−1.0 m) and incentive (−0.6 m). As mentioned before, the model of existing policy closely matches both the value and spatial distribution of changes in groundwater head, with the average absolute difference of 3.95 m between the model and observation wells over the period of study.

4. Discussion

[46] The groundwater economic model illustrates the spatial patterns that emerge from change in policy on groundwater availability as well as the economic response at individual parcels. This addresses the possibilities iden-

tified by *McDonnell* [2008] for truly integrated water resources management that require new methods and conceptual framework to represent the full dimension of variables, interactions and complexity that come into play in water policy. The groundwater economic foundation, presented here, brings together data and models to understand the interactions of this coupled natural-human system.

[47] This model provides the ability to incorporate spatial resolution in addressing location specific management questions and assessing the impacts of policies on individuals and communities. A typical economic model of irrigated agriculture presents findings similar to the aggregated results in Figure 6; a typical groundwater model presents spatial patterns similar to the results in Figure 5. Integration of these models enables answers to both process and pattern questions. For example, while the policies of regulation and incentive both address groundwater declines at a county level in Figure 6, the incentive policy more poorly targets a possible goal of minimizing groundwater declines in the high-priority area.

[48] This integrated model also provides a foundation for understanding aggregation and scaling issues. For example, the economic impact of well-on-well impairment is necessary to quantify errors associated with previous models assumptions, such as the *Gisser and Sánchez* [1980a] bathtub model with infinite conductivity in a horizontal, unconfined aquifer. The results could also be useful for economic impact assessment models, which consider how changes in the crop sector reverberate through other economic sectors to get a regional impact.

[49] In regards to existing efforts toward collective action in solving the problem of groundwater depletion in the Ogallala Aquifer, this study has revealed the inherent uneven spatial distribution of policy outcomes. This fact highlights the importance of this coupled model to shed light on potentially unexpected outcomes associated with related energy and agricultural production policies generally conceived at macroscopic scales (federal level) and whose potential effects at smaller scales (state, county and community level) are unknown. The modeling framework could also be applied to understand the impacts of alternative price scenarios on water levels and production income. Such knowledge is important for agencies and stakeholders to understand policy implications and plan for future economic activity.

[50] While the coupled groundwater-economic model provides information useful to inform public policy debate, results are limited by model assumptions and implementation procedures. For example, the groundwater model used a sloping base approximation [*Steward*, 2007] with uniform slope and did not incorporate aquifer heterogeneity. Likewise, the economic regressors were developed from a representative sample (obtained by eliminating wells with missing data) and then applied to all wells. Nonetheless, this groundwater economic foundation provides a new method to study and understand an irrigated agriculture system.

5. Conclusions

[51] An integrated groundwater economic model of irrigated agriculture is developed to forecast the impacts of policy on this coupled natural human system. Groundwater methods are organized around objects of wells and recharge and presented in equations (1)–(5). Economic methods are organized around crop choice and water use decisions at parcels and presented in equations (6)–(10). The integrated system in Figure 1 is organized in thematic GIS layers of agriculture, atmosphere, economic, groundwater, and parcel in Figure 2. A natural association exists between groundwater wells and economic parcels. This is employed to couple models in Figure 4, and the OpenMI GetValues protocol is used to facilitate model interactions.

[52] This new model is used to study the collective action problem of the common pool. Data were compiled for a study region in the semiarid grasslands overlying the Ogallala Aquifer in the Central Plains of the United States, and each model was individually calibrated to reproduce historical crop choices, groundwater decline and water use. Model results are presented in Figure 5 for existing policy over a time period from 1991 to 2004. The coupled model was also exercised for a regulation policy that examined the impacts of enforcement of the prior appropriations doctrine and for an incentive-based water buy-back policy. The cumulative impact of these policies across the study region is presented in Figure 6. While each policy achieved similar water use reductions within the study region, the spatial distribution of water savings and economic farm level activity differs.

[53] This study examines the worldwide problem of aquifer depletion by irrigated agriculture [*Alley et al.*, 2002]. Results address the need for science to help inform societal decisions and public policy debate associated with utilization of natural resources. This provides a foundation for interdisciplinary linkages and a means to understand interactions across a landscape containing intricately interwoven human and natural interactions.

