

INTEGRATING INSTITUTIONAL AND LOCAL DECISION-MAKING WITH EMERGENT
ENVIRONMENTAL PHENOMENA: THE CASE OF THE REPUBLICAN RIVER BASIN

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THESIS

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ABSTRACT

The concept of the river basin as a complex system necessitates integrated science and modeling frameworks. The linkages between policy and planning and the environment are important components governing societal response to and causes of environmental phenomena. However, large differences in theory and practice between disciplines make modeling and simulation of these interactions challenging. This study will seek to effectively understand and resolve these differences through an agent based-modeling framework. Traditional agent-based modeling in the social science seeks to understand emergent social properties and social theory by assigning simple behaviors at the small scale or individual level. This study will, instead, try and simulate emergent environmental phenomena (i.e. groundwater levels, stream flow, etc.) through a coupled agent-based model by assigning simple rules governing decision making to local institutions and farmers. The case of the Republican River Basin, a heavily utilized agricultural region with increasing interstate conflicts due receding to stream flow and groundwater levels, will serve as a basis on which to study and model the interactions between planning and emergent environmental phenomena. The model incorporates physical modeling of groundwater and hydrologic systems with a physically-based framework governing farmer's groundwater pumping and a greater social model representing local decision-making. From an initial statistical analysis, we find that spatial covariances between agricultural wells in the Republican River Basin are an important driver for decision-making and that a consideration of both environmental and social factors is key for understanding farmer's water-use behaviors. We use the coupled model to conclude that a behavioral threshold exists in which institutional and social variables may play a larger role in farmer's decision on water use than previously. In addition, we find that the implementation of water use regulations increase the heterogeneity in pumping decisions. Overall, the use of coupled physically-based and agent-based modeling illustrates the flexibility of the method to functionally integrate several models, particularly when dealing with multiple, interconnected systems.

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CHAPTER 1

INTRODUCTION

1.1 Background

River basins are frequently considered the primary unit for water resources planning and management (Barrow, 1998; Jaspers, 2003). Their spatial extent and boundaries are identified based upon hydrologic and geophysical properties. However, their geographic reach overlaps and transcends socio-political, economic and ecologic spheres in which both human and natural processes become tightly integrated (Lund and Palmer, 1997; Singh and Woolhiser, 2002; Hufschmidt, 1991; Barrow, 1998). The high level of interaction between these human and natural systems results in multifaceted cause and effect relationships in which feedbacks between hydrologic systems and human decision-making can propagate from local to basin scale and have profound system-wide effects (Schluter and Pahl-Wostl, 2007). Therefore, we can further define a river basin as a complex, coupled-human nature system (Liu *et al.*, 2007).

Management and planning of river basins must be able to adapt and consider the complex nature of these feedback effects at the system level. More specifically, management processes must be both physically and socially oriented and tasked with maximizing benefits upstream while minimizing environmental and social consequences downstream (Hufschmidt, 1991). Importantly, coordination of these processes must be able to handle future changes to physical and socio-economic phenomena so management can aim to be preventative instead of solely reactive (Barrow, 1998). This perspective is key for river basin planning and management as the linkages between policy, planning and the environment are important components governing societal response to and causes of environmental phenomena, see Figure 1 below (Liu *et al.*, 2007). The investigation of a river basin as a complex, coupled human-natural system necessitates innovative integrated science and modeling frameworks capable of understanding

the coupled river basin system as a complex entity. Overall, a better understanding of the dynamics of basin-wide hydrology and human behavior can contribute to future strategies for integrated planning and management.

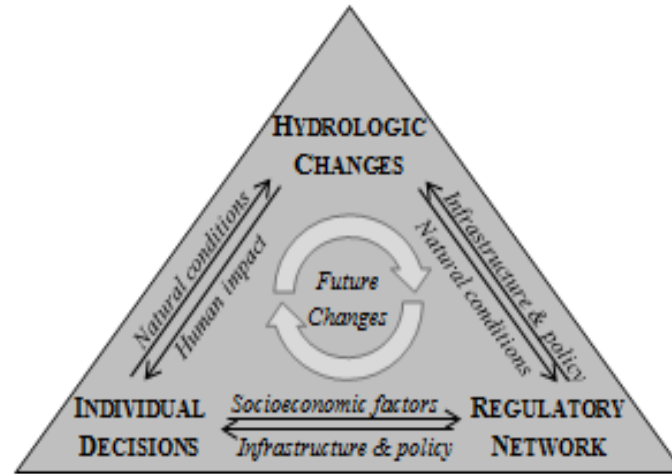


Figure 1: Conceptual diagram of river basin planning and management

River basin management offers the possibility to serve as a medium for interdisciplinary work and communication between physical and social scientists. Today, researches across disciplines seek to better understand water use behaviors (Athanasiadis and Mitkas, 2005; Kanyoka, *et al.*, 2008; Farolfi, *et al.*, 2007), appropriate management strategies (Galán, *et al.*, 2009; Abolpour and Javan, 2007; Yang, *et al.* 2010), and ecological and river dynamics (Yamazaki, *et al.*, 2011; Mao, *et al.*, 2010; Mathevet, *et al.* 2003) in a river basin context. Multiple studies currently exist in the field of coupled human-nature systems and water resources planning and management that work to bridge the gap between disciplines as well as foster collaboration between researchers. Mayer and Muñoz-Hernandez (2009) examine integrated water resources modeling and highlight the need for improvements in integrating biophysical systems and considering the impacts of water allocation and water users. López-Carr, *et al.*

(2012) use geographic weighted regression and multi-level models to understand the drivers of land cover change in a case study in Guatemala. Their work draws from geography, ecology, statistics and sociology and highlights the importance of spatial effects in analyzing human-environment interactions (López-Carr, *et al.*, 2012). Muñoz-Hernandez, *et al.* (2011) develop an integrated hydrologic-economic-institutional model to examine the relationship between environmental flows, agricultural benefits and agricultural water allocation.

Overall, this literature shows a strong emphasis on interdisciplinary work, but also points to the need for methods that are better able to incorporate multiple disciplines into the modeling, analysis and research of coupled human-nature systems. Coupled agent-based and physically-based models are presented in this work as a platform capable of dynamically simulating and addressing these issues that cross the boundaries between traditional disciplines.

In a river-basin context, one important component of these coupled dynamics is how local economic and social systems respond to management decisions as well as to the characteristics of their surrounding environment. This research aims to characterize the behavior of local human systems and the subsequent response of the surrounding hydrologic system to changes in management decisions as well as larger, system-wide hydrologic change. The Republican River Basin (RRB), where intensification of agriculture upstream has caused increasing interstate conflicts due to receding stream flow and groundwater levels, serves as a basis on which to study these phenomena.

1.2 The Republican River Basin

The Republican River Basin (RRB) is located in the western United States and covers approximately 25,018 square miles (Bjerke, 2009). The RRB has two main tributaries – the North Fork and the Arikaree – and flows from west to east eventually combining with the Smoky Hill River to form the Kansas River (RRBDP, 2008). The High Plains Aquifer, or the Ogallala Aquifer, underlies the basin and provides the baseflow to the Republican (Kelly, 2010). Thirty-one percent of the basin's area lays in Colorado, thirty percent in Kansas, and thirty-nine percent in Nebraska (Bjerke, 2009). Figure 2 shows the geographic boundaries of the basin along with local political divisions in Nebraska.

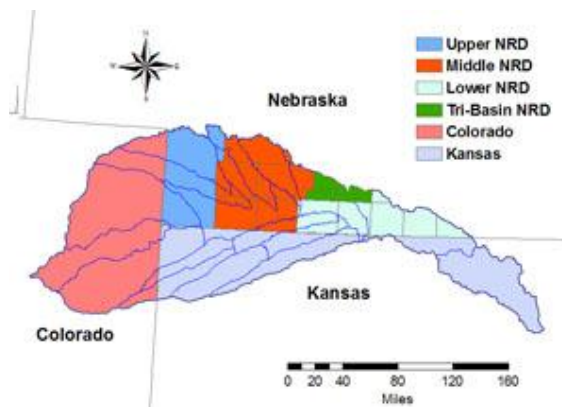


Figure 2: Republican River Basin

The RRB is of particular importance to study due to an important recent Supreme Court decision on the allocation of water within the basin. In 1942, Colorado, Nebraska and Kansas entered into a compact that allotted a certain amount of “virgin water supply”, that unaffected by human use, to each state (Kansas Department of Agriculture, 2006). Since this time, intensification of agriculture in the upstream portion of the basin (Colorado and Nebraska) has resulted in large environmental changes, most notably decreases in stream flows downstream in Kansas. Today, these significant environmental impacts of agricultural water use are the source

of conflict between the three states and a complex legal and management framework exists to uphold the 1942 Compact. Nebraska is the primary region of focus for this study, as much of the upstream water use for irrigation takes place there. Economic dependence on irrigated agriculture, with \$3.6 to \$4.5 billion in net economic impact annually, drives continued groundwater use for irrigation throughout the state (Kelly, 2010).

1.2.1 Land and Climate

The basin is composed of fairly well-drained silt loam or loam soil throughout most of Nebraska and Kansas, with some sandy and clayey soils in the western region of the basin (Finckner, 2006). Land cover is dominated by agriculture, which contributes to nearly 98 percent of water used for irrigation in some regions (RRBDP). Precipitation and temperature are less homogeneous and vary widely from upstream to downstream. Average annual precipitation is about 15 inches in the western or upstream reaches and increases to 25 inches further downstream (RRBDP, 2008). Basin-wide average annual temperature is 51°F and evaporation averages 55 inches per year due to high wind and low humidity (Kansas Water Office, 2009). Drought is also a common feature of the basin, with severe or extreme drought conditions occurring 10-20 percent of the time over the last one hundred years (RRBDP, 2008).

1.2.2 Historical Background and Current Issues

The river basin first began to develop starting in the late 1800s, with attempts to cultivate agriculture and utilize the river for irrigation following shortly after (RRBDP, 2008). In 1935, a large flood brought considerable damage and highlighted the need for better control of the river and development of the land (RRBDP, 2008). From the 1940's onwards, construction and

management of dams for flood control and surface water canals for irrigation intensified, lending itself to increasing agriculture in the region (RRBDP, 2008; Hansen, 1997). Concern over sharing of the river resources led to the Republican River Compact of 1942 in which Colorado was allocated 11 percent of the river's surface water, and Nebraska and Kansas received 49 and 40 percent, respectively (Kansas Water Office, 2010). At this time, water for irrigation was still predominantly from surface water. However, the introduction of center pivot irrigation in the 1960's and refinement in irrigation technology in the proceeding decades led to the rapid expansion of the use of groundwater for irrigation (Kelly, 2010; Nutt-Powell and Landers, 1979). During this time increasing acreage was also allocated to corn, which was predominately an irrigated, rather than rain-fed, crop (Kucharik and Ramankutty, 2005). By the 1990's, the intensification of groundwater use in the area had resulted in a large demand on the regions natural and water resources and led to groundwater and surface water declines across the basin (Nebraska NRCS, 2008). In some areas, groundwater declines of 30 to 40 feet were common and resultant surface water changes soon became a source of conflict between Kansas, Nebraska and Colorado (Kelly, 2010). In 1998, the state of Kansas filed suit against Nebraska stating that it had violated the compact through the significant use of groundwater, which is hydraulically connected to the river system, over time (Kansas Department of Agriculture, 2006). The case was brought to the Supreme Court and in 2001 settlement talks began, with a decision reached in 2002 (Kansas Department of Agriculture, 2006). As a result, Nebraska must maintain a specific level of streamflow at a gauging station downstream of the Kansas-Nebraska border and also regulates groundwater use upstream to control future depletion. In Nebraska alone, there are over 10,000 agricultural wells that are registered and fit with metering devices to monitor water use (Nebraska NRCS, 2008). Over the past 30 years, regulations on water use in Nebraska have

become stricter and today range from nine to 13 acre-inches per year depending on the area (Upper Republican NRD, 2011). Water use regulations constitute a key point of coupling between hydrologic, institutional and agricultural systems in the Republican River Basin and will be the focus of agent-based modeling efforts for this study.

1.2.3 Key Institutional Actors

This research will consider three main institutions involved at the local scale in agricultural water use and groundwater use regulations in the Nebraska portion of the basin – Natural Resource Districts (NRDs), Public Power Districts (PPDs) and Irrigation Districts (IDs). Natural Resource Districts are political bodies run by locally elected officials charged with, among other tasks, groundwater management (Kelly, 2010). Management plans are subject to approval by the state level Department of Natural Resources (DNR) who maintains authority over surface water, but the NRDs have sole authority to regulate groundwater in the state (Patent, 2008). NRDs can vote on, assess and change groundwater restrictions. Because NRDs are governed by elected boards of directors – often local irrigators – these institutions have a vested interest in continued groundwater use for irrigation. They are “reluctant to restrict their own and their neighbors’ use of groundwater” (Patent, 2008). Other research has agreed with this statement, describing NRDs as “a closed club of irrigators that are destined to preserve the status quo while giving the appearance of movement toward the solution of pressing water problems” (Stephenson, 1996). Public Power Districts (PPDs) and Irrigation Districts (IDs), conversely, do not have direct regulatory authority, but are still active in groundwater management in the region. PPDs share a strong interest in continued groundwater use for irrigation, as much of their revenue comes from irrigation. The Dawson Public Power District, for example, generates one

third of its revenue from irrigation services (Dawson PPD, 2012). Surface water irrigation districts, instead, are more concerned with surface water flows and have taken legal action against the state of Nebraska to preserve the 1942 Compact and ensure their water rights (Frenchman–Cambridge Irrigation District v. Department of Natural Resources) (Heavican, 2011).

1.3 Thesis overview

Overall, we seek to understand the dynamics of farmer behavior on groundwater use, regulatory institutions and decision-making and the feedbacks and response of natural groundwater and surface water systems in the Republican River Basin. We view the RRB as a coupled human-nature system and thus utilize integrated methods and draw from multiple disciplines to study it in a meaningful way. This research is broken down into the following components, to be described and analyzed in the subsequent chapters.

Statistical behavior analysis

This portion of the project aims to characterize the behavior of local human systems, in this case that of farmers, in response to environmental and social variables using a Bayesian analysis framework. Markov Chain Monte Carlo sampling is used to fit four different regression models, and the regression parameters and fit of each model are analyzed. Findings show that incorporation of both social and environmental variables leads to a better fit model and a better understanding of farmer decision-making in this region.

Agent-based modeling

In this section, we adopt an agent-based model (ABM) to simulate the behavior of farmers and regulatory systems, and a groundwater simulation model (MODFLOW2000) to simulate the impact of groundwater pumping on ground water levels and surrounding stream flows. The two models are coupled to simulate the interactions between farmer's irrigation decisions, regulatory measures and hydrologic systems. The agent-based model simulates: 1) farmer's daily decisions on irrigation; 2) institutional response to the streamflow decline; 3) institutional interactions with farmers. Farmer's daily decisions are simulated using an irrigation water balance approach based on soil water deficits. Three types of institutions, which have varied interests in the region, are also modeled. They respond to changes in the streamflow by changing regulations over time.

Coupling with MODFLOW 2000

A physically-based groundwater model was developed to simulate the response of groundwater and surface water to agricultural water use. MODFLOW-2000 and the stream package are utilized to solve for changes in the water table and changes in a nearby stream in response to the farmer's daily pumping decisions. The yearly changes in streamflow that are an output of this model are then used as a factor by which institutional agents make decisions on changes in regulations.

The following sections are organized around these three components. In the remainder of the document, we first present the statistical behavior analysis in order to gain understanding of the quantitative relationships between farmers, institutions and the environment. Next, the

background and methodology for the agent-based model and groundwater model will be described. Results and discussion that relate the output of the agent-based model to inferences on decision-making and water use in region then follow. Finally, conclusions will be presented as well as suggestions for possible management strategies in light of our findings.

CHAPTER 2

STATISTICAL BEHAVIOR ANALYSIS

In a river basin context, one important component of the dynamics of coupled human nature systems is how local economic and social systems respond to both management decisions as well as the characteristics of their surrounding environment. In this section, we use a Bayesian analysis framework to characterize the behavior of local human systems, farmers, in response to environmental and social variables. This goal is both important for deriving empirical relationships that will be inputs into the agent-based model as well as helping to guide water management in the region through a better understanding of the dynamic processes and reasons by which well owners (farmers) make decisions on water use. More specifically, this study seeks to answer two main research questions:

Q1: Is a farmer's neighborhood a significant factor in determining decisions on water-use?

Q2: Does the influence of institutions that play a role in water usage regulations in Nebraska impact a given farmer's annual pumping volume?

To address these questions, we first formulate a model with basic physical considerations and then extend it with three additional models that will help to understand more complex spatial and social relationships. The base linear regression model relates an independent variable, yearly groundwater use for irrigation, to the following dependent variables: 1) agricultural acreage; 2) crop evapotranspiration; 3) distance to nearest stream; 4) fully irrigated crop yield; 5) soil type; 6) precipitation. We fit this model for each well in the Nebraska portion of the Republican River Basin. By quantifying the multivariate relationship between physical parameters and water use,

we can first understand the impact that each parameter has on a farmer's irrigation decisions. We then extend the model by adding a random effects term to the base regression model to explicitly model the variance that is not captured by the covariates (Clark, 2007). Because both the independent and dependent variables vary in space, some of these unexplained differences can be attributed to spatial effects (Clark, 2007). The next extension replaces the general random effects term with conditional autoregression (CAR). This allows the model to take into account the correlation between nearest-neighbor wells (Clark, 2007). The final extension of the base model, simply adds an extra regression covariate – the distance to nearest institutional office. This is meant to serve as a proxy for institutional influence or engagement and provides some insight into the external social factors surrounding water management in the region (Wilson and Veuger, 2011). Because these three extensions integrate physical and social parameters, we also utilize them to help quantify spatial differences in farmer behavior for the ABM. Deviance information criteria (DIC) scores will assess the goodness of fit between the base model and each of the three extension models. The following sections will describe 1) the use of regression models in behavior analysis; 2) the methodology used for developing and fitting the four models; 3) results and key findings; 4) conclusions.

2.1 Methodology

2.1.1 Regression models for behavior analysis

Regression models have been used in the social sciences for the prediction of human behavior. A number of notable approaches and theories described here can aid in understanding how and why quantifying human behavior through data-driven regression is both effective and applicable. Research in the social sciences, as early as the 1970s, has shown that linear models

are capable of effectively capturing the decision-making and weighting behavior of individuals (Slovic, *et al.*, 1977; Slovic and Lichtenstein, 1971). The following methods that quantify or understand human behavior through regression are relevant to this study: the theory of planned behavior, information integration theory, and social judgment theory.

The theory of planned behavior from psychology, as reviewed and developed by Ajzen (1991), allows us to relate empirical relationships derived from regression to predictors for human behavior. Generally, the theory is based on the idea that general attitudes are not a good predictor of behavior, but instead the individual's perception is (Ajzen, 1991). Both "the resources and opportunities available to a person must to some extent dictate the likelihood of behavioral achievement" (Ajzen, 1991). These components can be thought of as predictors for behavior. This study does not reflect the complex relations and tenants of the theory but rather draws simply from one component of it - its emphasis on quantifying the causal factors or predictors that drive an individual's behavior through a mathematical equation. Ajzen relates the regression coefficients of this equation to the expected value of the response variable (1991).

Through information integration theory, Anderson (1971) used the integration model, below, to quantitatively describe attitude change, decision-making, perception and learning.

$$R = C + \sum_{i=0} w_i s_i$$

Where R is the individual's response variable, C is a constant, and w_i is a vector of weights associated with each stimuli or judgment, s_i (Anderson, 1971). The coefficient, w_i , can also be thought of as an individual's valuation of a given stimuli. In this study, stimuli are represented by various environmental and social factors for each well, such as crop

evapotranspiration, precipitation, location, proximity to local institutions, etc. By extending Anderson's approach and fitting a regression equation, we are empirically weighting the value of each social and environmental judgment for each well. This approach, the valuation of individual stimuli and the integration of them are key components of Anderson's theory (Anderson, 1971). Ultimately, he concludes that the use of the above integration model is useful quantitatively and qualitatively (Anderson, 1971). We adopt his concepts of valuation and integration to formulate the linear decision-making regression framework.

Social judgment theory also draws on the concept of stimulus-response as the basic unit for cognition (Hammond, *et al.*, 1975). Regression is one method employed by this theory to quantify and relate stimuli to an individual's response or decision (Hammond, *et al.*, 1975). The concepts of control and consistency are used in order to evaluate regression results. Control is defined as "the similarity between an individual's judgments and predictions based on a specific model", and consistency as "the similarity between repeated judgments of identical profiles" (Hammond, *et al.*, 1975). This theory is important to consider because it provides a mechanism and a background on how fitted regression models can be linked to behavior patterns.

Generally, linear models that relate stimuli to response are widely used for quantifying human decision-making and are employed by this study to determine significant stimuli for water-use decisions. From this, we address the stated hypotheses as well as extend these models to inform the coupled agent-based model in the following section.

2.1.2 Exploratory Data Analysis

The data used for this study include: yearly volume of water pumped in acre-feet, coordinates of every well (decimal degrees), distance to nearest stream (feet), potential

evapotranspiration for corn (inches per year), estimated fully-irrigated crop yield for corn (bushels per acre per year), annual precipitation (inches), soil class by category (silty, sandy, loamy), distance to nearest water institution (feet). All data is spatially referenced by well for 10,908 wells in Nebraska. These were collected and analyzed based upon a dataset created by Palazzo (2009), data from the Republican River Compact Administration and data on water institutions from a variety of sources. The sources and analysis on each are described in this section. The plotted figures shown in this section help in understanding the initial relationships between these covariates (plotted on the x-axis) and the response variable – acre-feet of water (plotted on the y-axis). Only active wells, those pumping more than zero acre-inches in the year, were used in this analysis.