Appendix A: Model Documentation

[54] This appendix describes the data and the estimation results for the econometric model. The data sources and groundwater parameters are shown in Table A1. The estimation data were extracted from the data set compiled by *Golden and Peterson* [2006] and *Hendricks* [2007], which include field-level observations for a 25-county region in western Kansas over the period 1991–2004. This data set was built around the Kansas Water Resources Information System (WRIS), which houses annual water use reports filed by Kansas irrigators. By Kansas state law, water-right holders must annually report water use on each point of diversion along with the area irrigated, crop grown, and type of irrigation system in use. The WRIS data were spatially merged with geophysical variables and were temporally merged with annual price data.

[55] The 1,956 observations in this database from Sheridan county were extracted for the current study and were augmented with additional variables related to the groundwater model, weather and soils. Table A2 summarizes the data set for the two staged econometric model for alfalfa, corn, sorghum, and soybean (indexed in the model, respectively, by $j = 0,1,2,3$). The price variables used in stage 1 are distinct from those in stage 2 because they reflect decisions made at different times in each production season. In stage 1, which represents the planting decisions made in the spring of each year, expected grain prices at harvest are

Table A1. Data for the Groundwater Economic Study in the Ogallala Aquifer Region of Western Kansas[a]

Object	Value	Data Source
	Groundwater Concepts	
Base Elevation	$\partial B/\partial x = -0.0023$, $\partial B/\partial y = -0.003$	*Macfarlane and Wilson* [2006]
Depth	28 m	*Gutentag et al.* [1988]
Hydraulic Conductivity	22 m/d	*Cederstrand and Becker* [1998b]
Specific Yield	0.17	*Cederstrand and Becker* [1998a]
Recharge	0.02 m/A	*Hansen* [1991]
Pumping Rate	–	Wilson (1998)[b]
Groundwater Elevation	–	*Hausberger et al.* [1998]
	Crop Production Economy	
Land Use	–	Wilson (1998)[b]
Water Use	–	Wilson (1998)[b]
Input Price	–	*Commodity Research Bureau* [2006]; USDA (2008a)[c]
Output Price	–	*Commodity Research Bureau* [2006]; USDA (2008a)[c]
Incentive	–	USDA (2008b)[d]
Regulation	–	GMD4 (2008)[e]
	Agriculture	
Irrigated Acres	–	Wilson (1998)[b]
Irrigation Type	–	Wilson (1998)[b]
Soils Detailed	–	USDA (1994,[f] 2006[g])
Irrigation Requirement	–	Kansas Weather Data Library (2008)[h]
	Parcel	
Administrative regulated use	–	GMD4 (2008)
Survey first division	–	USDA (2008c)[i]
	Atmosphere	
Weather Point Measurements	–	Kansas Weather Data Library (2008)[h]

[a]Object/attribute labels are taken from the data model. BaseElevation is shows slope and Depth is predevelopment saturated thickness. PumpingRate and GroundwaterElevation, LandUse, and WaterUse are historical.
[b]B. B. Wilson, Water Information Management and Analysis System (WIMAS), user manual, 1998, available at http://hercules.kgs.ku.edu/geohydro/ofr/2005\30/wimas\ofr2005\30.pdf.
[c]National Agricultural Statistics Service, 2008, available at www.nass.usda.gov.
[d]USDA, Conservation Reserve Enhancement Program, 2008, www.usda.gov/FSA.
[e]GMD4, High-priority aquifer sub-unit Northwest Kansas Groundwater Management District number 4, 2008, available at http://www.gmd4.org/EnhancedMgt/protocol.htm.
[f]U.S. general soil map (STATSGO), 1994, available at http://soildatamart.nrcs.usda.gov.
[g]Soil survey geographic (SSURGO) database, available at www.soildatamart.nrcs.usda.gov.
[h]Kansas Weather Data Library, 2008, available at www.oznet.ksu.edu/wdl.
[i]FSA Aerial Photography Field Office, common land unit for Sheridan, Kansas, 2008, available at http://datagateway.nrcs.usda.gov.

Table A2. Data Description

Variable	Description	Units[a]	Stage 1 Data Means	Stage 2 Data Means			
				Alfalfa	Corn	Sorghum	Soybeans
ALFP_E	Expected alfalfa price, stage 1	dollars/t	78.873				
ALFP	Expected alfalfa price, stage 2	dollars/t		77.643			
CRNP_E	Expected corn price, stage 1	dollars/bu	2.220				
CRNP	Expected corn price, stage 2	dollars/bu			2.104		
SRGP	Expected sorghum price, stage 2	dollars/cwt				1.969	
SOYP	Expected soybean price, stage 2	dollars/bu					4.298
NTGP_E	Expected natural gas price, stage 1	cents/m^1	7.983				
NTGP	Natural gas price, stage 2	cents/m^1		8.310	8.517	7.336	11.110
NIR	Net irrigation requirement	cm		58.88	66.29	57.99	79.45
AWC	Available water capacity	proportion	0.208	0.207	0.208	0.210	0.207
WAPERMP	Average permeability of the root profile	cm/h	3.368	3.518	3.365	3.368	3.332
CLAY	Clay content of soil	%	23.714				
CLSNIRR	Land productivity classification[b]		2.733				
ORGMATTE	Organic matter content in soil	%	1.655				
WC3RDBAR	Water content, 1/3 bar	%	28.271				
FLOOD	Dummy for flood irrigation system[c]		1.326	0.000	0.138	0.527	0.075
STDCP	Dummy for standard center pivot system[c]		0.151	0.717	0.393	0.398	0.183
ST	Aquifer saturated thickness	m	22.981	18.508	23.174	22.617	22.329
T	Time trend[d]		7.564	7.132	7.527	5.774	10.290
Observations			1956	53	1717	93	93

[a]Here cwt is hundredweight, bu is bushel, and mcf is thousand cubic feet.
[b]Land classification codes range from 1 to 8, with lower values indicating the greatest suitability for field crops.
[c]Here 1 means yes and 0 means no.
[d]Here 1991 = 1, 1992 = 2, etc.

Table A3. Stage 1 Estimation Results[a]

Variable	Corn	Sorghum	Soybean
Constant	−374.7703*** (−4.015)	−679.5443*** (−5.566)	−499.6358*** (−4.745)
ALFP_E	2.2161 (0.929)	8.7115*** (2.807)	5.1310* (1.880)
$(ALFP\_E)^2$	−0.1526 (−0.892)	−0.6166*** (−2.764)	−0.3711* (−1.884)
CRNP_E	−33.6192** (−2.236)	−52.6358***(−3.08)	−30.8674* (−1.825)
$(CRNP\_E)^2$	6.9609** (2.162)	10.9851*** (2.979)	6.3951* (1.731)
NTGP_E	1.6199 (0.765)	1.9592 (0.785)	−1.9375 (−0.689)
$(NTGP\_E)^2$	−0.1794 (−0.552)	−0.2143 (−0.55)	0.4521 (1.051)
AWC	874.5496*** (7.190)	1161.0307*** (7.511)	926.7094*** (6.839)
CLAY	−0.8874 (−1.538)	−0.5391 (−0.085)	−1.3655** (−2.101)
CLSNIRR	0.3616 (1.216)	0.5042 (1.475)	0.1214 (0.328)
ORGMATTE	6.4284*** (5.072)	4.5507*** (2.779)	6.6417*** (4.190)
WC3RDBAR	5.8795*** (3.861)	6.6369*** (4.116)	6.8426*** (4.156)
WAPERMP	−0.8612 (−0.309)	−2.9133 (−0.929)	−2.4160 (−0.722)
FLOOD	0.3788 (0.423)	3.8968*** (3.853)	0.6823 (0.068)
STDCP	−1.9962*** (−3.748)	0.2210 (−0.313)	−2.6487 (−4.246)
ST	0.1235*** (3.414)	0.8782** (2.108)	0.1212 (2.895)
T	−0.3327** (−2.375)	−0.3857** (−2.500)	−0.1406** (−0.803)
Likelihood ratio	439.47		
Count R^2	0.885		
Pseudo R^2	0.224		

[a]Numbers in parentheses are *t* ratios. Asterisks indicate statistical significance at the 90% (one asterisk), 95% (two asterisks), and 99% (three asterisks) levels of confidence.

proxied by the February price of a December futures contract for corn. Soybean and sorghum futures prices were not included in the stage 1 model because they were highly collinear with corn prices. For alfalfa, which does not have a futures market, the expected price was proxied by a 3 year moving average of previous prices. The expected natural gas price, which would be paid during the summer irrigation season, was measured by the average of the February prices of June and July futures contracts.