Water use and well data: Nebraska's Department of Natural Resources (DNR) collects data and maintains a database for all agricultural wells across the state that includes well-specific data on water-use, certified irrigated acreage, owner identification, etc. (Palazzo, 2009). Water use data is acquired by the DNR from well meters which are mandatory for all wells across the Nebraska portion of the basin (Palazzo, 2009). Data was obtained for every well in the Nebraska portion of the Republican River Basin for one year, 1996, from a dataset prepared by Palazzo (2009). The dataset included 10,908 wells but only those with water-use values greater than zero were used in this analysis.

Evapotranspiration for corn: Using evapotranspiration (ET) data for corn from Nebraska's Cooperative Extension program, ET values were obtained for the centroid of each county (Palazzo, 2009). This was interpolated across space to calculate values for all wells using a cubic spline (Palazzo, 2009). Figure 3 below shows there is a slight positive relationship between ET for corn and annual volume of water for irrigation.

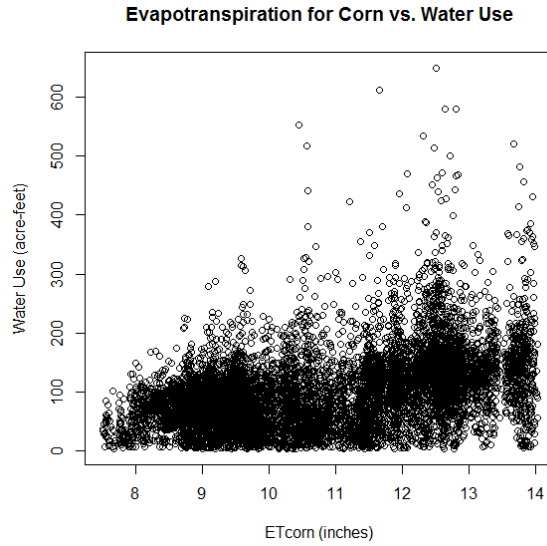


Figure 3: Evapotranspiration for corn (inches per year) plotted against annual water use (acre-feet), referenced by well

Distance to nearest stream: Using DNR data on the stream network in Nebraska, distances between each well and the nearest stream were calculated in ArcMap (Palazzo, 2009). Figure 4 below does not show a significant relationship between distance to nearest stream and agricultural water uses.

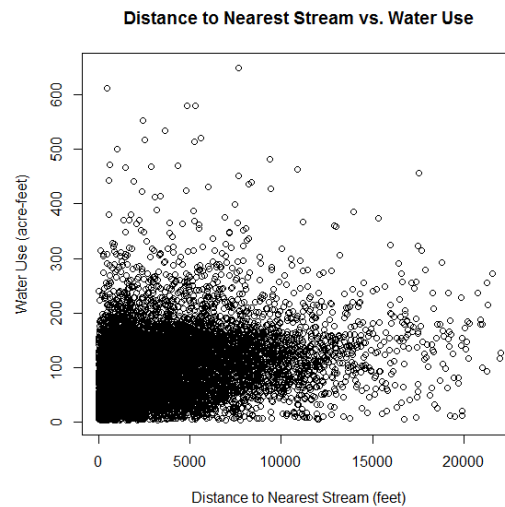


Figure 4: Distance to nearest stream (feet) plotted against annual water use (acre-feet), referenced by well

Certified acreage: Certified irrigated acres were obtained from input files for the RRCA groundwater model, as these data better reflect real historical irrigated acres than other estimates of irrigated acreage and are also those used for determining water allocation in the region (Palazzo, 2009). Figure 5 below shows a strong positive relationship between irrigated acreage and water use.

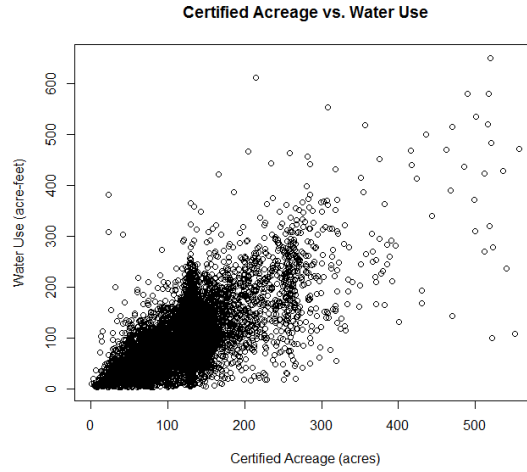


Figure 5: Certified irrigated acres plotted against annual water use (acre-feet), referenced by well

Fully irrigated crop yield for corn: Fully irrigated crop yield was calculated by Palazzo according to the following equation (2009):

$$Y_j(I_j) = Y_j^d + (Y_j^m - Y_j^d) \left(1 - \left(1 - \frac{I_j}{I_j^m} \right)^{1/B_j} \right)$$

Where Y_j is the irrigated yield for crop j ; I_j is the irrigation water applied; Y_j^d is the dryland yield for crop j ; Y_j^m is the maximum irrigated yield for crop j ; I_j^m is the water applied that yields Y_j^m ; and B_j is the technical efficiency (Palazzo, 2009).

Figure 6 below shows the relationship between fully irrigated crop yield and volume of water use.

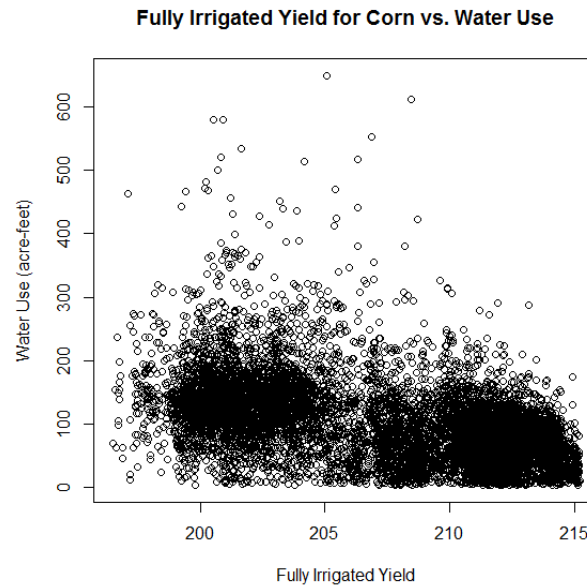


Figure 6: Fully irrigated yield for corn plotted against annual water use (acre-feet), referenced by well

Precipitation: Data for annual precipitation in Nebraska was obtained from the Republican River Compact Administration website's data files for the RRCA groundwater model (Republican River Compact Administration 2012). From this dataset, four average values were determined for four zones across the Nebraska portion of the basin. In this way, the most arid region received 16 inches per year and the wettest received 27 inches per year. These values were taken from the 2006 dataset to keep them consistent with water use and evapotranspiration data.

Soil type: This dataset was transformed into categorical presence-absence data for regression. The STATSGO geospatial database of soil types was related to each well in ArcMap to create well-specific soil types (Palazzo, 2009).

Distance to nearest institution: For analysis of proximity to water institutions in the region, a shape file was created in ArcGIS using longitude and latitude of known institutions obtained from Google Maps. These included office locations for: Nebraska's Department of Natural Resources, more local Natural Resources Districts, surface water irrigation districts, public power districts, and local groundwater and irrigation organizations. Using the Near Table tool in the Arc Toolbox in ArcGIS, the distance in feet between every well and the nearest institution was determined. Figure 7 illustrates the spatial layout of institutions and agricultural wells.

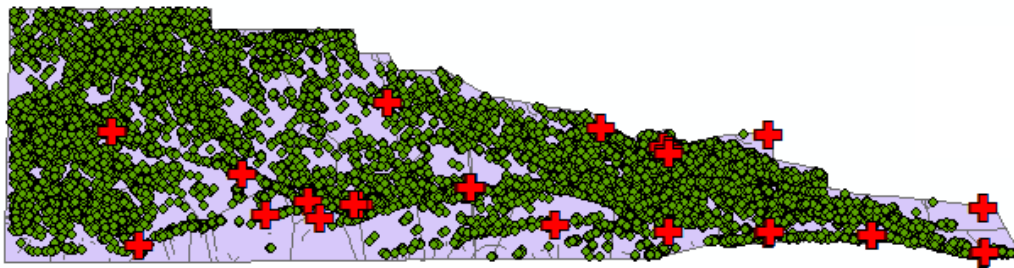


Figure 7: Map of Active Groundwater Wells (green) and Water Institutions (red) in the Nebraska portion of the Republican River Basin

Figure 8 below does not show a significant relationship between distance to nearest water institution and pumping volume for agriculture.

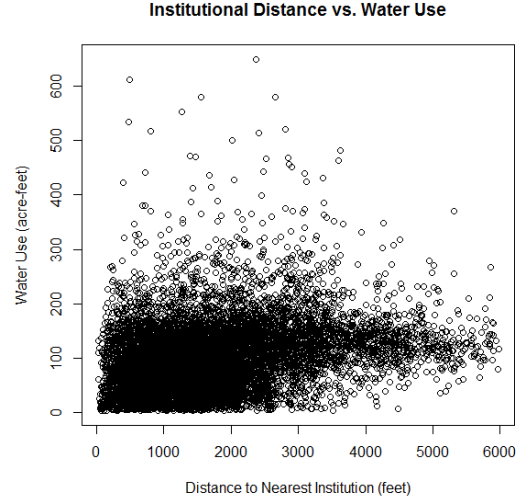


Figure 8: Distance to nearest institution (feet) plotted against annual water use (acre-feet), referenced by well

2.1.3 Bayesian Analysis for Regression

Bayesian inference is a statistical method through which statistical models can be analyzed with the incorporation of prior knowledge about the model or its parameters (Clark, 2007). The general framework for a Bayesian analysis is based on Bayes' Theorem (Clark, 2007):

$$p(\theta|y) = \frac{p(y|\theta)p(\theta)}{p(y)}$$

Where $p(\theta|y)$ is the posterior distribution, or the probability of our model given our data

$p(y|\theta)$ is the likelihood, or the probability of our data given our model

$p(\theta)$ is the prior distribution, or prior knowledge, of our parameters

$p(y)$ is the probability of our data

Solving for the posterior distribution involves fitting model parameter values, such as μ or σ^2 . In cases that cannot be solved analytically, numerical methods are used to fit models to the data. Numerical methods for Bayesian analysis are achieved through random draws, or samples, from the posterior and are assessed based on a certain criteria (Clark, 2007). For this study, Markov Chain Monte Carlo (MCMC) simulation is used to estimate our posterior model via the OpenBUGS software platform (OpenBUGS, 2009).

In our regression framework, the posterior distribution of interest is that of the regression parameters. We assume a data model $p(y|\theta)$ that is normally distributed around the expected value of the regression model and a normally distributed error, $Y_i \sim N(wt_i, \sigma^2)$. The prior distributions, $p(\theta)$, selected for the analysis were uninformative normal prior distributions. Priors on the error variances were represented by uninformative inverse gamma distributions.

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2.1.4 Process Regression Model

Bayesian analysis is also widely used for fitting regression equations (Clark, 2007). A regression model is also appropriate for this study due to its ability to simulate multivariate decision-making (Dawes and Corrigan, 1979). For the purposes of modeling farmer behavior, we formulate one base regression model and three extensions that take into account more complex relationships.

Model 1 – Base model

The base model serves to quantify the impact each of the dependent variables – agricultural acreage; crop evapotranspiration; distance to nearest stream; fully irrigated crop

yield; soil type; precipitation – has on a given farmer's yearly water use for agriculture. We consider all these variables together, assuming they each play a role in impacting a farmer's decision on irrigation. From this, we hope to derive some basic quantitative relationships between the physical environment and a farmer's water use. We fit this model for all wells with an annual pumping volume greater than zero.

The following regression equation is used for Model 1:

$$\begin{aligned}
Y_i &\sim N(wt_i, \sigma^2) \\
wt_i &= \sum \beta_i X_i \\
\beta_i &= [b_0 \ b_1 \ b_2 \ b_3 \ b_4 \ b_5 \ b_6] \\
X_i &= [x_1 \ x_2 \ x_3 \ x_4 \ x_5 \ x_6] \\
b_6 &= [s_1 \ s_2 \ s_3 \ s_4 \ s_5] \\
x_6 &= [t_1 \ t_2 \ t_3 \ t_4 \ t_5] \\
\epsilon_i &\sim N(0, \sigma^2)
\end{aligned}$$

Where Y_i is the normally distributed data model with mean wt_i and variance σ^2 ; wt_i is the expected water use for well i ; β_i is a vector of covariate coefficients with b_0 as the intercept; X_i from (4) is a vector of covariate input data: x_1 is ET_{corn} ; x_2 is distance to stream; x_3 is certified acres; x_4 is expected crop yield; x_5 is precipitation; x_6 is an additional vector that signifies soil type, a categorical variable; ϵ_i is the error which is assumed to be normally distributed with variance σ^2 . Because we use a linear model, we make the standard assumption of a normally distributed error and normal data model (Dietze, 2008; Clark, 2007). This set of equations represents the basic regression model, Model 1, and only explicitly model these physical factors and how they impact annual groundwater use for irrigation.

Model 2 – Base model and random effects

Model 2 extends the base model to include α_i , a term that explicitly models the variance due to differences between wells. These “random effects” models are typically used in cases where there may be other unmeasurable covariates that significantly contribute to the response variable (Clark, 2007). Because a linear regression model assumes all error is in y_i , the independent variable, we need to incorporate a term to account for error between wells (Clark, 2007). In this case, α_i represents a specific partitioning of error between wells. Here, α_i allows us to quantify the impact of unmeasurable covariates that may be due to space, time or other local social factors. In this case, we can interpret α_i as a generalized way to quantify the impact of a farmer’s location. By comparing the model fit to that of Model 1, we can also justify the use of a more explicit spatial model, Model 3. The equations below show how α_i is added to the base model.

$$\begin{aligned} Y_i &\sim N(wt_i, \sigma^2) \\ wt_i &= \sum \beta_i X_i + \alpha_i \\ \alpha_i &\sim N(0, \tau^2) \end{aligned}$$

Model 3 – Base model with conditional autoregression (CAR)

Model 3 uses the method of conditional autoregression (CAR) to specifically model the interdependence among water-use between adjacent wells. To formulate this model, additional steps are required to create an additional dataset that is generated based on spatial adjacencies. We first treat our dataset of point-referenced data as block referenced data in order to carry out CAR. Because we are interested in the relationships between neighboring or adjacent wells, rather than the actual distances between them, this assumption is made. To represent point-

referenced data as areal data, ArcGIS is used to generate a shape file of all active wells and then a shape file of surrounding area is created using a Thiessen polygon network. This shape file is then converted into a Splus format readable by GeoBUGS. Figure 9 shows the adjacency map in OpenBUGS.



Figure 9: Thiessen Polygons for active agricultural wells in the Nebraska portion of the Republican River Basin.

CAR is incorporated into the existing model through an additional term in the regression equation. Inclusion of this term allows us to specify the expected response, wt_i , conditioned, in part, on nearby wells. The term in bold shows the addition of spatial covariance to the existing model, and can be re-written as ρ in the following equation (Clark, 2007). The elements of matrix w are weights that specify the covariance within the area (Clark, 2007).

$$wt_j = \beta_j X_j + \frac{1}{w_j} \sum_k w_{jk} (wt_k - \beta_j X_j) + \epsilon_j$$

$$\rho \sim N\left(0, (I - \tilde{W})^{-1} \sigma^2 I\right)$$

In OpenBUGS, the GeoBUGS tools generate the adjacency matrix and input data that make up the above CAR distribution. From the model shown below for Model 3: w_{ij} represents

the adjacency matrix; the weights, w_i are all set to one to signify unnormalized weights between neighboring areas (OpenBUGS, 2007).

$$\begin{aligned}
Y_i &\sim N(wt_i, \sigma^2) \\
wt_i &= \sum \beta_i X_i + rho_i \\
rho_i &= \frac{1}{w_i} \sum_{j \neq i} w_{ij} (y_i - wt_i) & w_{ij} = \text{spatial proximity matrix} \\
rho_i &\sim N\left(E[wt_i], \left((1 - w_{ij})^{-1} \tau^2 I\right)\right)
\end{aligned}$$

Model 4 – Base model with institutional distances

Finally, Model 4 incorporates the data generated on institutional distances, x_7 , and an additional regression coefficient, b_7 , in order to address Question 2. By comparing the fit of this model to the base model that only considers physical parameters we can make conclusions about the role that institutional proximity and influence play in annual decisions on water use.

$$\begin{aligned}
Y_i &\sim N(wt_i, \sigma^2) \\
wt_i &= \sum \beta_i X_i + b_7 x_7
\end{aligned}$$

2.1.5 Numerical Estimation Methods

Using the tools from OpenBUGS, the four models were solved using MCMC numerical methods. OpenBUGS automatically selects the algorithm from one of three families – Gibbs Sampling, Metropolis-Hasting and Slice Sampling (OpenBUGS, 2009). The general framework for an MCMC algorithm starts at an initial value for each parameter (Clark, 2007). From this value, a Markov chain that estimates the target distribution from a random walk is generated

(Clark, 2007). Samples are then drawn to guess new parameter values and a new posterior distribution (Clark, 2007). The algorithm then assesses the two posterior estimates and decides whether to accept or reject the new distribution (Clark, 2007). Over time, this method converges to a target distribution (Clark, 2007). For this analysis, OpenBUGS uses the Metropolis-Hastings algorithm, which uses a non-symmetric jump distribution to sample random candidate parameter values and assess candidate acceptance (Clark, 2007). This is important to mention, because our target distribution needs to remain positive and a Metropolis sampler could not insure this as it requires a symmetric jump distribution.

Convergence of the models was determined based examining the smoothness of posterior distributions and the behavior of the three MCMC chains every 10,000 iterations. Use of autocorrelation plots in OpenBUGS made it possible to observe the correlations between the three MCMC chains. High autocorrelation typically indicates slow convergence and should be reduced (Plummer *et al.* 2002). For convergence, autocorrelation was monitored and the output was thinned until there was zero autocorrelation at a lag of one. Another issue impacting the results is multicollinearity, or correlation between model parameters. Due to the large sample size, we assume that the multicollinearity between dependent variables does not dramatically impact the regression fit (Ayyangar, 2007). In addition, because our interest is focused on the differences between different models instead of within a single model, multicollinearity is not a large concern (Motulsky, 2002).

2.2 Results

2.2.1 Deviance Information Criterion (DIC)

Deviance Information Criterion (DIC) scores are commonly used to assess the fit of models used in Bayesian analyses (Clark, 2007). To compute the DIC scores, we can calculate and store the deviance at each MCMC iteration that is given by the following equation:

$$D(\theta_i) = -2\ln L(y|\theta_i)$$

After sampling is complete, posterior means for parameters are calculated, $\bar{\theta}$, and the deviance is calculated again for this average value.

$$D(\bar{\theta}) = -2\ln L(y|\bar{\theta})$$

The average deviance $\overline{D(\theta)}$ is also computed as:

$$\overline{D(\theta)} = \sum_{i=1}^n D(\theta_i) / n$$

Finally, we compute the DIC score as:

$$DIC = 2\overline{D(\theta)} - D(\bar{\theta})$$

Table 1, below shows the DIC scores and the results of the four models

	Model 1 Basic Regression		Model 2 Random Effects		Model 3 CAR		Model 4 With Institutions	
<i>DIC</i>	104100		76410		53510		104000	
	μ	σ^2	μ	σ^2	μ	σ^2	μ	σ^2
<i>b0</i>	465	58.67	462.9	51.94	-1232	702.1	466.1	56.36
<i>b1</i>	2.592	0.7714	2.63	0.6908	56.97	5.647	2.608	0.7461
<i>b2</i>	0.000402	0.0001292	0.0004045	0.0001286	0.001053	0.0002559	0.0004051	0.0001287
<i>b3</i>	0.6675	0.007781	0.667	0.007745	0.6773	0.01521	0.6674	0.007734
<i>b4</i>	-2.336	0.2432	-2.329	0.2162	5.124	0.5715	-2.328	0.2335
<i>b5</i>	0.1335	0.1054	0.1365	0.1045	9.268	24.42	0.05378	0.114
<i>b6</i>	-	-	-	-	-	-	-0.0007414	0.0003986
<i>s1</i>	9.594	5.778	9.619	5.662	74.95	84.87	9.564	5.768
<i>s2</i>	14.76	3.894	14.85	3.866	74.56	78.92	14.78	3.893
<i>s3</i>	5.592	3.62	5.693	3.639	25.6	82.81	5.568	3.629
<i>s4</i>	3.808	3.677	3.944	3.724	23.15	85.74	3.748	3.684
<i>s5</i>	12.11	3.741	12.25	3.737	48.09	81.78	12.09	3.749
<i>Precision Y[i]</i>	0.0006073	0.000008536	0.03496	0.1823	0.199	1.544	0.0006074	0.000008514
<i>Precision a[i]</i>	-	-	1.855	4.533	-	-	-	-
<i>Precision p[i]</i>	-	-	-	-	0.7145	2.64	-	-

Table 1: Regression parameter values and model DIC scores for each of the four models tested

Recall, Y_i is the normally distributed data model with mean wt_i and variance σ^2 ; wt_i is the expected water use for well i ; β_i is a vector of covariate coefficients with b_0 as the intercept; X_i is a vector of covariate input data: x_1 is ET_{corn} ; x_2 is distance to stream; x_3 is certified acres; x_4 is expected crop yield; x_5 is precipitation; x_6 is an additional vector that signifies soil type, a categorical variable, with coefficients s_i ; ϵ_i is the error which is assumed to be normally distributed with variance σ^2 . Here $\text{precision} = 1 / \sigma^2$.