[56] The decisions in stage 2 are made during the irrigation season. Expected prices in stage 2 were measured by the July prices of December futures contracts for each of the grain crops (a November contract for soybeans), while the expected alfalfa price was the current marketing year average price. Natural gas prices were the prices of average prices of June and July nearby futures contracts.

[57] Weather conditions influencing water use in stage 2 were summarized by the net irrigation requirement (NIR). The NIR was computed as the growing season potential evapotranspiration for alfalfa minus precipitation. Given the lack of detailed spatial data to compute crop-specific ET, the alfalfa ET (also known as "reference ET") at the Colby weather station was used. Variables representing the irrigator's resource setting included measures of soil characteristics, irrigation technology, and water availability. Soil variables included in both model stages were available water capacity and soil permeability. Several additional soil measures were included in stage 1 only, as they had no statistically detectable impact on water use in stage 2. Soil data were obtained from the SSURGO and STATSGO databases and were spatially merged with the WRIS data.

[58] Irrigation technologies were represented by dummy variables corresponding to the reported system in the WRIS database. There are three possible technologies: flood, standard center pivot, and center pivots with drop nozzles; the latter was the omitted base group. Water availability was represented by aquifer saturated thickness. An interpolated surface of saturated thickness was constructed across the study region for each year on the basis of well measurements at specific locations in the study region, which are taken annually by the Kansas Geological Survey during the winter months. This procedure yields data consistent with the groundwater model, but yields slightly different values for some locations compared to the data used by *Hendricks* [2007], which were obtained from a separate database.

A1. Estimation Results

[59] Tables A3 and A4 report the results of two stages of the regression model. Because of an inherent indeterminacy in the logit model, the utility function, $h_j(\mathbf{x_i},\gamma_\mathbf{j})$ in (6), must be normalized to zero for one of the choices. Here, alfalfa (j = 0) was the normalized crop and is accordingly omitted from Table A3. The fairly low R^2 measures in Tables A3 and A4 imply that a significant share of the variation in water use arise from factors our data do not capture. Nevertheless, the key parameters for the policy simulations were estimated with high precision. The parameters related to saturated thickness, which provides the link to the hydrologic model, were statistically significant at the 99% level of confidence for all crops except soybean in stage 1 and for all crops except sorghum in stage 2. These two crops are small in terms of planted acreage in our study region. The most predominant crop is corn, and most of the parameters relating corn production to the variables that change through time in the simulations had high statistical significance. A more relevant way to assess model performance for our purposes is its prediction accuracy, which is discussed below.

[60] The estimated values of the logit parameters, $\hat{\gamma}_j$, represent the marginal impact of a given variable on the utility of growing crop j. They can also be interpreted as the marginal impact on what is known as the log odds ratio, $\ln(\hat{P}_j/\hat{P}_0)$, which is an indicator of the probability of choosing crop j relative to the base crop (alfalfa). Among the variables where theory informs a direction of impact on this ratio, most were estimated with the expected sign. For

Table A4. Stage 2 Estimation Results[a]

Variable	Alfalfa	Corn	Sorghum	Soybean
Constant	−87.2349 (−1.298)	−7.2935 (−1.072)	−108.6367 (−0.806)	−17.7498 (−0.634)
ALFP	0.0487 (0.437)			
CRNP		4.3099*** (9.226)		
SRGP			1.3931 (0.504)	
SOYP				1.5321 (1.223)
NTGP	0.3145 (0.176)	−0.0613 (−0.223)	−5.9103* (−1.858)	−2.9116** (−2.146)
FLOOD(NTGP)		−1.7124*** (−3.358)	−0.9744 (−0.300)	−2.7157 (−1.544)
STDCP(NTGP)	−4.4964** (−2.061)	−0.5100 (−1.411)	3.0379 (1.055)	−0.6876 (−0.600)
NIR	−0.0263 (−0.310)	0.3033*** (16.168)	0.1348 (1.140)	0.1960** (2.307)
AWC	154.3897 (0.594)	42.4307 (1.379)	595.1839 (0.986)	45.1215 (0.381)
WAPERMP	26.2596** (−2.338)	−1.7176 (−1.462)	−13.2026* (−1.738)	4.5971 (0.696)
FLOOD		5.6767*** (4.784)	16.8968 (1.619)	11.0235** (2.317)
STDCP	9.2359* (0.087)	0.5895*** (0.656)	2.4338 0.298)	3.1528 (0.888)
ST	0.6232*** (3.524)	0.0852*** (4.257)	−0.1615 (−1.414)	0.3805*** (3.025)
T	3.3777*** (3.179)	−1.3433 (−8.831)	−2.6240*** (−2.785)	−1.6036* (−1.865)
T^2	−0.1501* (−1.849)	0.0873*** (7.752)	0.2370*** (2.616)	0.1642*** (2.926)
LAMBDA			9.1224** (2.040)	
Adjusted R^2	0.525	0.2429	0.129	0.276