In general, a DIC score that is 10 points lower than another is considered to have a better fit (Clark, 2007). When analyzing the DIC scores in Table XX, we can see that Model 3 is the best fit as it has a much lower value than the other three models, this suggests that a farmer's neighborhood has a strong impact on water use. From the DIC scores of the other three models, we can see that Model 2, which considers random unmeasurable effects, is a significantly better fit than either Model 1 (base model) or Model 4 (base model with institutional distances). These effects could generally be linked to a farmer's neighborhood given the results of Model 3, but could also be a result of socio-political factors that we are unable to quantify in these analyses. By comparing the DIC scores of Model 1 and Model 4, it can be concluded that Model 4 is a better fit. However, the magnitude of difference between these two DIC scores is considerably lower than the other two cases. This comparison indicates that institutional influence may play a role in a farmer's water-usage decisions. Ranking the models in order of best fit: 1) Model 3 (CAR); 2) Model 2 (Random Effects); 3) Model 4 (Institutional Influence); 4) Model 1 (Base model). Overall, the results of these four models show that both social and physical factors are important considerations for farmers.

2.2.2 Regression Parameters

From Table 1, we can see the resultant regression parameter mean values and standard deviations. In a few cases, there are obvious changes in the magnitude of the regression coefficients between different models. In general, models 1, 2 and 4 gave similar results to each other. The coefficient, $b1$, on crop evapotranspiration increased by a factor of about 20-30 between these two sets of models. Precipitation, $b5$, increased by a factor of 90-100 between the models. The coefficients on soil types showed an increase of about 5-6 for all soil types, with overall higher coefficient values from the sandier soil types. In addition, $b4$, the coefficient for

fully irrigated yield changed direction from a positive relationship with water-use for Models 1, 2 and 4 to a negative relationship for Model 3. The coefficients for certified irrigated acres, b_3 , and for b_2 , distance to nearest stream, were the most consistent across the four models. The coefficients which showed large changes between Models 1, 2, and 4 and the CAR model, Model 3, we can conclude that these parameters are important spatial considerations in a farmer's water-use decisions and therefore, so is a farmer's spatial orientation or neighborhood.

2.2.3 Predictive Intervals

A predictive distribution was determined at each MCMC step in order to gather additional information about the predictive ability of each model. Figure 10 shows the predictive median value at the end of sampling along with the 95% predictive interval. Here, we can see that all four approximate the median value fairly similarly, but Model 3 has a slightly wider predictive interval than the other three. This shows us the predictive power of the model is higher when it takes into account the effect of a farmer's spatial orientation, or neighborhood.

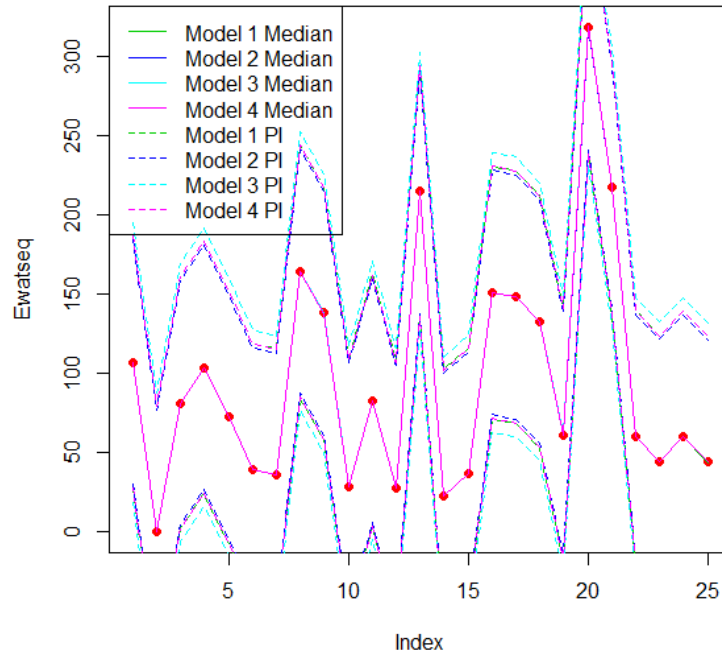


Figure 10: Model 1-4 Predictive intervals over a subset of observational data

2.2.4 Spatial Analysis

Figures 11 and 12 show the spatial layout of ρ_{ho_i} , the spatial covariance, and the expected pumping volume wt_i , respectively. We can see that wt_i appears to be slightly higher along the outline of the Republican River (not pictured). The spatial covariance also seems to follow this trend. In general, there appears to be a relationship between a moderate wt_i and more spatial covariance.

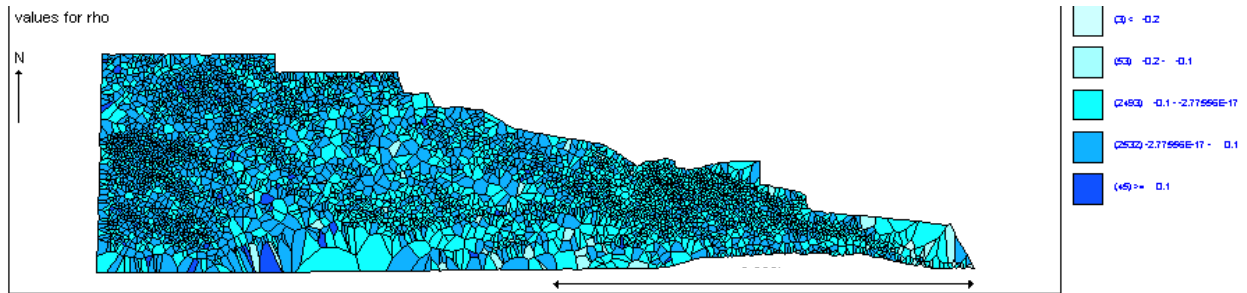


Figure 11: Spatial distribution of covariance between neighboring blocks

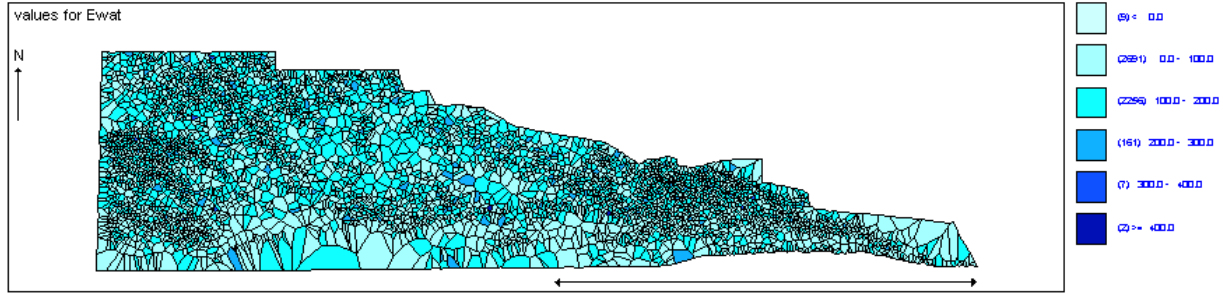


Figure 12: Spatial distribution of expected pumping values in the Nebraska portion of the Republican River Basin

2.2.5 Conclusions

From the above results, we can address each of the initial research questions and relate results to the development of the agent-based model. Overall, we suggest that: 1) spatial covariances between agricultural wells in the Republican River Basin are an important driver for decision-making and could be the result of collaboration between neighboring farmers; 2) a consideration of both environmental and social factors is key for understanding farmer's water-use behaviors.

Q1: Is a farmer's neighborhood a significant factor in determining decisions on water-use?

From the DIC scores, we can show that the two models (Model 2 and Model 3) which took into account spatial variables were better fits to the data. These conclusions are also supported by the predictive intervals in Figure 10. From these results, it seems there is a spatial trend between farmers pumping behaviors which suggest similarities between neighboring wells. This conclusion is strengthened by the fact that Model 3 (CAR model) is significantly the best fit of the four models. Overall, from Figures 11 and 12, we can see that there does appear to be some clustering of water usage that can be related to higher values of spatial covariance. Based

on these analyses, the results suggest that the spatial correlations between neighboring wells have an impact on the expected pumping volumes over the given time period. The magnitude of this impact, however, requires further analysis.

From an analysis of the regression parameter values, we can also suggest that some covariates are more strongly impacted by spatial location than others. Most notably, the coefficient for irrigated acreage, $b3$, does not undergo a large change between the four models. This can be interpreted to mean irrigated acreage is less spatially dependent than some of the other covariates, such as soil type and evapotranspiration which generally have stronger spatial patterns.

We also utilize the spatial dependency of these regression covariates to empirically inform the structure and function of the ABM. The variables which show the strongest relationships with space – evapotranspiration ($b1$), precipitation ($b5$), crop yield ($b4$), soil type ($s1$, $s2$, $s3$, $s4$, $s5$) – are utilized as important environmental factors which drive farmer behavior in the ABM.

Q2: Does the influence of institutions that play a role in water usage regulations in Nebraska impact a given farmer's annual pumping volume?

In general, these models suggest that considering environmental factors alone when understanding irrigation water use is not enough, and that social factors play a role in farmer decision-making. More specifically, the DIC scores suggest that Model 4, which considers institutional distance as a proxy for influence is a better fit than Model 1, which only explicitly models physical conditions. This could show that institutions play a role in determining pumping volume, particularly as the regression coefficients for institutional distance exhibited a negative

relationship with pumping volumes. However, the small DIC difference between Models 1 and 4 might suggest that farmers are not truly restricted by these regulations, or that spatial location, used as a proxy for influence, is not directly related to institutional regulatory influence. The slightly better fit for Model 4, may instead be the result of success in explicitly modeling social factors in addition to physical ones. The fit of Model 2, the random effects model, also indicates that unmeasurable factors do play a large role in farmer's decisions. These findings are not surprising as the region is characterized by heavy human influence from agriculture, as well as via water use regulations. Thus, farmers are not able to make decisions solely based on environmental factors as there is a water-usage framework as well as an economic system which drives their decisions (Palazzo, 2009). The results of this analysis do not suggest which social factors guide farmers more than others, but further investigation could more explicitly elucidate the impact of regulations and water use institutions on farmer's behavior.

CHAPTER 3

AGENT-BASED MODELING

In order to understand the environmental impacts of management decisions, how management decisions react to changes in the environment, and, importantly, how local human systems behave in response to these dynamics, we need a method capable of accurately representing the connections between human and physical systems. Agent-based modeling (ABM) allows researchers to investigate the relationship between simple individual behaviors, collective social structures and interactions with the environment (Macy and Willer, 2002). ABM takes a decentralized approach that models the behaviors of individual entities (Bonabeau, 2002). Because of this, simple models can exhibit complex behavior patterns and provide valuable information about real-world systems (Macy and Willer, 2002). ABMs can be combined with physically-based models to simulate the exchanges and relationships between physical and social systems. To achieve this, agent-based modeling is employed to simulate the human systems in our case study and the environment is represented by a physically-based groundwater model. The two models are coupled so they can be used to simulate the coevolution of environmental and social phenomena over a given period of time.

For application to the Republican River Basin, the agent based model was designed with two classes of agents: farmers and institutions. Farmer agents were tasked with: 1) deciding when to “activate” their land for agriculture and begin irrigating; 2) how much water is needed to irrigate their crop daily. Institutions controlled the impact of this water use on a nearby stream through 1) implementation and change of water-use regulations; 2) enforcement of these

regulations. The ABM was created using NetLogo 5.0.1, a macro language and platform designed for agent-based modeling (Wilensky 2012).

Overall, this section seeks to answer the following questions:

Q1: What key points or thresholds can we identify and how are they critical to both the human and natural systems involved?

Q2: How has regulatory change impacted farmer decision-making?

Q3: What role do physical considerations play in a farmer's actual decision on water use?

For modeling the environment, climate and land cover were included in the ABM, while the groundwater and surface water were modeled with MODFLOW-2000, a modular finite-difference flow model that was used to simulate the flow of groundwater in response to agricultural extraction and its interaction with a nearby stream (USGS Groundwater Software 2010).

An overview of the interactions between different agents and the environment are shown below in Figure 13. The red arrows represent the interactions between social systems and the environment and the grey and black arrows represent interactions between agents in the social systems.

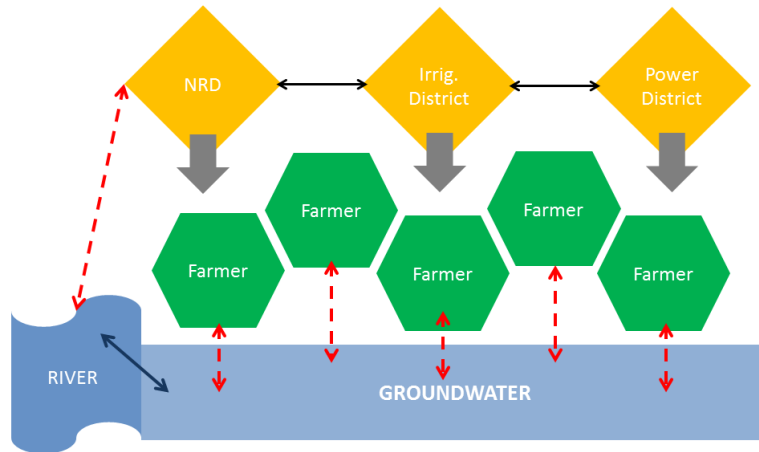


Figure 13: Schematic of coupled ABM interactions

The following sections serve to introduce the reader to the uses of ABM in coupled-human nature systems, describe the methodology and formulation of the coupled ABM and MODFLOW-2000 models in greater detail, and provide modeling assumptions and justifications.

3.1 Agent-based modeling for coupled human-nature systems

3.1.1 ABM in the social sciences

Agent-based modeling is defined in the literature as a system of autonomous interactive decision-making agents. Each agent assesses its situation and makes decisions on the basis of a set of rules. Agents can interact with one another based upon these rules. Agents can evolve, adapt or learn. These complex behavior patterns at the individual scale can generate system-level patterns that provide valuable information about real-world systems (Macy and Willer 2002). Agent-based modeling is particularly important to the study of social systems because of its ability to capture the following phenomena:

Emergence: By showing how simple individual behaviors can produce recognizable and/or surprising behaviors at a larger scale, ABMs empower researchers to examine the relationship between individual action and emergent social structures (Gilbert and Terna 1999 and Macy and Willer 2002). Modeling this relationship becomes complicated, though, as individuals can also respond to the emergent properties of collective individual decisions (Gilbert and Terna 1999). Incorporating agent learning can aid modelers in increasing the complexity of their model.

Cooperative Action: Cooperative action, or agent interaction, occurs when an agent makes decisions based not just on its own working memory and set of rules, but on those of others (Xie 2011).

Social Networks: ABMs can represent the links between individuals, organizations, etc. When facing a decision, agents can query other individuals or interact with individuals based on their social network (Walter *et al.* 2007). The surrounding network of agents, which can change dynamically over time, can respond to this interaction (Walter *et al.* 2007).

Utility: “Utility maximization is one of the most important mechanisms theorized to guide social choice” and is commonly incorporated into the agent’s framework as one mechanism that drives behavior (Hummon 2000).

Social Hierarchy: Because of the flexibility of ABM, the modeler can alter the levels of description and aggregation (Bonabeau 2002). Agents can be designed at different levels, and in a way that allows for social hierarchies to be present.

Different methods and techniques have been developed to simulate these phenomena in an agent-based modeling context. Bonabeau (2002) identifies four key areas where application of ABM to social systems is appropriate. These are: flows, markets, organizations and diffusion. More generally, Bonabeau explains that ABM is particularly useful when agents, their behaviors, and/or their interactions exhibit a high level of heterogeneity and complexity. Epstein (1999) further concludes that ABM is well-suited to interdisciplinary and multi-dimensional study.

We can also look at examples of data-driven ABMs, as this study incorporates empirical findings from a statistical analysis into agent design. Data-driven ABMs are used in social science for modeling real populations. One example is an ABM of the cultural change of the Kayenta Anasazi, a population which inhabited parts of modern day Arizona from 200-1300 A.D by Dean *et al.*, (1999). The population size and spatial extent generated from the model were compared against demographic records and used to measure model performance. The study of interaction rules, agent's attributes and environmental factors was used to illuminate social processes and theories about the population. Other models utilize data on economic growth rates, price distributions or political alliances to test behavioral and social theories (Axtell, 1999; Bak *et al.*, 1996; Axelrod, 1993). Overall, Epstein (1999) argues that the empirical issue for data-driven ABMs is: Are the agent's behavior rules sufficient to generate the patterns observed in reality? This perspective governs much of the ABM work in the social sciences. In general, social scientists use ABMs to test theories of behavior and agent interaction with a focus on proving, or disproving, these theories. Said another way, ABMs are successful if they can represent a target social property or pattern in a way deemed accurate by the modeler. Key modeling insights are, thus, based on behavior rules or "hypothesized microspecifications" (Epstein, 1999).

Overall, we can see that ABM in the social sciences tends to focus more on theoretical questions that can be discerned through case studies or modeling exercises. For this model, we utilize principals and concepts from social science in order to understand the behavior of our current system and identify key points in time. These thresholds are points where the social systems behavior can only be better understood through its coupling with physical systems. These insights are not utilized to test theories, as is generally the case, but rather to understand the actual driver's behind the behavior of our case study for the purposes of informing future management strategies. This study's model also follows the commonly used data-driven ABM approach, but extends it by modeling and calibrating the behavior of two classes of agents in a hierarchical ABM.

3.1.2 ABMs in Coupled Human-Natural Systems

By coupling ABMs with physically-based models, natural processes, their environmental feedbacks and societal responses can be further analyzed. Monticino *et al.* (2007) modeled the interactions between human decisions on land use change and forest ecosystems. Their descriptive ABM is coupled with three physically-based models to quantify the effect of environmental feedbacks on subsequent human decisions (Monticino *et al.* 2007). Berger and Ringler (2002) utilize an ABM for land and water management by modeling farmer's decisions on farm investment, land and water use with a mixed integer linear program. Ng *et al.* (2011) couple farmer decision-making on crop choice and best management practices with a hydrologic-agronomic model of the surrounding environmental systems. Their results show trends in farmer behavior over time in response to the physical model and the authors conclude that the coupled model is both flexible and useful for research in water management (Ng *et al.* 2011). Reeves and Zellner (2010) investigate the impacts of land-use on groundwater levels using an ABM and the

MODFLOW groundwater model. The coupled model is used to test different modeling scenarios and the response of the system to each (Reeves and Zellner, 2010). In general, the results and findings of coupled physical-agent-based models are promising. Robinson *et al.* (2002) argue that these simulations are not accurate, however, without “credible and defensible representations of micro-processes”. They develop five approaches for “empirically informing ABMs” for use in human-environmental sciences - sample surveys, direct observation, field and laboratory experiments, companion modeling, and GIS and remotely sensed data (Robinson *et al.* 2002). These studies are important to understanding the limitations and extensions of coupled ABMs and can help bolster both the accuracy and complexity of future ABMs.

ABM for coupled human-natural systems has tended to focus primarily on optimization as the primary strategy for agent-design. This study is a departure from this trend, and instead seeks to simulate behavior through a more accurate representation of the physically-based decision-making framework and incorporation of principles from the social sciences. It considers both: the interactions between agents and the environment as well as those between agents themselves. The former is more generally the focus of ABMs in coupled systems and the latter constitutes the focus of ABMs in the social sciences. Here we draw on both of these modeling areas to more accurately model the coupling of the complex human systems with the natural systems.

3.2 Methodology

The coupled ABM can be broken down conceptually into four main parts: 1) modeling of physical characteristics; 2) modeling of farmer behavior; 3) modeling of water institutions; 4) coupling the groundwater model and the ABM. The ABM was written in NetLogo 5.0.1, an

ABM platform developed at Northwestern University (Wilenski, 2012). MODFLOW-2000, a modular finite-difference flow model that is maintained by the U.S. Geological Survey, was used to model the groundwater and surface water systems (USGS Groundwater Software 2010). Details on these models and their methodologies are explained in the following section.

3.2.1 Part 1: Physical modeling

Modeling of the land surface properties, climate, surface water and groundwater were intended to reasonably simulate the region overseen by the Upper Republican Natural Resources District of Nebraska (URNRD). This choice was meant to limit the institutional scope, but also to allow for a simple physical model of the region. The URNRD is the most upstream portion of the RRB in Nebraska, and is an important area to model as the consequences of heavy pumping are felt throughout the downstream reaches of the RRB. For simplicity, we divide this area into two climatic zones, four different soil types, and model a homogeneous aquifer and a small stream. Figure 14 shows the spatial layout of how these characteristics are modeled in the ABM. This section outlines the different design features of the physical model, including descriptions of data and justifications of any assumptions made.

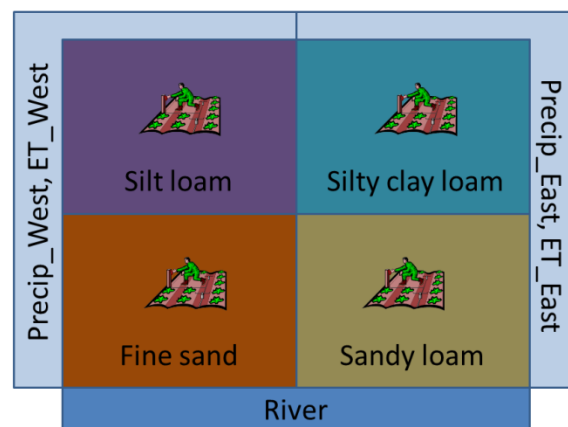


Figure 14: Environmental spatial layout of the ABM

Spatial Extent

The areal extent of the model covers 13,000 acres (~20.3 square miles). We assume all farmers in the modeled region own one well, use center pivot irrigation, and irrigate the same set area. This area, 130 acres, comes from publications targeted at farmers on specifications for center pivot irrigation by the University of Nebraska at Lincoln (Kranz *et al.* 2008). This assumption is carried over into the groundwater model as well as used to calculate farmer's irrigation volume in Part 2 of the model.