[a]Numbers in parentheses are *t* ratios. Asterisks indicate statistical significance at the 90% (one asterisk), 95% (two asterisks), and 99% (three asterisks) levels of confidence. The dependent variable is irrigation water use, measured in inches.

the price variables, which enter quadratically, all estimated impacts are negative at the means of the data. This result was expected for the alfalfa price in all three equations because alfalfa and grain crops are substitutes in production. The negative impacts of the expected corn price on sorghum and soybean plantings were expected for the same reason. However, the estimated negative impact of corn prices on corn plantings was contrary to expectations. Although negative at the mean corn price, the effect becomes positive at higher corn prices in the observed range (the impact is positive for all corn prices above \$2.41, while the mean is \$2.22). One explanation for the negative estimated effect at low corn prices is that near the end of the data period (2000–2004), corn prices were unusually low while irrigators in the region continued to plant corn in large numbers. The continued preference for corn was likely caused by other time trend factors such as continuing improvements in crop varieties. If these factors were not fully captured by the linear time trend variable, part of their effect would have been picked up by the (downward trending) corn price variable. In any event, the model predicts corn with quite high accuracy. The impact of natural gas prices was estimated to be positive for all crops at the sample mean, but was not statistically significant. Among the soil attributes, available water capacity, organic matter, and field capacity water content were the most significant variables; all had a positive impact on the relative odds of growing the grain crops. Aquifer saturated thickness had a positive estimated impact on the relative odds of planting the grain crops, while the estimated time trend was negative, suggesting an increasing preference toward alfalfa over time.

[61] The estimated parameters from stage 2 can be interpreted as the marginal impacts of the regressors on within-season water use, conditional on a known crop selection from stage 1. Farmers' water use decisions during the growing season do not appear to depend strongly on the crop price, with the exception of corn. However, water use responds negatively to energy prices for all crops (except alfalfa, for which the impact is not statistically different from zero), and the significant coefficients on the energy price-system type interaction terms imply that the impacts of energy prices differ across systems. Among the remaining variables, saturated thickness had a consistently positive impact across crops (except for sorghum where the coefficient was statistically insignificant), fulfilling the expectation that farmers pump more water in thicker parts of the aquifer where well capacities are greater.

[62] While the parameters in stage 2 have a direct interpretation regarding water use after planting decisions have been made, they do not necessarily measure the impacts on expected water use before crop choices are known. Because of the sample selection problem discussed in the paper, the impacts of the variables on expected water use for crop j (where the expectation is taken prior to planting choices), depend not only on the estimated coefficients, $\hat{\beta}_j$, but also on the correction for sample selection through the variable λ_{ij}. To illustrate, consider a variable that is a regressor in both stages and let r_{it} denote its value for site year (i,t). This regressor affects $\hat{P}_{ij}$ in stage 1 and as such alters the value of λ_{ij} in stage 2 (see equation (9)). By equation (10) the estimated marginal effect of r_{it} on predicted water use, $\hat{w}_{ij}$, is

$$\frac{\partial \hat{w}_{ij}}{\partial r_{it}} = \frac{\partial g_j}{\partial r_{it}} + \hat{\kappa}_j \frac{\partial \lambda_{ij}}{\partial P_{ij}} \frac{\partial P_{ij}}{\partial r_{it}}$$

where $\hat{\kappa}_j$ is the estimated coefficient on λ_{ij} and $\partial P_{ij}/\partial r_{it}$ is the estimated marginal effect of the regressor from stage 1. In our models estimated from Sheridan County data, we could not reject the hypothesis that $\kappa_j = 0$ for alfalfa, corn, and soybean, indicating that sample selection effects are not significant for these crops. Accordingly, λ_{ij} only appears in the equation for sorghum.