The surface physical characteristic that varies across space is soil type. Soil types were based on the STATSGO database in which the soil types basin-wide are: 13 percent sand, 18 percent loam and 69 percent silt (Finkner 2006; Palazzo 2009). The silt category was further divided into silt loam and silty clay loam based on work by Finkner (2006). We assumed four main soil types of equal spatial extent for modeling purposes – fine sand, sandy loam, silt loam and silty clay loam.

Soil moisture is a critical metric by which to judge crop stress, need for irrigation, suitability of land, etc. In order to determine soil moisture on a given day, the available water content (AWC) or available moisture of each soil type was needed. This is a property of the soil that we use to determine the soil moisture, or soil water deficit, in a given day. Figure 15 below shows the range of values for each soil type (Corn Production Guide, 1997). The average value for each type was used.

Soil Texture	Available Moisture	
	Inches/Inch	Inches/Foot
Coarse sand and gravel	0.02 to 0.06	0.2 to 0.7
Sand	0.04 to 0.09	0.5 to 1.1
Loamy sand	0.06 to 0.12	0.7 to 1.4
Sandy loam	0.11 to 0.15	1.3 to 1.8
Fine sandy loam	0.14 to 0.18	1.7 to 2.2
Loam and silt loam	0.17 to 0.23	2.0 to 2.8
Clay loam and silty clay loam	0.14 to 0.21	1.7 to 2.5
Silty clay and clay	0.13 to 0.18	1.6 to 2.2

Figure 15: Available soil moisture for each soil type (Corn Production Guide, 1997)

Temporal Considerations

Two properties of time are taken into account – the number of years and the number of days within a year. The model is set-up to allow the modeler to run for any set number of years, with the intention that year zero will represent year 1950. This start point represents the end of the pre-development time for the region in which both groundwater use and agriculture were minimal (Nebraska NRCS, 2008). The discretization within a year is critical for the collection of data, the design of the decision-making process and the consideration of intra-annual variability. We assume that the growing season is 140 days long, starting in late April and continuing through mid- to late September. This is based on a report in the National Corn Handbook which calculates regional growing degree days for corn and the equivalent growing season length for areas across the corn belt of the U.S. (Neild and Newman). Corn growth stages, represented by the daily rooting depth of corn, are included for each of the 140 day growing season (McWilliams *et al.* 1999). Including corn growth stages in the model helps quantify the crop water demand, which varies throughout the time period regardless of climatic variations (Kranz

et al. 2008). Figure 16, below, illustrates that more water is used by the plant at earlier stages in crop development (Kranz *et al.* 2008).

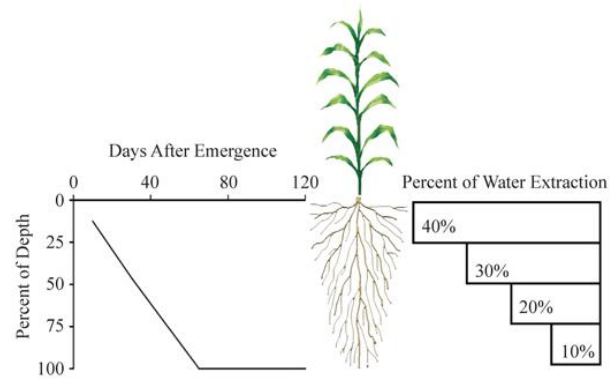


Figure 16: Corn rooting depth and water use during the growing season (Kranz *et al.* 2008)

Climatic Factors

Two different climatic zones were modeled through precipitation and potential evapotranspiration (ET). Together these two variables can reasonably reflect the aridity, humidity and general climate in each region. The Republican River Basin is characterized by a steep rainfall and ET gradient, so the presence of two climatic zones within the modeled area is realistic (Kranz *et al.* 2008). Figure 17 below shows the rainfall gradient across Nebraska – the modeled area falls under two zones in the southwestern portion of the state.

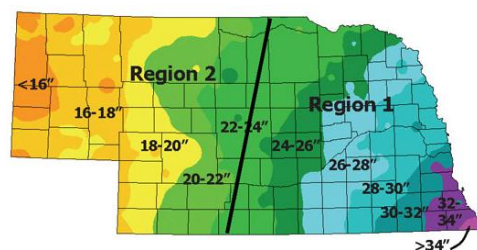


Figure 17: Average annual rainfall values across Nebraska (Kranz *et al.* 2008)

Daily data, over the length of the growing season, was collected for each variable for all years from 1950 to 2010. The National Oceanic and Atmospheric Administration (NOAA) keep daily data of precipitation and maximum and minimum for multiple locations across Nebraska in its online climate data directory. Daily rainfall and temperature values were obtained for two gauging stations in the Upper Republican NRD - Imperial and McCook. Daily values of potential evapotranspiration for corn and a reference ET were calculated using the Hargreaves-Samani equation recommended by the Food and Agricultural Organization (FAO) when weather data is incomplete. This equation, shown below, required the daily maximum and minimum temperatures from the NOAA database as well as extraterrestrial radiation (Hargreaves and Samani, 1985; FAO, 1998). The crop coefficient for corn, K_c , was determined using FAO recommendations for maize for three time-averaged periods in the crop growth cycle (FAO, 1998).

$$ET_0 = 0.0135(KT)(R_a)(TD^{0.5})(TC + 17.8) \quad (1)$$

Where KT is an empirical coefficient which varies by region and is defined as 0.162 for this study (Hargreaves, 1994); R_a is extraterrestrial radiation; TD is the difference between maximum and minimum daily temperatures; TC is the daily mean temperature. Maximum, minimum and daily means were obtained from the NOAA dataset. R_a is defined monthly for by latitude for 41° N (Hargreaves and Samani 1985).

In order to enable the model to simulate daily climate for future time periods the climate must vary year to year. To do this, we adopt an approach commonly used for the study of climate change with global circulation models (GCMs) (Hewiston, 2003). Using daily data from 2011, we perturbed the observed data by a small amount every year (Hewiston, 2003). This amount

was determined based on a random draw from a normal distribution centered at one and with a standard deviation determined by historical data. In this way, we assumed that the observed daily data for 2011 were the average values over all years in the simulation period, and that these values vary year to year by a standard deviation based on historical rainfall and evapotranspiration data from the Great Plains WATERS Network Observatory. These were found to be 10 percent for rainfall and 4 percent for evapotranspiration (Average Annual Precipitation, 2007; Mean Annual Potential Evapotranspiration, 2007).

Modeling of groundwater and surface water

The MODFLOW-2000 package from the US Geological Survey, a modular finite-difference flow model, was used to simulate the flow of groundwater and subsequent changes to a nearby stream (USGS Groundwater Software 2010). MODFLOW-2000 input files were generated using the Groundwater Vistas 5 platform, see Figure 18 (Groundwater Vistas, 2012).

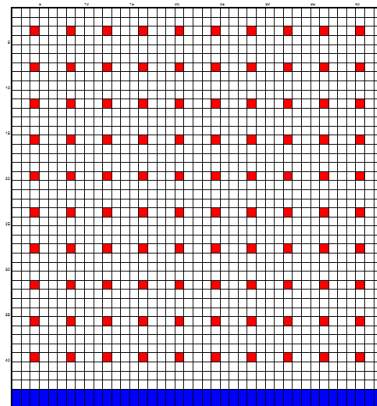


Figure 18: Groundwater model visualization from Groundwater Vistas

Included in the MODFLOW model were 100 extraction wells to represent the agricultural water use. The areal extent used for the ABM (20.3 square miles) was carried over into the

groundwater model, with each well irrigating 130 acres (Kranz *et al.* 2008). The dimensions of the stream modeled on the southern portion of both the ABM and MODFLOW were taken from the stream input files of the RRCA model, which also uses MODFLOW (Republican River Compact Administration). The properties defined in MODFLOW are shown below with their relevant data sources. All data shown are average values for the Upper Republican portion of the Great Plains Aquifer. A homogeneous groundwater and surface water system was assumed for modeling simplicity.

The following properties defined the homogeneous aquifer and stream system:

- Hydraulic conductivity = 60 feet/day (USGS Groundwater Atlas)
- Recharge = 0.01 feet/day (USGS Groundwater Atlas)
- Specific yield = 0.15 (McGuire, 2009)
- Stream width = 5 feet (RRCA)
- Streambed thickness = 5 feet (RRCA)
- Streambed conductance = $0.004820 \text{ ft}^2/\text{day}$ (RRCA)

Return flow was accounted for using a similar conceptual approach to the RRCA Groundwater Model for groundwater recharge, but was factored into ABM rather than as a component of the MODFLOW-2000 model in order to simplify the coupling between the two models. The RRCA model uses the inverse of irrigation efficiency, assumed to vary from 70-80 percent, to compute return flows (RRCA Groundwater Model, 2003). Because returns to surface water are difficult to determine, the RRCA models uses a fixed fraction that changes across space and is constant in time (RRCA Groundwater Model, 2003). We interpret this by grading overall return flows based on proximity to the stream, with those closest to the stream having a return flow of 30 percent and those furthest having a return flow of 15 percent.

3.2.2 Part 2: Farmer design

Farmers were modeled in two phases – one stage in which they were able to make decisions on when to begin agriculture in the region and a second stage in which their main decision was daily groundwater use for agricultural irrigation. In both stages, a farmer behavior factor was included to add heterogeneity to the model, as well as to simulate changes in behaviors over time. The decision-making framework for both stages, along with a description of the behavior factor, is described below.

Well activation

In the Republican River Basin, the proliferation of groundwater use closely followed the spread of center pivot irrigation. In Figure 19, we can see the rapid increase in the number of wells from the 1950's to present day (Draper).

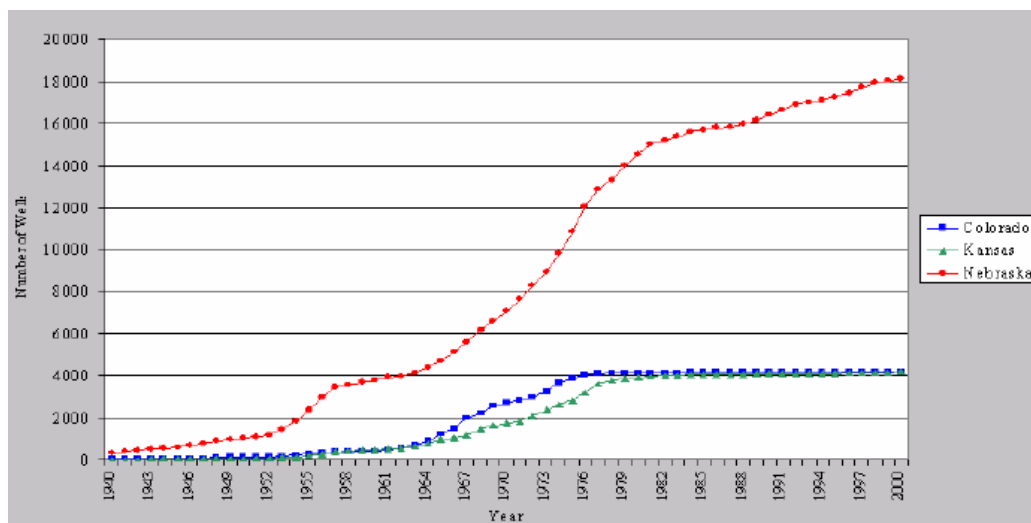


Figure 19: Number of wells from 1940s to present, Republican River Basin (Draper)

Because the economic, agronomic and social relationships that drive land conversion are difficult to model explicitly, we utilize empirical relationships to drive farmer behavior. We use these relationships as proxies to simulate irrigation adoption. These are not assumed to be functional relationships, nor do we explicitly model the complex economics of the decision to switch to irrigation. To simulate both the spatial spread and increasing trend of wells, additional data was collected on: 1) the number of wells at different points during the simulation period (Republican River Compact Administration); 2) agricultural land value changes over time for each soil type in the ABM (Schob, 1994; URNRD, 2011; Johnson and Rosener, 2010); 3) net profit per bushel of corn at different points during the simulation period (Kranz *et al.* 2008; Johnson and Rosener, 2010); 4) county and state level corn yield historical data (USDA NASS Nebraska Field Office, 2012). Figures 20 and 21, below, show the trend of well growth with net profit, and changes in land value over time for each soil type.

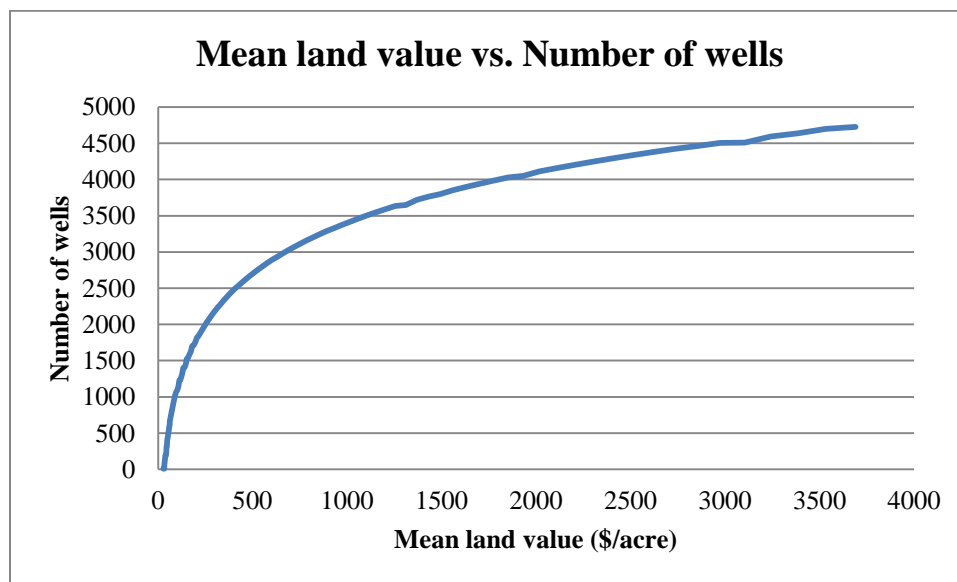


Figure 20: Number of wells over time vs. mean land value over time (Kranz *et al.* 2008; Johnson and Rosener, 2010; RRCA)

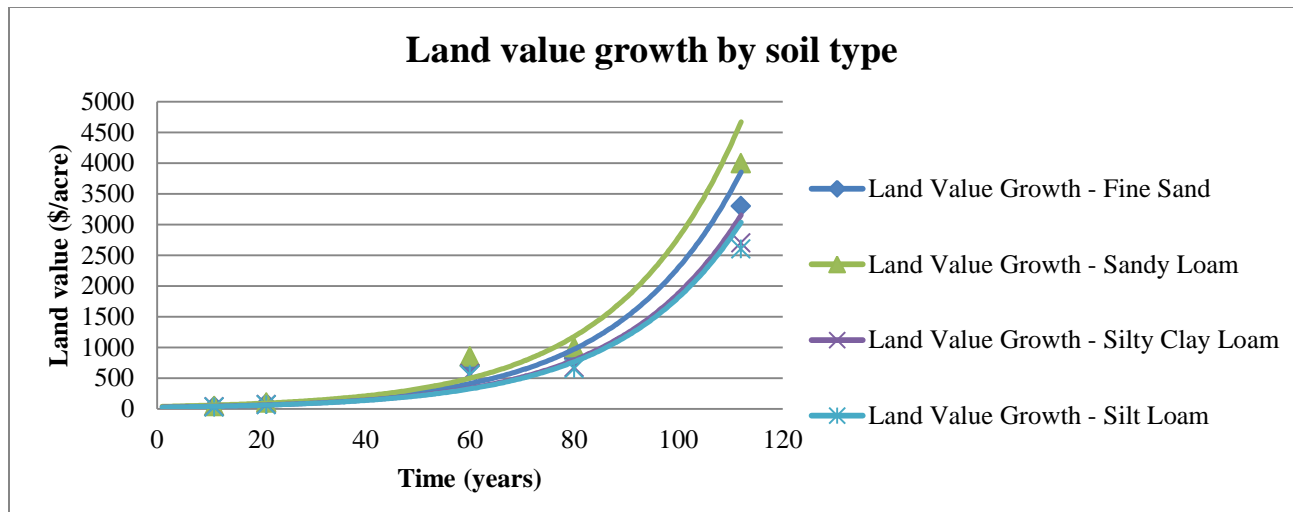


Figure 21: Land value change over time, by soil type (Schob, 1994; URNRD, 2011; Johnson and Rosener, 2010)

Using this data, farmer's decisions on well activation were designed based on the following conceptual rules:

1. Land value growth motivates farmers towards activating wells.
2. Land values increase based on empirical, historical relationships with soil type.
3. Land also begins to increase in value if it is located near land that already has an active well.
4. The total number of active wells at a given period of time is constrained by historical relationships between number of wells and mean land value, as shown above in Figure 20.
5. The location of newly activated wells is a decision made by individual farmers and occurs when the value of a given field met or exceeded the historical value.

The historical relationship between number of wells and mean land value were used to govern timing of farmer's decisions, and the land value changes over time impact which wells

will become active. The major assumption in this portion of the modeling was that land value was an important factor in farmer's decisions on well activation. We also assumed that land value was a measure of land quality. A study in Nebraska on land transition to agriculture by Drozd and Johnson (2004) concluded that land use decisions are significantly based on farmability characteristics, and most notably on that of soil type. Agricultural land assessments of land capability and value, according to the administrative code of the Nebraska Department of Revenue, are largely based on soil surveys (Nebraska Department of Revenue, 2012). Drozd and Johnson (2004) also conclude that the willingness to convert land to agriculture changes dynamically over time based on market forces. Here empirical land values are also used to represent external market factors. We use soil type as a way to categorize land value at various points in time, as seen above in Figure 21. It is also important to note that these empirical relationships implicitly include many other variables (such as well yield, cost of adoption, etc.) that would add more complexity to our modeling framework. Instead we use these relationships as a proxy for the multiple drivers and causes of irrigation adoption.

In the ABM, farmer's land gained value over time via the above relationships and a farmer's given location (due to the spatial orientation of soil types). If a nearby farmer activated their field and well, the value of all neighboring fields would increase. This is meant to simulate the diffusion of technology adoption through time (Berger, 2005; Fuglie and Kascak, 2001; Abdulai and Huffman, 2005; Marra *et al.*, 2003). When the value of a given field met or exceeded the expected value at that point in time (given by the time series in Figure 21 above), a farmer was able to activate its well. The number of wells that could be active during a given year was constrained by the land value-well growth relationship shown above in Figure 20. Following this system, the model simulation showed that all wells became active by the 1980s.

The spatial spread of wells, seen in Figure 22, is an emergent property of the system based on individual farmer decisions on when to activate their wells. From historical data, we see a basic trend of well growth from riparian areas to areas further from streams (RRCA, 2012). This is implemented into the model by starting the model with one active farmer in the first simulation year. The farmer chosen to be activated by the modeler is one most proximate to the stream.

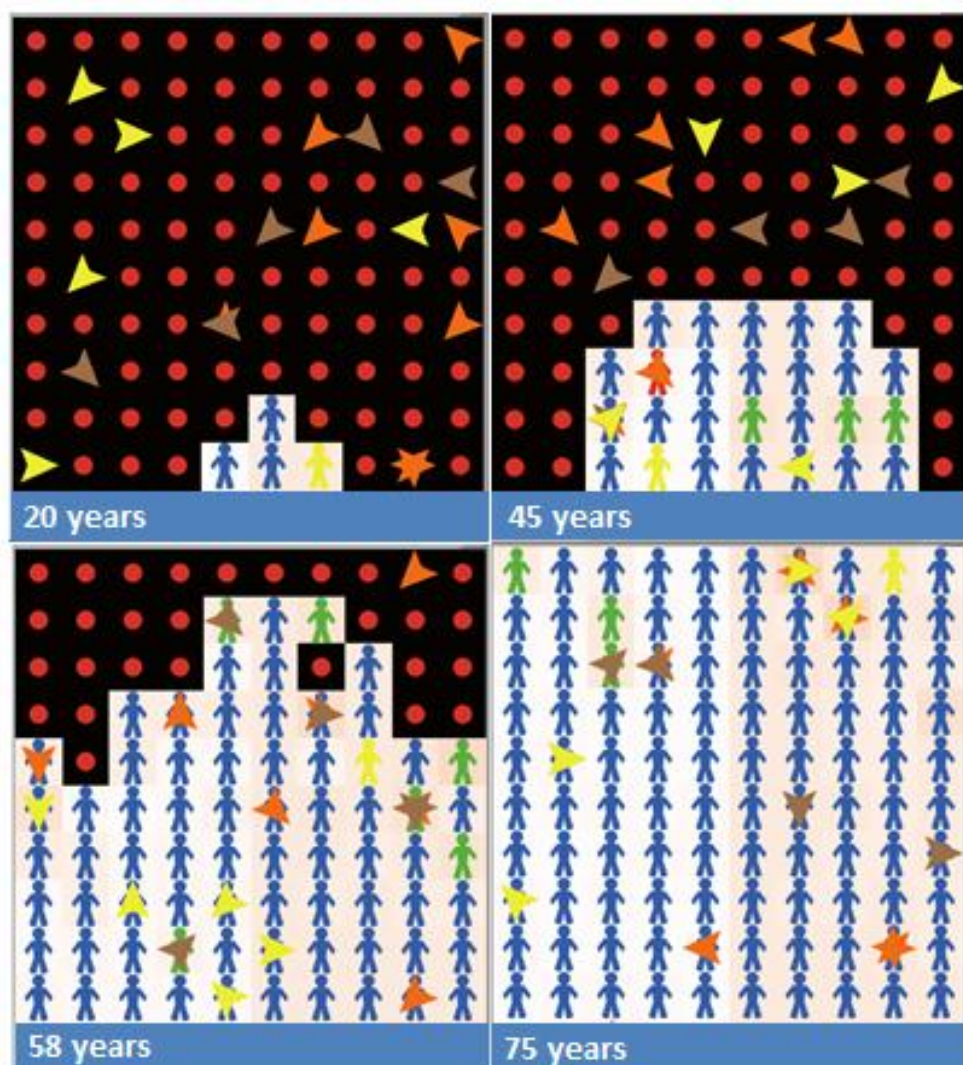


Figure 22: Well activation in the model simulation period

Farmer pumping behavior

To simulate agricultural water-use through time, we model farmer's decision-making on the quantity of agricultural irrigation. We assume that these decisions are: 1) made on a daily basis; 2) based on physical factors that impact the water requirement of a crop; 3) heterogeneous and impacted by the behavior of individual farmers. The decision-making framework and a discussion of these basic concepts are included below.

Daily decisions on irrigation allow farmers to consider the stage of growth of a crop, daily climatic conditions and the condition of a crop based on former irrigation decisions during that growing season (Andales *et al.*, 2011). Management strategies, such as the irrigation scheduling approach, depend on these daily decisions, are simple and easy to follow, and can lead to more efficient water use (Evans *et al.*, 1996). This strategy rests on the assumption that farmers understand basic relationships between climate, crop water demand and soil moisture (Evans *et al.*, 1996). Overall, the goal of this approach is to only irrigate slightly above the level at which crops would undergo stress or their yield would be impacted in a negative way. This strategy is widely supported by extension programs and agricultural engineers (Evans *et al.*, 1996; Andales *et al.*, 2011). We adopt this approach to guide farmer behavior in the ABM. The equations below describe the basic framework (Andales *et al.* 2011).

$$D_c = D_p + ET_{corn} - P - I \quad (2)$$

Where D_c = soil water deficit (inches), D_p = soil water deficit from previous day (inches), ET_{corn} = water demand via potential evapotranspiration from corn (inches), P = precipitation (inches) and I = irrigation (inches) (Andales *et al.* 2011). In this way, if the farmer decides on no soil water deficit ($D_c = 0$), then the deficit from the previous day plus the crop water demand

(together these are the daily water demand) will be equal to the inputs of precipitation and irrigation (daily water supply). Because D_c can be negative due to high amounts of precipitation, we correct for this by setting D_c to zero when a negative value is calculated.

Implicit in these equations is the relationship between crop yield and the crop's water requirement. Here, the crop water requirement is represented through evapotranspiration, ET. This requirement can be met through the three other components of the equation – water stored in the soil, water from precipitation, or water from irrigation (Andales *et al.* 2011). The water requirement, ET, changes daily based on the stage of crop growth, daily climate and crop stress (Andales *et al.* 2011). The equation used for ET is shown below.

$$ET_{corn} = ET_0 \times K_c \times K_{st} \quad (3)$$

if $K_{st} < 1$, crops undergo stress

ET_{corn} is calculated daily using the reference ET_0 obtained for historical data (explained earlier), K_c is the crop coefficient for corn, taken from the FAO procedures, and K_{st} a crop stress coefficient that adjusts K_c (Andales *et al.* 2011). The method used here is also called the Dual Crop Coefficient Method, or the FAO-56 procedure, and is used by the FAO as a way to more accurately correct actual ET values for short term (daily) irrigation scheduling (Allen *et al.* 2005). The sources of ET_{corn} and K_c are described in Part 1. The crop stress coefficient K_{st} [0-1] accounts for time periods in which the crop root zone does not hold enough water for crop transpiration to occur at its potential (non-water limited) rate (Andales *et al.* 2011; Allen *et al.* 2005). In these cases, K_{st} is less than one. K_{st} is calculated with the equation below:

$$K_{st} = \left(\frac{TAW - D_P}{(1 - MAD) \times TAW} \right) \quad (4)$$

TAW is the total available water for the crop. This varies with soil type and is calculated by multiplying the available water capacity of the soil (AWC) by rooting depth for corn (D_{rz}). The variable D_{rz} changes throughout the growing season for corn and is input daily. D_p is the soil water deficit for the previous day, allowing the crop stress level, K_{st} to also reflect previous irrigation management. MAD is the managed allowed depletion for a crop, for corn this is generally 50% (Andales *et al.* 2011). Figure 23 illustrates the relationships between the daily water requirement for corn, corn growth stages and allowed depletion (MAD) (Corn Production Guide, 1997). We add heterogeneity to each farmer's MAD by multiplying it by a unique and dynamic behavior factor; this process be detailed in the following section.

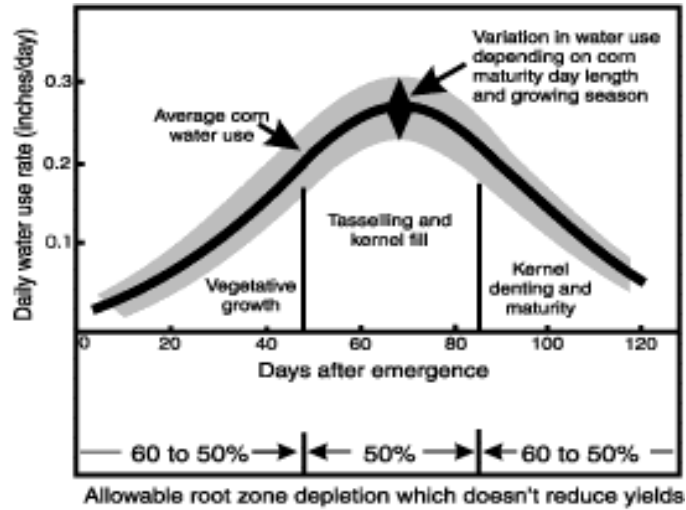


Figure 23: MAD , crop water demand and growth stage (Corn Production Guide, 1997)

Using this framework, the farmer's actual decision is on D_c , the allowed soil water deficit, or the fraction of the total available water to the plant at a given stage of growth. We first use equation 2 to find the deficit in the soil on a given day. If D_c is greater than or equal to the

managed allowed fraction of the available water capacity of the soil during that day (see equation 5), then the farmer irrigates until D_c is less than $MAD \times AWC \times D_{rz}$. Further, D_c should remain below the managed allowed deficit in that day – $MAD \times AWC \times D_{rz}$ – in order to minimize water stress on the crop.

$$D_c \geq MAD \times AWC \times D_{rz} \quad (5)$$

Other important metrics that are calculated include crop yield, net annual profit, return flow and a daily pumping rate. Crop yield is calculated using the following equation:

$$Y = Y_R + (Y_M - Y_R) \left[1 - (1 - \beta \cdot I) / (ET_{corn} - P)^{1/\beta} \right] \quad (6)$$

Where Y_R is rainfed corn yield (bushels/acre), Y_M is maximum corn yield (bu/acre), β is the irrigation coefficient, 0.75, I is irrigation (inches), ET_{corn} is the potential evapotranspiration for corn (inches) and P is the effective precipitation (inches) (Palazzo, 2009). This calculation is performed at the end of each growing season for each farmer and impacts farmer decisions on water use in the following year. This mechanism is a component of a farmer's behavior factor, explained in the following section.

Annual net profit is to drive the timing of well activation in the first stage of farmer behavior. Recall that the relationship between annual net profit per acre and the number of wells is an empirically derived equation that constrains the number of wells that can be active in a given year. At the end of each year, we calculated annual net profit by multiplying a farmer's annual crop yield (bushels of corn) by the net profit per bushel in the given year. This is used as an input to determine the maximum number of wells that could be active at the beginning of the

following year. In this way, the model can follow the correct trend of well activation over time using both empirical relationships and model output.

Daily pumping rates are also calculated for each farmer, as they are needed as inputs for MODFLOW-2000. An irrigation depth, I , of inches per acre, determined using the soil water deficit approach, is multiplied by the following equation to get daily pumping rates, Q , in feet³/day. 23.8 is a conversion factor for acre-inch to cubic feet per second (Schwab):

$$Q = I \text{ inches} \cdot 130 \text{ acres} \cdot 23.8 \cdot 86400 \text{ sec/day} \quad (7)$$

There are two other factors which may limit the pumping volume on a given day: well yield and the cost of irrigation. In order to take into account well yield, we limit a farmer's daily water depth based on a maximum well yield value of 3,600 gallons per minute from the RRB (Kuwayama and Brozovic, 2010). Using a similar calculation to the one above, this limits farmers at 1.47 inches per day. In some cases, the cost of irrigation may limit the farmers choice on how frequent and how much to irrigate. To consider this as a component of the model, we constrained the frequency of pumping to three days per week and limited his volume of water use over one week to three inches (Mortensen, 2011; Melvin and Payero, 2007). Both of these values were taken from literature on irrigation management strategies for farmers. These are common values for the area studied and are assumed to reflect both crop requirement as well as an economically feasible pumping rate.

Figure 24, below, shows an overview of this framework along with the inputs which guide farmer decisions and outputs that impact decisions in the following year and the physical and regulatory environments. The dashed arrow represents an area of coupling between the physical model and the ABM.

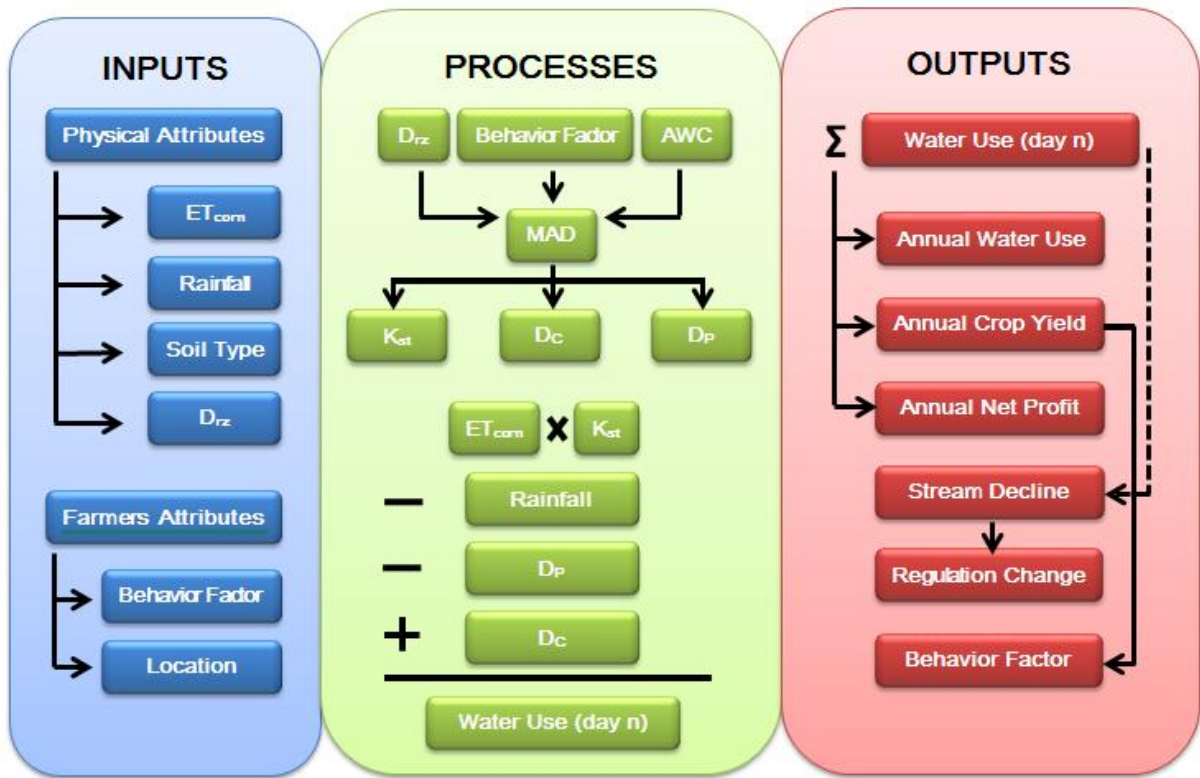


Figure 24: Daily farmer decision-making framework

Farmer's Behavior Factor

Modeling of farmer decision-making can be categorized, according to the literature, into three general areas: 1) physically-based or climatic-based; 2) economically-based; or 3) perception-based or sociological (Riebsame, *et al.*, 1994; Foster and Rausser, 1991; Ning and Hongji, 1998). Riebsame, *et al.* argues the study of agronomic systems in the Great Plains of the United States has considered the following factors for modeling agricultural land use, change and behavior: population, technology, consumption, attitudes, and values (1994). However, much of this work has been at a conceptual level or multi-year scale and fails to address how these factors directly impact local-scale patterns (Riebsame, *et al.* 1994). This model is, instead, grounded in a

physically-based and daily decision-making approach in order to focus more concretely on small scale spatial and climatic variability. However, the factors listed above are important drivers that bring heterogeneity in behavior at the local scale. We adopt a behavior factor to reflect, in a simplistic form, the possible heterogeneity that stems from attitudes, values, technology, etc. This section describes the mechanisms and assumptions by which we incorporate behavioral differences into the model.

Using the irrigation scheduling approach, the managed allowed depletion, MAD , depends on crop and soil type as shown in Figure 24. However, this parameter also reflects the choice of an individual, as a farmer may choose to deplete or water crops in different ways. To add this variability into the framework, we develop an additional parameter that is meant to simulate the unique behavior of an individual farmer. This is termed the behavior factor and impacts multiple decisions in the modeling framework. The primary purpose of this factor is to add heterogeneity to the model. By incorporating a variable that captures some variability in farmer decision-making with physical parameters through the formulation of MAD , we can couple local behavioral differences with the physical principles that drive the framework.

Step 1: Determine assumptions and limitations

Behavioral modeling in the social sciences is generally informed or guided by some degree of surveying, interviewing, economic or social theory. Different economic choice models, social trust-based models and models of valuation or utility exist for this purpose; these can be both qualitative and quantitative (Brink and McCarl, 1978; Stewart, 1992). However, in this case, the behavior factor is not mean to reflect choices of actual individuals, as no surveying, sociological or psychological analyses were performed to inform the model at this level of detail.

Instead, we take this simple approach to simulate the emergent behavior patterns that stem from individual heterogeneous decision-making. For our task, the behavioral modeling portion of this research is fairly limited and is primarily meant to reflect water-use choices that are based on natural conditions. The behavior factor solely exists to add heterogeneity to the framework in a reasonable, non-random way. In quantifying the behavior factor, we take two additional assumptions:

1. *Farmer's behavior is predominantly affected by physical conditions.*

The behavior factor serves to perturb choices that would just be based on physical surroundings to instead reflect an individual's personality. This factor is incorporated into *MAD* by directly multiplying it by the original *MAD* value. In order to achieve this, the behavior factor (on average) needs to be close to 1 so the simulated behavior is not dramatically different on average than what the physical conditions would suggest. This assumption follows the choice of the irrigation scheduling - that the population behaves according to physical conditions and is not homogeneous in its decision-making (Evans *et al.*, 1996; Andales *et al.*, 2011).

2. *The distribution of the behavior factor in our population follows a standard normal distribution.*

Due to the limitations of our study, we assume that a normal distribution reasonably approximates the differences in behaviors among the population. With more local knowledge or sociological study, our quantitative treatment of the behavior factor could be improved. Specifically, the standard deviation of the distributions could be decreased with this knowledge or we could address any possible skewness in the behavior distribution (if a higher probability of a specific behavior was found among the population).

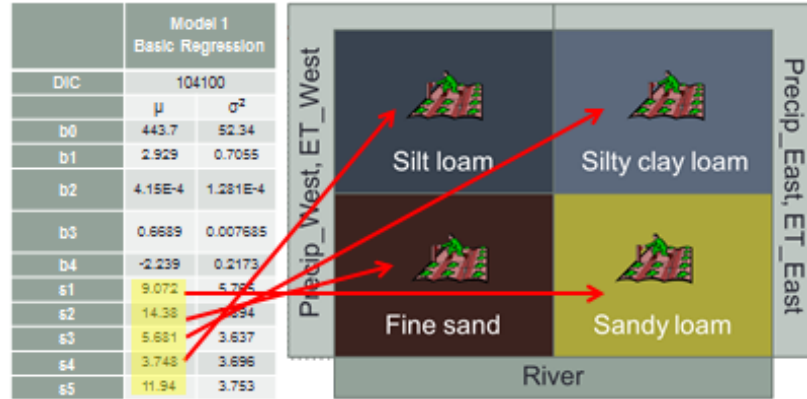


Figure 25: Relating soil type regression coefficients to the ABM environment

Step 2: Empirically inform the behavior factor

To develop this factor in a reasonable way, we utilize the results of the statistical analyses from Chapter 2 to gain insights into the differences in farmer behavior and empirically inform the ABM. In Chapter 2, we found that differences in farmer behavior could be attributed to spatial differences in the environment as well as the impact of one's neighborhood. Soil type is used as a proxy for spatial differences in the environment. Figure 25 shows the results of the basic multivariate regression in relation to the physical layout for the ABM described earlier. More specifically, we can interpret Figure 25 qualitatively to mean farmers with a fine sand soil type (s_2) will be more likely to use more water for irrigation annually than those with other soil types (s_1, s_3, s_4). From the statistical analysis, we observe a trend in behavior based on soil type. These zoned behavior factors for the four different soil types are initially slightly weighted to reflect qualitative relationships between soil type and pumping behavior found using the regression model. We can think of this as a weighting system to help quantify farmer behavior based on qualitative relationships between empirical values. Following this framework, we can assign initial values for the behavior factor as shown in Figure 26.

SOIL TYPE	REGRESSION COEFFICIENT	BEHAVIOR FACTOR (mean)	INTERPRETATION
SILT LOAM	3.748	0.90	Tend to pump less
SILTY CLAY LOAM	5.681	0.95	
SANDY LOAM	9.072	1.05	
FINE SAND	14.38	1.10	Tend to pump more

Figure 26: Mean initial values of the behavior factor for each soil type

When the model is initialized, each farmer is assigned a value for the behavior factor. This is randomly generated from a normal distribution centered at the mean values from Figure 26 and with a standard deviation of 0.05. We convert the quantitative behavioral impacts of soil type to qualitative relationships between the results of our statistical analysis to relate this behavior factors to one another. Bonabeau (2002) argues that for agent-based modeling this can be a more appropriate choice, particularly when output will be interpreted on a more qualitative level and there is high variability in the accuracy and completeness of model data. The homogeneity in the physical setting also helps us derive simple, qualitative insights between physical properties and farmer behavior. Figure 27, below, shows a conceptual diagram of the relationship between the soil type regression coefficient and the behavior factor.

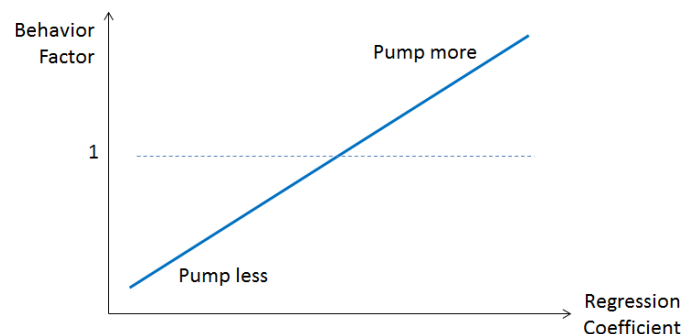


Figure 27: Qualitative relationship between empirical soil type coefficients and farmer's behavior factor

A farmer's behavior factor is a dynamic parameter that changes through the simulation period in two ways: diffusion processes between neighboring wells and adaptation or learning based on annual net profit (Berger, 2005; Fuglie and Kascak, 2001; Abdulai and Huffman, 2005; Marra *et al.*, 2003).

Behavior diffusion

One mechanism by which the behavior factor changes over time is through diffusion, or adjusting an individual's behavior factor based on its neighbors. This assumption is driven by the statistical analyses which showed farmer behavior could be better predicted by taking into account its neighborhood. A weighted average is used to quantify changes in the parameter and depends on a radius around a given farmer. The number of neighbors included, the farmers radius, is dependent on the year or time point in the simulation. This radius, r , increases over time based on a simple linear equation that relates year to radius, shown in the equation below.

$$r = 0.0389 \times year + 0.6831 \quad (9)$$

Equation 9 is based on the relative distances used in the agent-based model and historical data on pivot irrigation adoption in the region. We set the maximum radius to be slightly bigger than the soil type divisions to reflect the extent of a farmer's neighborhood. We justify this through literature from agricultural economics that looks at behaviors related to technology diffusion. The spatial network, or the linkages between individuals, is frequently modeled or considered as one driver for diffusion (Berger, 2005; Fuglie and Kascak, 2001; Abdulai and Huffman, 2005; Marra *et al.*, 2003). According to equation 9, by year 30 farmers will consider the choices of all farmers in their neighborhood. In our simulation, year 30 represents 1980. Studies on the region show that the "boom" in center pivot technology adoption occurs in the years before 1980, so we assume full diffusion of the behavior factor by this time (Nutt-Powell

and Landers, 1979). Full diffusion of farmer behavior is scaled to match the spatial layout of the ABM in which the extent of one's neighborhood is, at most, five units away. We assume a constant rate of acceptance of technology from year 1 to year 30, so we simply assign a linear function to fit these two points. We take the concept of rate of acceptance of new technology from an empirical study on technology diffusion among corn farmers by Griliches (1957). The rate of acceptance corresponds to the annual increase in the radius, r . Because we take a simple approach with a linear trend in technology diffusion, this equation could be refined further in future work. Other studies suggest alternate models that depend on more complex socio-economic and technologic factors instead of just time (Metcalf, 1988).

Behavior adaptation

The behavior factor also changes based on the decisions of an individual farmer. Conceptually, if crops undergo too much stress (i.e. $K_{st} < 1$) or if crop production is higher than the average, behaviors will adapt. A farmer who loses crops due to poor soil water deficit management in a given year will not allow as much soil water deficit in the following year. We use increases or decreases in net profit to elicit changes in farmer behavior.