[63] Table A5 shows the marginal effects of a change in energy prices on expected water use, accounting for sample selection in the sorghum equation. Two general patterns emerge in the results. First, the marginal effects on corn are much smaller compared to the other crops, suggesting that

corn producers are unresponsive to changes in energy prices during the growing season. This result is consistent with agronomic evidence that corn yields are sensitive to water stress, particularly at critical growth stages [*Scheierling et al.*, 1997]; corn producers thus apply the crop's water requirements to avoid low yields even if pumping costs increase. The second pattern is that water use is less responsive on parcels irrigated with more efficient technologies, with water demand being most responsive on flood-irrigated fields and least responsive on fields irrigated with high-efficiency center pivot systems. This implies that water demand became more rigid over time as farmers upgraded their irrigation technology.

A2. Prediction Accuracy

[64] Several site years from the WRIS database were unusable for estimation, either because some regressors were missing or the crop reported was not included in our model. The full data set has 8,888 observations, 6,169 of which had one of the four modeled crops. Of these observations, 1,956 of them had enough information on all other variables to estimate the model. Prediction accuracy in stage 1 is measured by the frequency that the model predicts the observed crop. In the estimation data set, the crop was correctly predicted for 1,582 of 1,956 observations, implying an accuracy of 81%. In the full data set the crop was correctly predicted for 4,507 of 8,888 observations (51%). However, many of the incorrect predictions arose simply because the observed crop choice was not included in the model. Within the subset of observations reporting modeled crops, the prediction accuracy was 73% (= 4,507/6,169).

[65] The water use prediction error on site year (i,t) is defined as $e_{it} = \hat{w}_{it} - w_{it}$, where w_{it} is observed water use. Table A6 reports the mean error (sample mean of e_{it}), the mean absolute error (sample mean of $|e_{it}|$), and the root-mean-square error ($\sqrt{\sum_i \sum_t e_{it}^2 / n}$ where n is the number of observations). As expected from the mean-reproducing property of regressions, ME is nearly zero in the estimation data set. It is slightly larger in the full data set (ME = 0.373), but it is still not statistically different from zero given a standard deviation of observed water use of 7.23. The error dispersion increases somewhat as the model is transferred from the estimation data set to the full data set; MAE increases from 3.71 to 4.55 inches and RMSE increase from 5.04 to 6.03 inches. The first and second columns of data compare the water prediction errors when the crop is correctly and incorrectly predicted, and column 3 is a weighted average of those in columns 1 and 2, with the share of crop predictions in each column as the weights. Naturally, the water errors are highest in column 2 where the model uses the wrong equation to forecast water use in stage 2. As noted above, the lack of crop information leads to a greater share of incorrect crop predictions in the full data set. Thus, error dispersion is higher in the full data set in large part because of data limitations. When the crop is correctly predicted (column 1), water use error dispersion is only slightly higher in the full data set compared to the estimation data.

Table A5. Estimated Marginal Effects With Respect to Natural Gas Price

Irrigation System	Crop: Alfalfa	Corn	Sorghum	Soybean
High-efficiency center pivot	0.315	−0.061	−5.913	−2.912
Standard center pivot	−4.182	−0.571	−2.875	−3.599
Flood		−1.774	−6.887	−5.627

Table A6. Econometric Model Prediction Error

Item	Crop Prediction: Correct	Incorrect	Overall
Estimation Data			
Observations	1582	374	1956
Mean observed water use	14.101	13.664	14.017
Mean error	0.022	−0.531	−0.084
Mean absolute error	3.419	4.945	3.711
Root-mean-square error	4.675	6.371	5.043
All Data			
Observations	4507	4381	8888
Mean predicted water use	14.015	13.426	13.725
Mean error	−0.016	0.774	0.373
Mean absolute error	3.728	5.400	4.552
Root-mean-square error	5.067	7.148	6.032

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