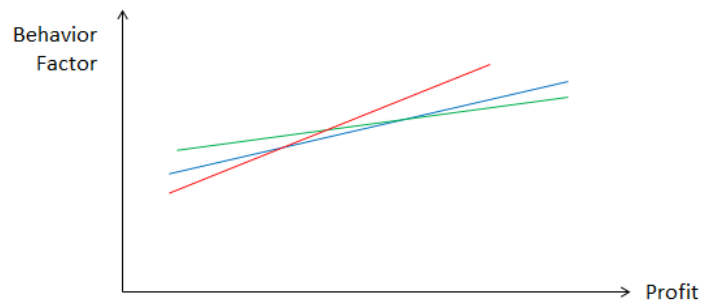


Figure 28: Conceptual relationship between behavior factor and annual net profit

Figure 28 shows how behavior factors have a positive relationship with net profit: increasing as farmers become more profitable and decreasing as they become less profitable. Importantly, this relationship is unique for all farmers. The assumption here is that as farmers meet less success with their management strategies, they are more likely to strictly follow the proposed irrigation scheduling approach to improve their yields and profit. Because net profit is impacted by market forces, physical factors that affect crop yield, and the behaviors of the individual farmer, we are able to incorporate a variety of components that drive farmer behavior and behavior change.

3.2.3 Part 3: Regulatory agent design

To simulate the regulatory structure in the RRB, three different institutions were modeled in the ABM framework – Natural Resources Districts (NRDs), Irrigation Districts (IDs) and Public Power Districts (PPDs). These institutions served two purposes in the ABM related to water-usage restrictions. The first was the enforcement of regulations and the second was observation of environmental conditions and alteration of regulations. We assume that institutions follow a “command-and-control” approach in which regulations are enforced based on institutional arrangements and do not consider direct input from farmers (Holling and Meffe, 2002; Pahl-Wostl *et al.* 2007). The following chart, Table 2, summarizes the assumptions made about the interests and relative power of each agent. These assumptions are based on the expert field knowledge from a sociologist working in the region (Dr. Stephen Gasteyer). The agents are numbered 1-3 for each category. 1 corresponds to a strong interest/influence and 3 to a weak interest/influence, relative to the other agents.

	NRDs	IDs	PPDs
Influence on farmers	1	3	2
Influence on change	1	3	2
Interest in streamflow	2	1	2
Interest in pumping	1	3	2

Table 2: Regulatory agent behavior patterns

Based upon these assumptions the influence of each agent was weighted to correspond to both its interest and its relative ability to enact change – NRDs were weighted highest in both cases.

Sphere of influence modeling

Throughout the simulation period, regulatory agents interacted with farmers by means of a “sphere of influence” (Santos and Eisenhardt, 2005). This concept is taken from the principle of organizational boundaries in which the power of an organization can be defined or understood through its sphere of influence (Santos and Eisenhardt, 2005). For our model, this sphere was designed to represent the agent’s relative levels of influence over farmers. At the beginning of the simulation, each regulatory agent was assigned a sphere of influence with a different radius: NRDs with the largest and IDs with the smallest, following the above assumptions. Regulatory agents then scanned farmers and searched for those whose pumping behavior was higher than average. When a farmer was identified by a regulatory agent, the agent moved in space to the farmer. All farmers in the agent’s specified radius were then subject to water-use regulations for the duration of the growing season, see Figure 29. This mechanism is meant to simulate possible interactions between farmer’s and regulatory agents, both directly and indirectly as the sphere

boundaries extend out to other farmers. Regulatory agents are able to change locations every year and thus interact with a variety of different farmers throughout the simulation period. Realistically, we do not assume that institutions move through space in this way every year, but instead interact with farmers in multiple ways (educational programs, mailings, meetings, etc.) that are out of the scope of this framework to simulate. This is meant to represent the level of influence on farmers, rather than the exact mechanism of influence.

The mechanism by which regulations were applied to farmers reflects principles of social heterogeneity, based on individual beliefs, which are a key component of social-institutional interactions (Mehta *et al.* 1999). Following this, farmers responded to these regulations based on their behavior factor. To meet regulations, the amount of water for irrigation was scaled down daily for those farmers located in a sphere of influence. However, farmer's decisions on water use were only scaled down to an amount equal to the regulations multiplied by their behavior factor. In this way, some farmers (those with behavior factors greater than one) would not be strictly bound by the regulations. This procedure was meant to mimic the heterogeneity found in regulation adoption in reality.



Figure 29: Regulatory spheres of influence

Changing regulations

The development of resource dependence theory has guided researchers to explore the causes and processes behind institutional responses to their environment (Oliver, 1991). Social theorists have studied this as the “strategic choice” of an organization in response to institutional pressures (Oliver, 1991; Goodstein, 1994). Here, we utilize this theory through the idea that external drivers, or external organizations, are part of the environment and that these organizations can exert institutional pressures (Oliver, 1991; Goodstein, 1994). We view regulation change as the “strategic choice” of the NRDs resulting from institutional pressures coming from IDs, PPDs and within the NRDs themselves.

Over time, regulations in the RRB have changed, moving from 20 inches/acre in the 1980s to 13.5 inches/acre at present (RRCA). In order to simulate these changes, as well as the response of regulatory agents to environmental alteration a pressure-based system of influence was implemented. Again, each agent received a different weight according to the assumptions made on their level of influence in the region. It is important to note that only the NRDs have a direct decision on regulation change, and they remain the primary institution according to the theoretical basis. Because of their interactions with the other two classes of agents, we can assume that both PPDs and IDs can exert institutional pressures on these decisions, or strategic choices (Goodstein, 1994).

The main response variable that regulatory agents could react to was streamflow, and these reactions were governed by the interests of the individual agent classes. Agents with stronger interests in preserving streamflows (IDs) begin to exert influence in favor of changing regulations sooner than NRDs, who are more interested in preserving groundwater usage rights.

This influence is quantified in the model through increasing the value of a pressure variable numerically. This variable represents the current level of influence, or institutional pressure, of a regulatory agent. Because IDs have less influence than NRDs, their influence was not weighted as strongly, so their level of influence increased more slowly. When the combined interests of the agents, or the sum of the pressure variables, reached a certain level, the regulations changed. This level is specified by the modeler and was a way to calibrate the model against historical data on the timing and magnitude of these changes. When streamflow declines became more evident at a simulated gauging station along the stream, these changes were higher. The results section shows that the simulation results in a final restriction of about 12.89 inches/acre for the year 2010. This makes sense given that regulations in the region today are 13 inches/acre and are expected to decrease in the future (RRCA).

3.2.4 Part 4: Coupling with MODFLOW-2000

The ABM was coupled to MODFLOW-2000 to connect daily pumping with actual declines in the water table and water level in the stream. This was a necessary component of this study as it allowed for physically-based responses from the environment and a more accurate depiction of the relationships between the human and natural systems. The coupling was achieved through a Java code which connected the inputs and outputs of both models. A schematic of these linkages is shown below in Figure 30. We can see that the farmer's daily decisions on pumping were input into MODFLOW2000 for the 140 day growing season (corresponding to 140 stress periods in MODFLOW). MODFLOW then computed changes in groundwater table head and stream head. These results re-updated the MODFLOW input files for

the following year and were also input into NetLogo for the agents to respond to. The regulatory agents read-in the new level in the stream at every year in the simulation and are able to respond directly to these changes by increasing their levels of influence.

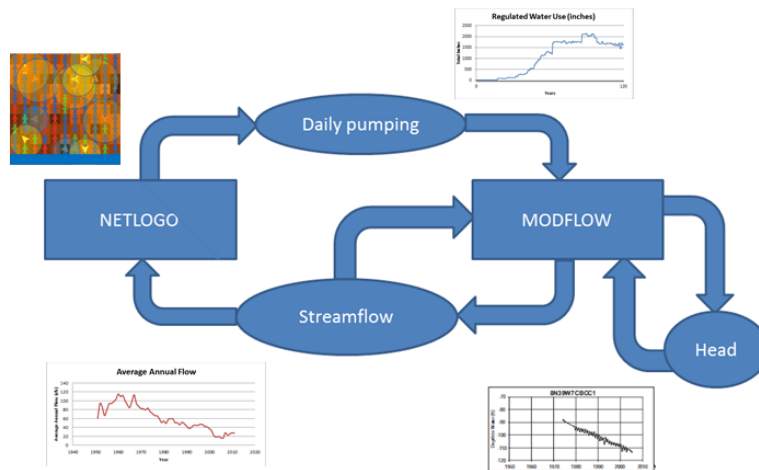


Figure 30: MODFLOW 2000 and NetLogo coupling, as facilitated by Java

CHAPTER 4

RESULTS

4.1 Calibration and Validation

Calibration of the ABM was achieved through a trial and error approach in which specific model parameters were adjusted to achieve simulation results that followed real patterns. For this purpose, two different historical trends were used to calibrate the model – water usage regulation changes (Palazzo, 2009; State of Nebraska, 2008; Upper Republican NRD, 2012) and average annual pumping volumes for the period from 1980 to 2010 in the Upper Republican NRD (Mieno and Brozovic, 2012). In order to calibrate the model to these data, two components of the ABM framework were adjusted: 1) the magnitude of response of the regulatory agents to changes in the level of the stream; 2) the magnitude of change of the behavior factor in response to water usage regulations. Both of these were components of the human system that did not have direct, empirical data to drive them. Instead, by adjusting these and re-running the model we were able to fit both of these social variables as well as achieve the target simulation results. Other ABM calibration procedures have targeted similar parameter values by, for example, adjusting the weights of preference towards physical factors in order to calibrate the model to historical data (Evans and Kelley, 2004). On each run of the calibration, both the timing and magnitude of water use were examined, along with the timing of regulation change. For example, if regulations were implemented too early, we decreased the magnitude of response of the different regulatory agents to changes in the level of the stream. If water-use patterns were off, we adjusted the ways in which the behavior factor could change in response to regulations. In the final run, we see that farmers respond to regulation changes by increasing their behavior factor by 10-15% from the initial values. This shows that farmers are highly sensitive to

regulations as well as the causal changes in the environments. Overall, the results of this calibration show that in both cases these responses needed to be more sensitive to environmental and institutional changes than the initial modeling assumptions. We saw that sensitivity of regulatory agents to changes in the stream level needed to be higher, reacting to a 20% change in stream level, and that farmer's response to regulatory agents needed to be more exaggerated. The dynamics of regulatory influence also played a role in the calibration. On the final simulation, we ended up with values that gave irrigation districts 85% as much influence as NRDs, and PPDs 95% as much influence as NRDs. We can see that the coupling of the ABM with the physically-based groundwater model is a critical step in understanding system dynamics, as the physical and socio-economic systems are sensitive to one another.

Figure 31 shows the simulation results for water usage regulation change and Table 3 compares these values with historical data. We can see from Table 3 that the simulation produces regulation changes within one year of the actual occurrence. Although we start the model with an initial condition of 20 inches/acre regulation, regulatory agents initiate interest in first changing regulations around 1983, which fits into the correct time frame of the real 20 inches/acre allocation.

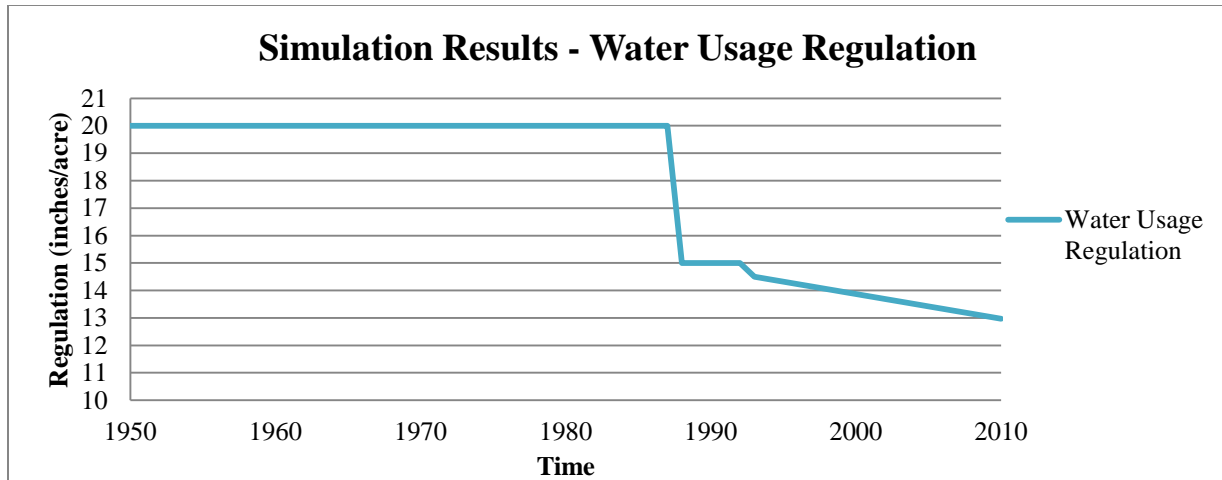


Figure 31: ABM Simulation results - water usage regulation changes through time

Year – Simulation	Regulation – Simulation (inches/acre)	Year – URNRD	Regulation – URNRD (inches/acre)
Starting value	20	1982	20
1988	15	1988	15
1993	14.5	1993	14.5
2004	13.5	2005	13.5
2009	13	2008	13

Table 3: Simulation results and historical occurrences for regulation change in the Upper Republican NRD (Palazzo, 2009; State of Nebraska, 2008; Upper Republican NRD, 2012)

Figure 32 shows the simulation results for average annual pumping volume. The overall trend of the real data, particularly between the years 1990 and 2010, and the magnitude of the peak in the early 2000s, is represented by the simulated data (Mieno and Brozovic, 2012).

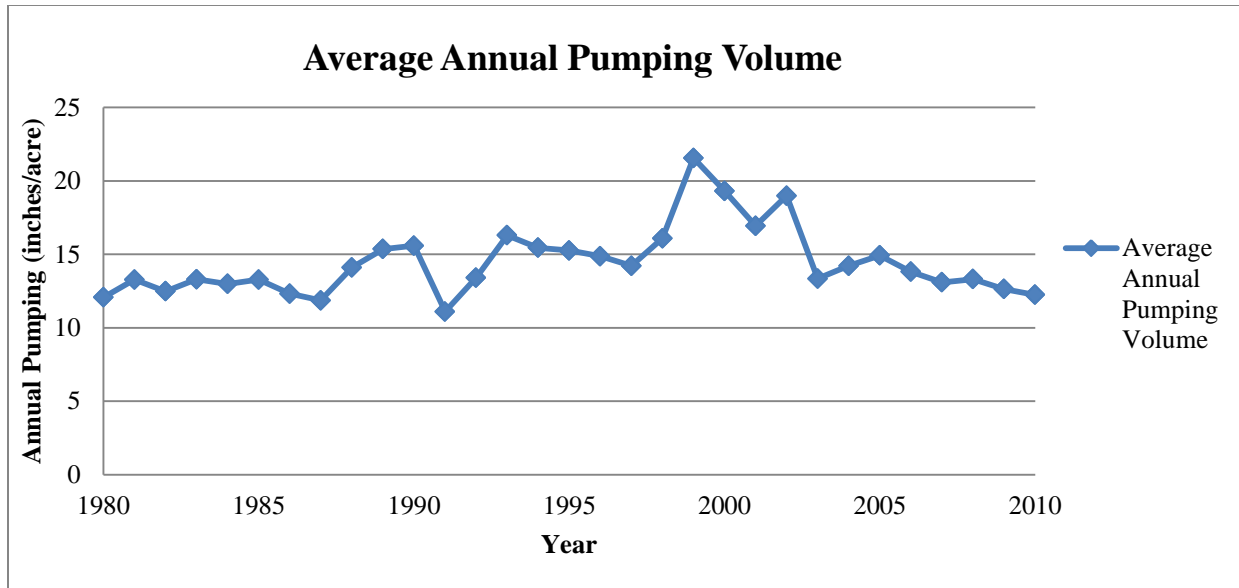


Figure 32: ABM simulation results - Average annual pumping (1980-2010)

Validation of the ABM is treated in a qualitative manner in which the overall pattern of the two systems is analyzed (Bharathy and Silverman, 2010). We examine the general cause and effect relationships between the timing of regulation change and average annual volume of water use. These basic relationships, explained in the following section, follow a similar pattern as seen in the real case and serve as a basis on which to perform scenario testing.

4.2 Historical Simulation

The ABM was first run under historical conditions in order to better understand the past dynamics between environmental systems and farmer and regulatory agent behavior. Figures 33 and 34, below, show these results.

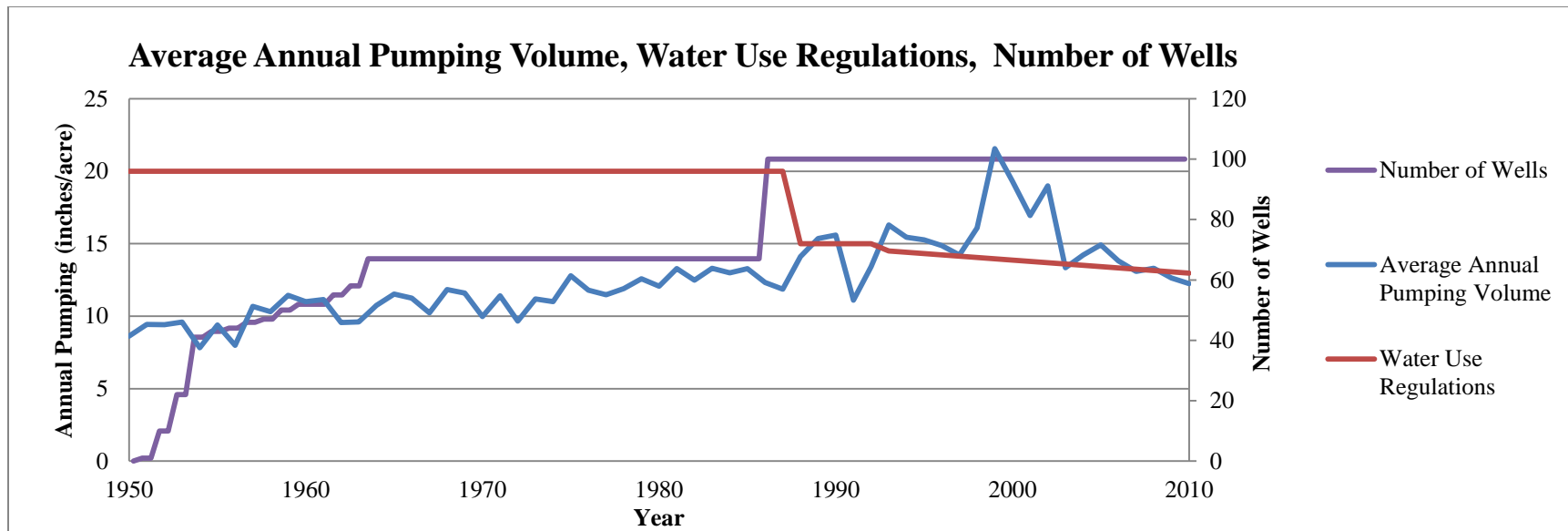


Figure 33: ABM simulation results - A comparison of average annual pumping to changes in water use regulations and wells growth

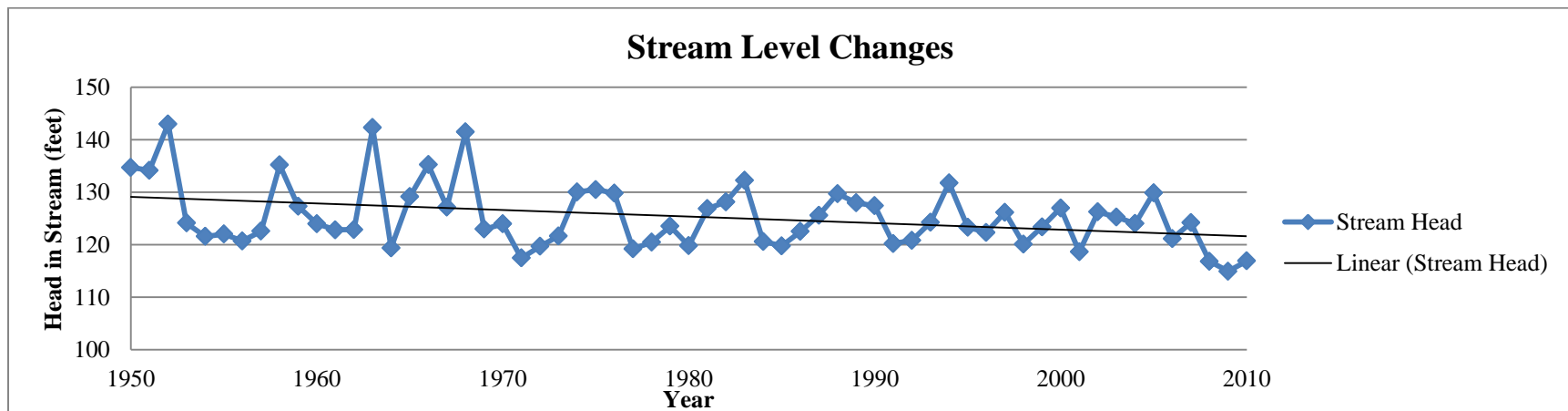


Figure 34: ABM-MODFLOW simulation results - Stream level declines

From these figures we can see an obvious shift in water-use behavior around 1990, corresponding to an eight percent decrease in the stream level. Before this, water usage followed a fairly constant upward trend. In 1990, a switch occurs where behavior becomes more variable. Around 2000, we can observe a second shift where mean water-use begins to decline in value. Figure 33 also shows that around 1990, both water-use regulations and the number of wells experienced a large change. Water-use regulations dropped from 20 inches/acre to 15 inches/acre around this time, and the number of wells increased from about 65 to 100. In addition, average net profit per acre was increasing throughout this time period, see Figure 35. We also observe changes in farmer behavior starting in the late 1980s and continuing through the remainder of the simulation, see Figure 36. The changes coincide with the timing of regulation changes, increases in number of wells and increasing average annual net profit. These trends may be causal factors for the observed shift in farmer behavior and are investigated through re-running the model with the following scenarios: 1) no regulation change; 2) holding price for corn constant after 1985; 3) no regulation change and constant crop price; 4) regulation change beginning at an earlier time period; 5) regulation change beginning at a later time period. The results of these model runs are shown in the following sections.

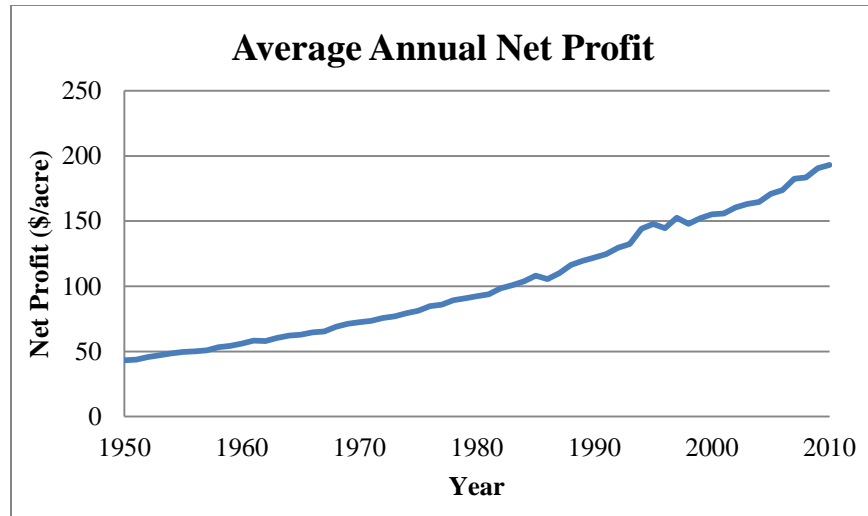


Figure 35: ABM simulation results - Average annual net profit per acre

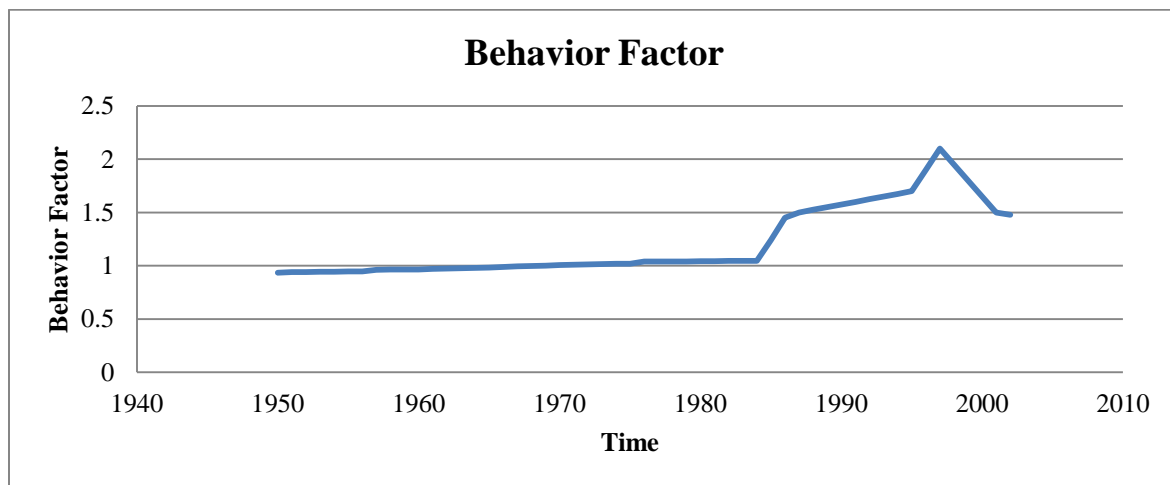


Figure 36: ABM simulation results – Behavior factor changes over time

4.3 Scenario 1: No regulations

In this scenario, the model was run in the absence of institutional oversight and without regulation change. The goal of this was to understand the impact institutional changes may have had on both farmer behavior and stream levels. From Figures 37 and 38 we can see the

relationships between pumping volume, net profit per acre, number of wells and stream level. By comparing these results to the simulation run, it is apparent that in the absence of regulations, the upward trend in pumping may be primarily driven by net profit. A steeper decline in stream level is also evident without the regulations in place. We can see the absence of the erratic pumping behavior that occurred prior to regulation change in 2003. Instead the trend continues upwards more smoothly through this time period. The pumping volume also appears to level off naturally around 14.5 – 15 inches per acre. Because the farmer decision-making framework is based on physical relationships between soil type, climate and crop growth, at the individual level this quantity of water use is probably the maximum water allowable by the irrigation scheduling framework. Recall that with implementation of the 13.5 in/acre regulation, we observed a strong behavioral reaction by farmers. These physical considerations may explain why this reaction occurred at 13.5 in/acre instead of at the onset of regulation change.

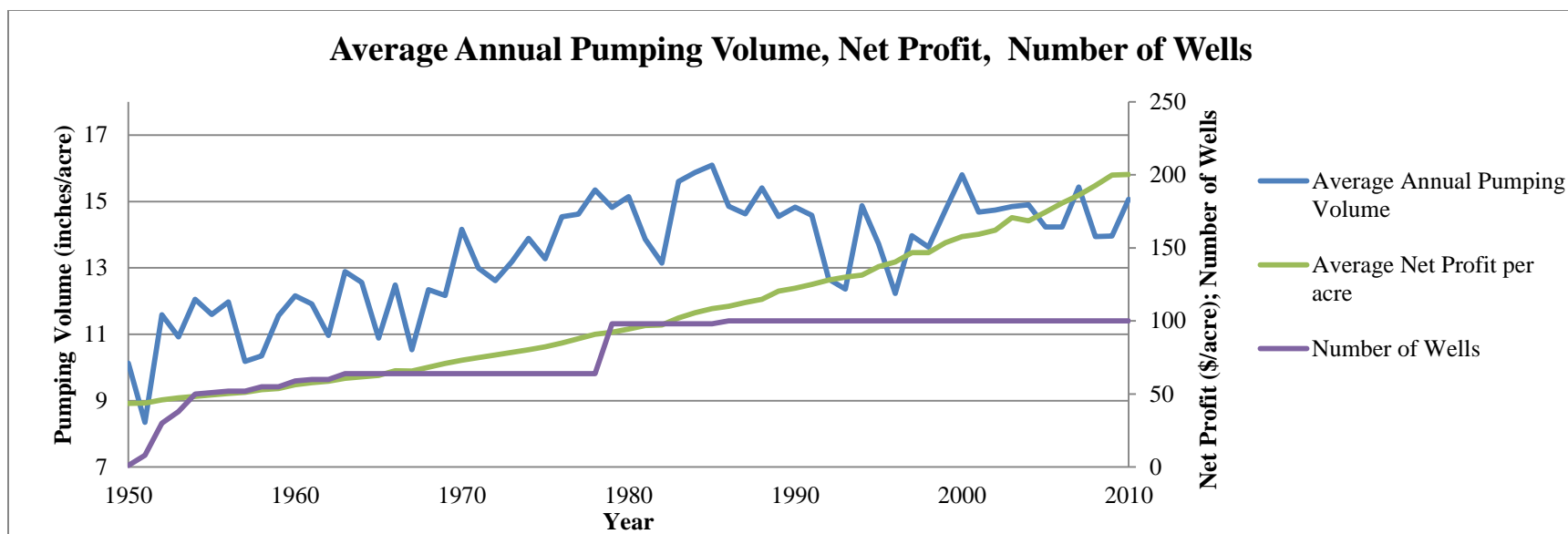


Figure 37: ABM Scenario 1 - A comparison of average annual pumping to average net profit and well growth

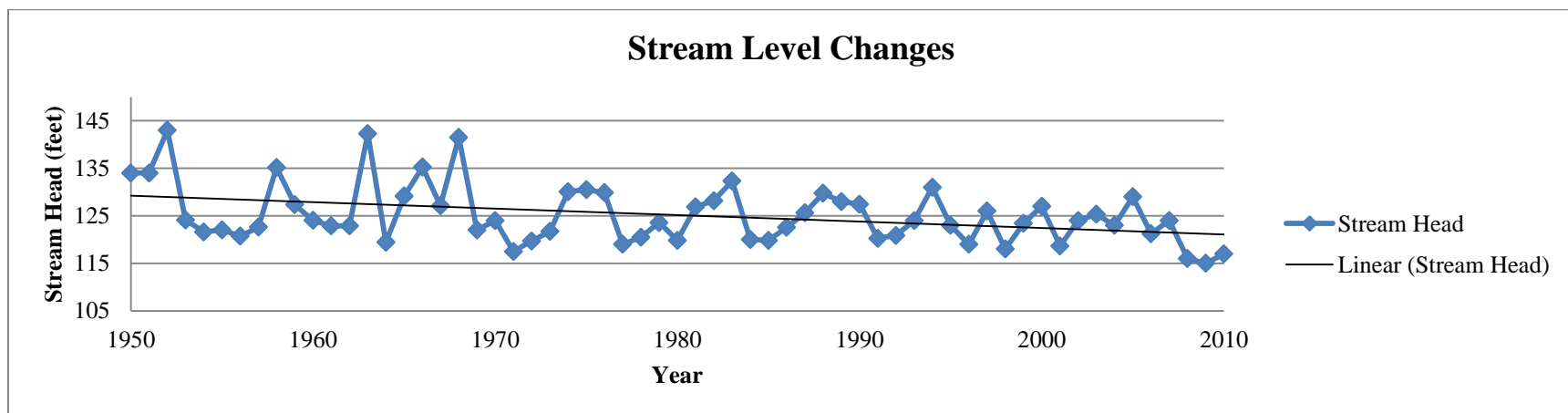


Figure 38: ABM-MODFLOW Scenario 1 results - Stream level declines

4.4 Scenario 2: Constant price for corn after 1985

In this scenario, the model was run with institutional oversight and regulation change, but with holding the price per bushel of corn at a constant level starting in 1985. This year was chosen to ensure all wells were able to activate, as this process also depends on net profit and the price of corn. The goal of this scenario was to understand if the price of corn was impacting the change in farmer behavior observed between the mid-1990 through the early 2000s or if this was only due to regulation change. Figure 39 below shows the resultant annual net profit per acre of corn. We can see the leveling out of profit starting in the mid-1980's.

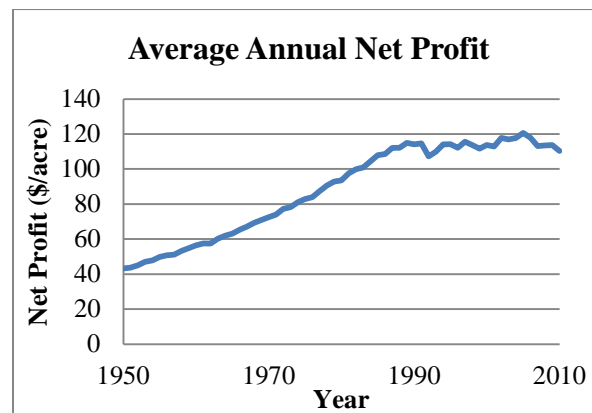


Figure 39: ABM scenario 2 results - Average annual net profit per acre

From Figures 40 and 41 below, we can see the impact of a constant crop price on farmer behavior. Before 1985, the pattern of pumping largely followed the trend seen in the simulation run as well as in first scenario. This upward trend still seems to be governed by the increasing price for corn. After 1985, however, we begin to see the same leveling off of water use as farmers are only pumping what they physically need and crop price no longer is driving behavior. Because regulations are still in place, we again observe the peak in water use right before regulations change to the 13.5 in/acre level. The timing and magnitude of this peak

follows the simulation run, but the time period directly before and after this peak are not nearly as reactive or variable. By holding the price of corn constant, we can conclude that some of the variability in farmer behavior from the simulation run can be attributed to price considerations. Further, the 13.5 in/acre threshold drives farmer behavioral change, and their profit considerations heightens this reaction. Scenario 3, which again holds crop price constant also removes institutional oversight in order to confirm these inferences.

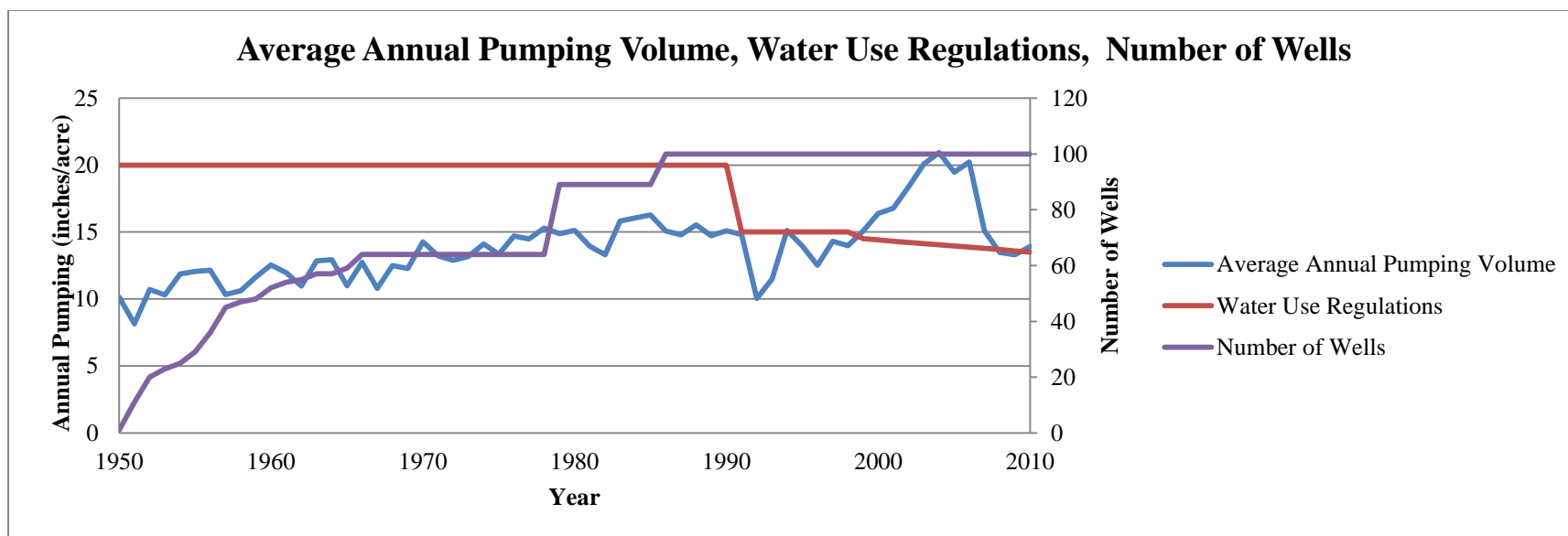


Figure 40: ABM Scenario 2 - A comparison of average annual pumping to water use regulations and well growth

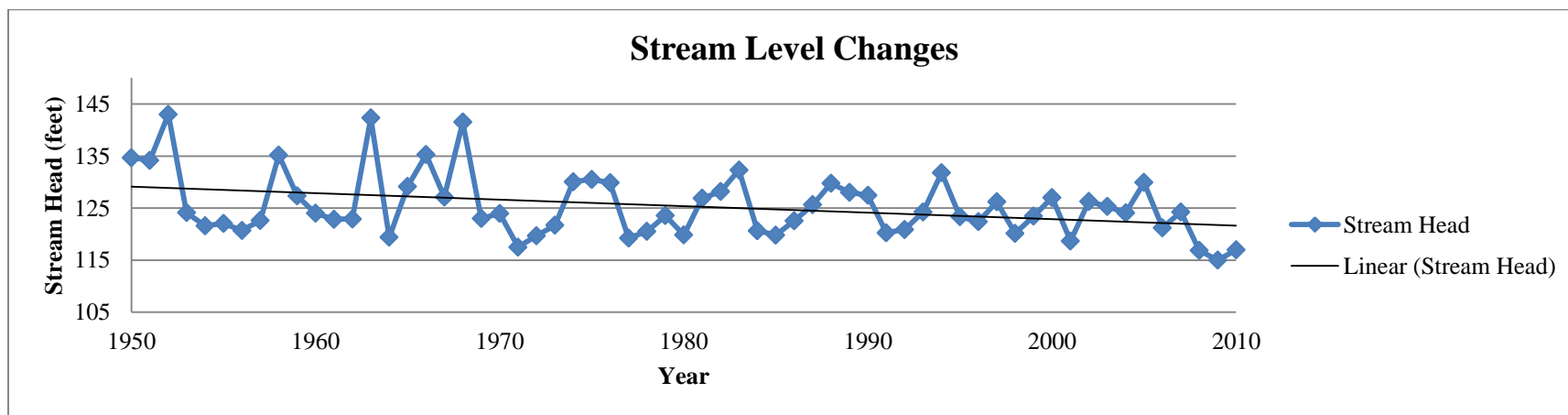


Figure 41: ABM-MODFLOW Scenario 2 results - Stream level declines

4.5 Scenario 3: Constant crop price, no regulatory change

In Scenario 3, we neglect institutional oversight and hold crop price constant after 1985 with the goal of confirming our observations and conclusions from Scenarios 1 and 2. If the results follow in the same way, we should see a gradual increase in pumping volume due to price increases until 1985, followed by a smooth leveling off of behavior due to the absence of regulations, the constant price, and the physical conditions which do not necessitate further increases in water use. Figures 42 and 43, below, show that this is the case. We see no large peak in water-use in the early 2000s, as there is no regulatory change in this scenario. The leveling off of pumping volumes can again be attributed to both physical agricultural need as well as the constant net profit from the mid-1980s onwards. Scenario 3 reaffirms our inferences from Scenarios 1 and 2 as it follows the same general patterns. The absence of both profit change as well as regulatory oversight show the steady pattern water use would follow if this were the case. We can conclude that under these circumstances, water use decisions would be governed strongly by environmental factors instead of dominated by individual behavior.

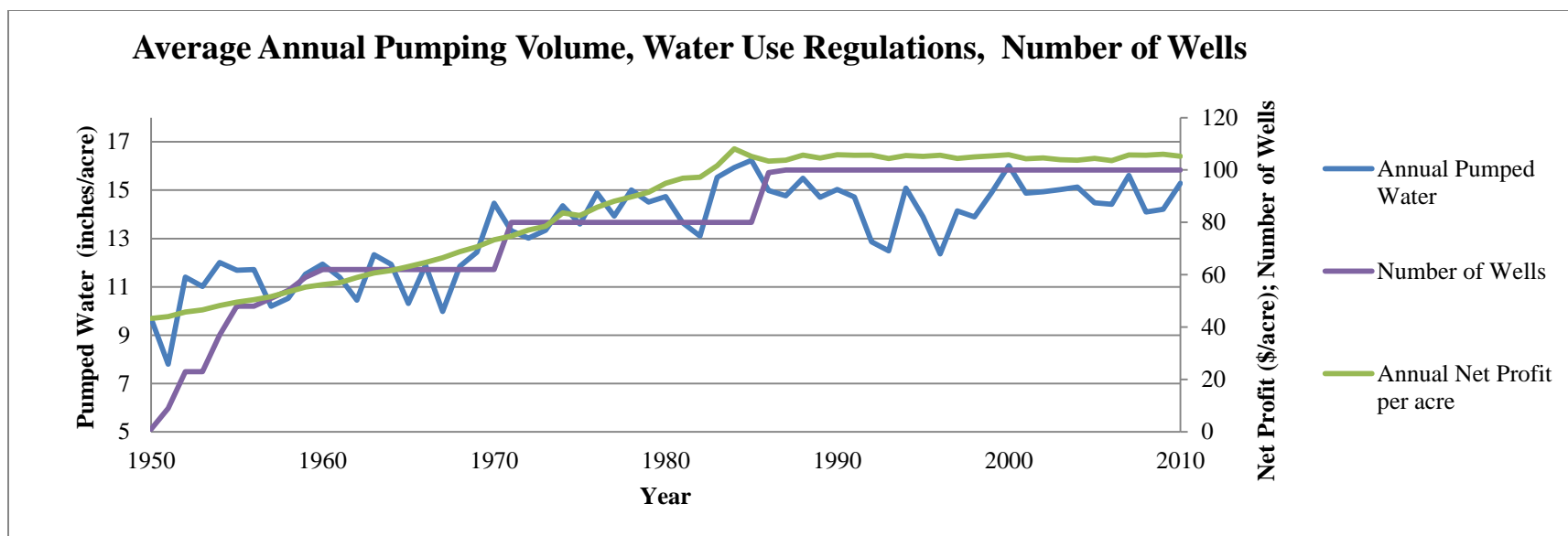


Figure 42: ABM Scenario 3 - A comparison of average annual pumping to annual net profit per acre and well growth

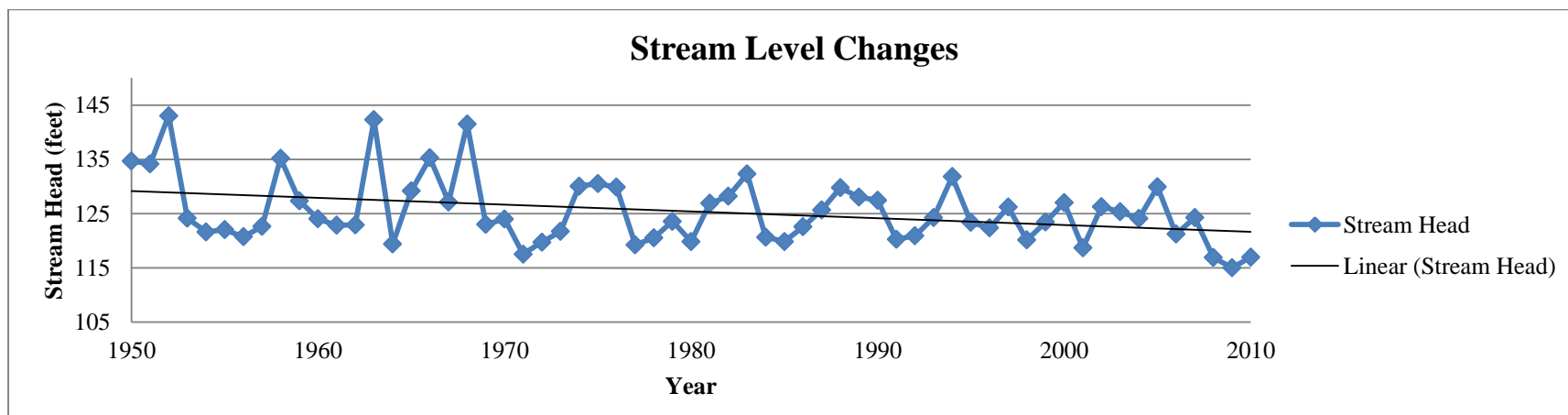


Figure 43: ABM-MODFLOW Scenario 3 results - Stream level declines

4.6 Scenario 4 and 5: Early and late timing of regulation change

Overall, it appears that both Scenarios 4 and 5 confirm that the timing of regulations does impact stream level decline. We can also gain some insights on the way farmer behavior has reacted in response to the timing of regulation change from these two scenarios.

In Scenario 4, the timing of regulation change is adjusted by increasing the sensitivity of regulatory agents to changes in the level of the stream. The results of this are shown in Figure 44 and 45. This adjustment causes a shift in the timing of regulation change such that the initial drop from 20 inches/acre to 15 inches/acre occurs in 1980, rather than 1988 in the historical simulation. At this point in time, not all farmers have switched to groundwater irrigation, but we still see a similar peak in water use following the shift from 14.5 in/acre to 13.5 in/acre as in the historical simulation. Although, it does appear that this peak is slightly delayed, occurring closer to the timing of the regulation change from 13.5 in/acre to 13 in/acre. In this scenario, we are also able to see the slow decline in water use following this peak as regulations decline further through time. Stream level change declines more slowly in this scenario than in the historical simulation, indicating that earlier regulation changes did have a more positive environmental impact.

In Scenario 5, see Figures 46 and 47, the sensitivity of regulatory agents to changes in stream level was decreased, lessening their responsiveness to stream declines. With this formulation, regulations initially changed in 1996, eight years later than the historical simulation. Stream level declines are slightly higher in this scenario as a result of this delay. Similar to the other scenarios, we do observe a peak in average annual water use, but the timing is slightly different in this scenario as compared to others.

Between these two scenarios, we can see that shifting when regulatory change occurred showed us that the timing of peak of water use also was affected. When regulation changes happened sooner in the simulation, the peak occurred at a lower regulation threshold, closer to 13 in/acre. In the other scenario, we saw the opposite effect – a delayed timing of regulation change caused the peak water use to occur at 15 in/acre.

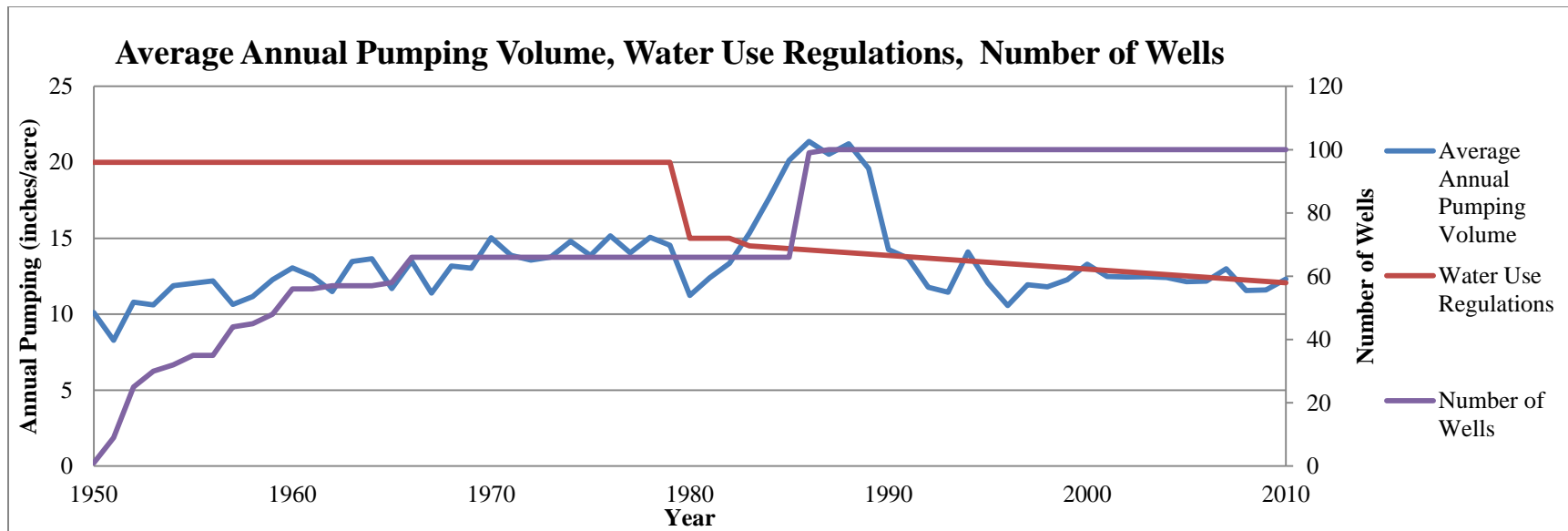


Figure 44: ABM Scenario 4 - A comparison of average annual pumping to changes in water use regulations and well growth

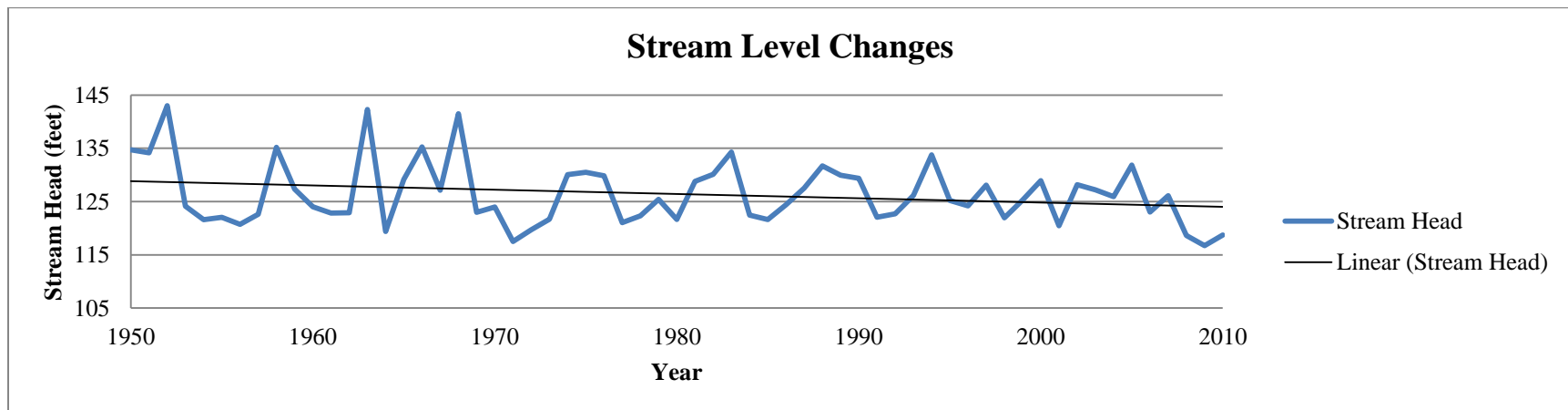


Figure 45: ABM-MODFLOW Scenario 4 results - Stream level declines

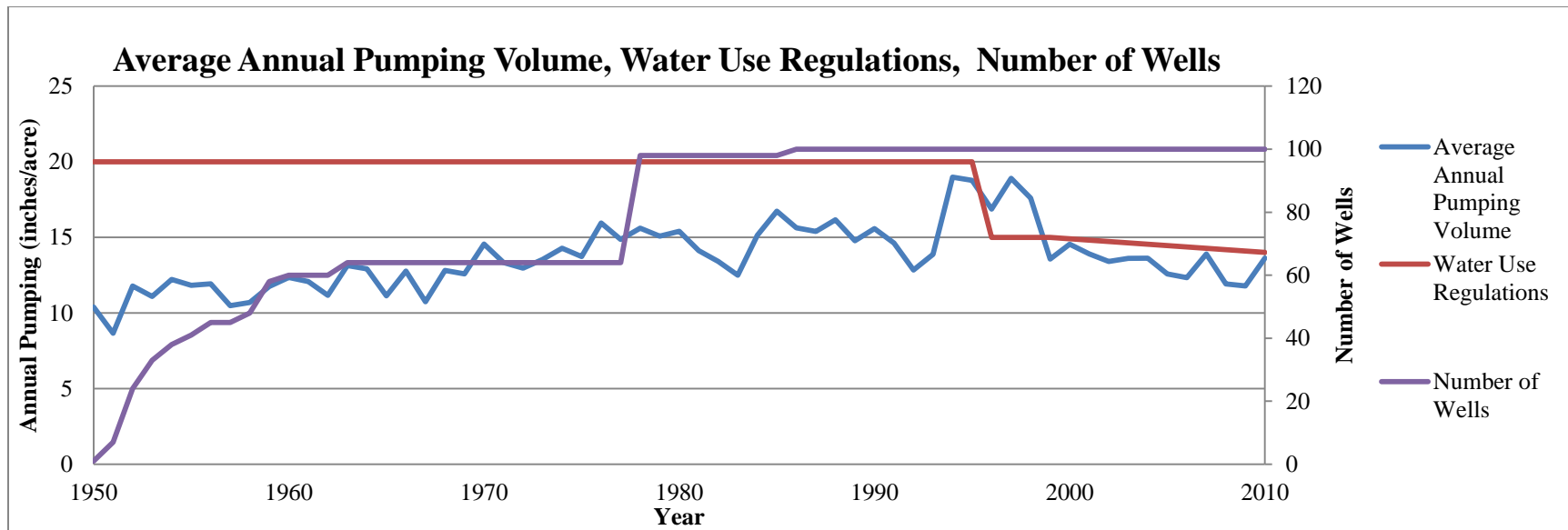


Figure 46: ABM Scenario 5 - A comparison of average annual pumping to changes in water use regulations and well growth

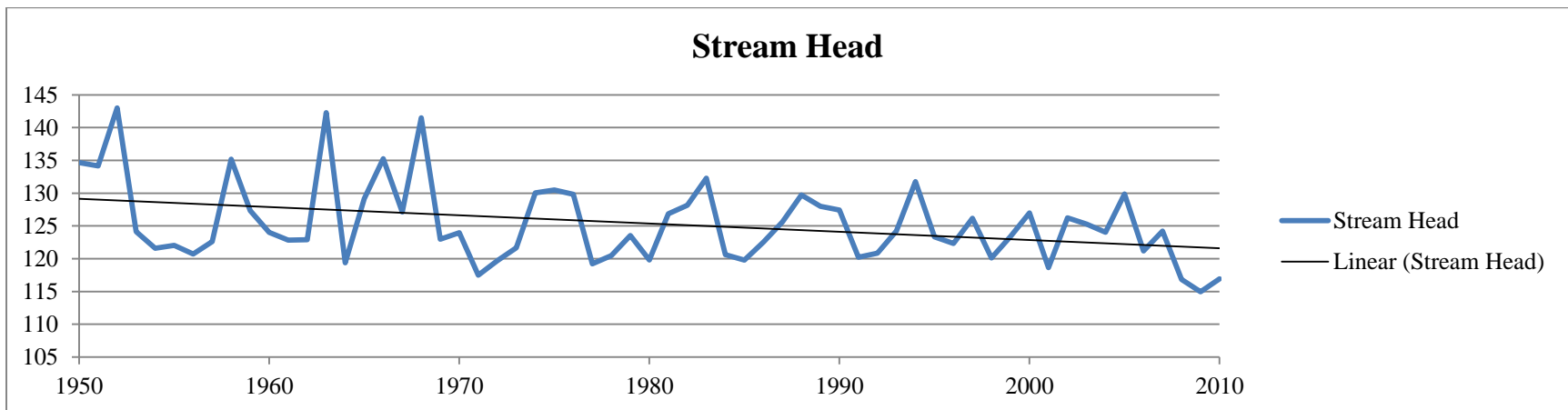


Figure 47: ABM-MODFLOW Scenario 5 results - Stream level declines

4.7 Spatial Considerations

Additional inferences can be made about the drivers of farmer behavior from an analysis of the spatial distribution of water use. The first set of images in Figure 48 below show the spatial distribution of farmer behavior at three time points during the simulation. The color of the farmer indicates the annual pumping volume; these colors change at each year during the simulation. Red indicates a volume of 9 in/acre or less, green a volume of 9 – 13 in/acre and blue a volume greater than 13 in/acre. The yellow colored farmers show the the farmers with the highest pumping volumes in a given year. Below, we can see that the farmer’s behavior is fairly heterogeneous in all three images and follows a slight spatial trend, with red farmers closer to the stream and blue and green farmers further away. In general, this trend suggests that farmers pump more water as their distance to the stream increases.

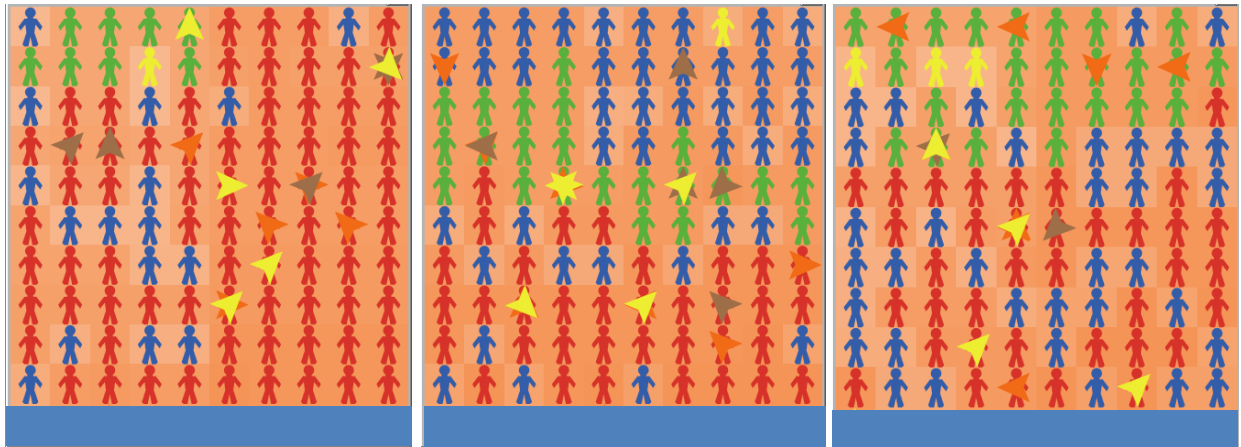


Figure 48: Spatial distribution of pumping behavior for simulation scenario

The images from Figure 48 are taken from three points in time after water use regulations have been implemented. Regulations decrease from 15 in/acre in the lefthand image to 13.5 in/acre in the righthand image. This is important because it shows the increase in spatial heterogeneity as regulations become more restrictive. Because the behavior model used is highly dependent on physical

relationships, we can attribute this heterogeneity to the farmer's behavior factor, and these shifts in behavior to regulation change. To further explore this, the spatial trend among farmers in Scenario 1, where institutions and regulations were inactive, was examined. Figure 48, below, shows images from the same three points in the simulation period as in Figure 48, above.

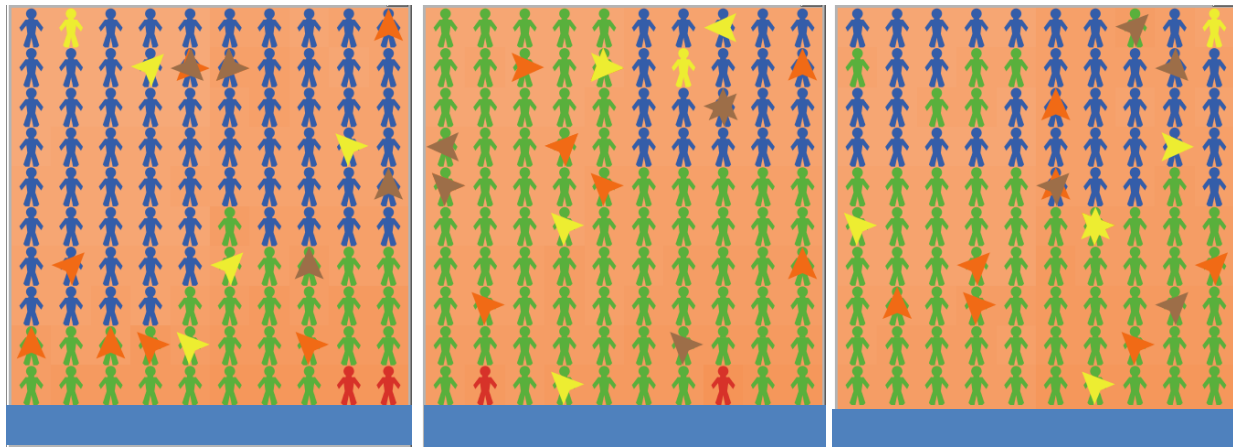


Figure 49: Spatial distribution of pumping behavior for Scenario 1, with no regulations

In Figure 49, we can see farmers generally pump a higher volume of water in this scenario, which is most likely due to the lack of regulations. The spatial trend that suggests higher pumping values further from the stream is also apparent in these images, with more green colored farmer's closer to the stream and the higher water-users, the blue farmers, in the upper portion of the images. The same pattern is observed in Scenario 3.

It is also evident that the same heterogeneity seen in the simulation run does not dominate the spatial pattern here. Instead, there are strong spatial zones of homogeneous pumping behavior. These zones can be further identified by the four soil types that make up the physical environment of the model. This is important as we can see evidence of the effect of environmental characteristics on farmer's behavior.

Overall, it seems that as regulations become more restrictive, the behavior factor of a farmer is more evident in pumping decisions. More specifically, we can see that in the absence of regulations, farmer behavior is more strongly dominated by physical factors, such as soil type and distance to the river, than it is when regulations are in place.

4.8 Regulation change and streamflow

To analyze the impact of regulation change on stream level, we can look at the results of the simulation run, those from Scenario 1, which was run with no regulations, and two more scenarios – 4 and 5, which altered the timing of regulation change. In Scenario 4, we increased the sensitivity of regulatory agents to changes in streamflow. In this way, regulations were first changed in 1980 – eight years sooner than the historical simulation. In Scenario 5, the sensitivity of regulatory agents was again adjusted such that regulations first began to change later, in 1996. Figure 50, below, shows the timing of regulation change with stream level declines from the simulation run.

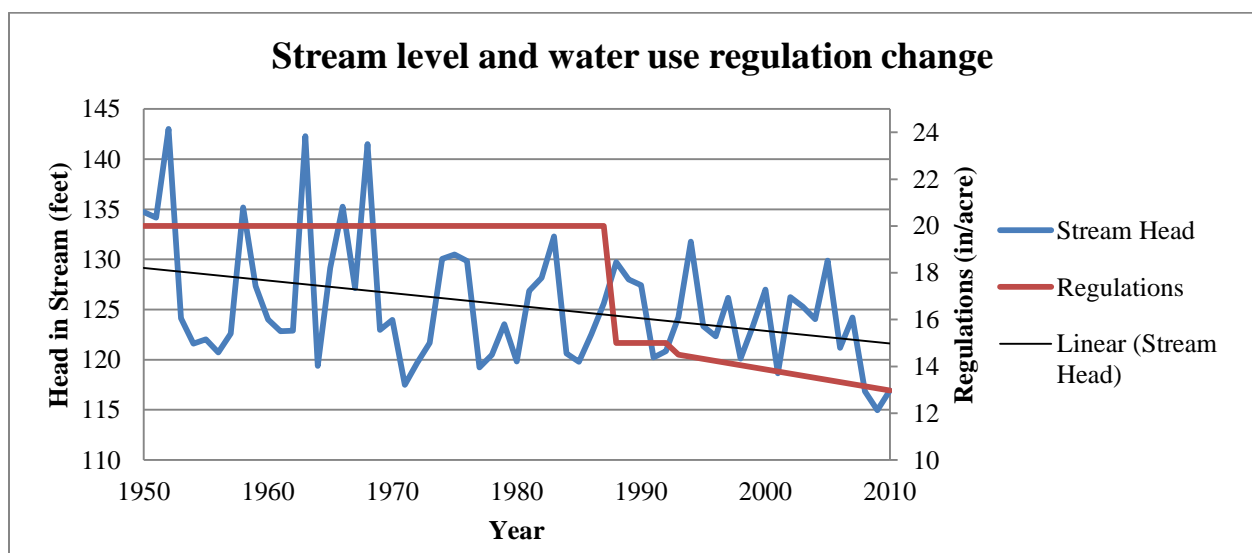


Figure 50: ABM simulation results – stream level declines and regulation change

From Figure 50, there are no dramatic shifts in stream level, rather a gradual decline that results from years of continued groundwater use for agriculture. This decline is also shown in the black linear trendline in the figure. When comparing these results to the stream level changes from Scenario 1, it is apparent from the slope of the trendline that there is a larger drop in the water level when regulations are not in place, see Figure 51 below. From Scenarios 4 and 5, those that had early and delayed implementation of regulations, respectively, we can also see a higher drop in stream level when regulations are not applied as soon. Again, we do not see a dramatic change in stream level following the regulations in these scenarios.

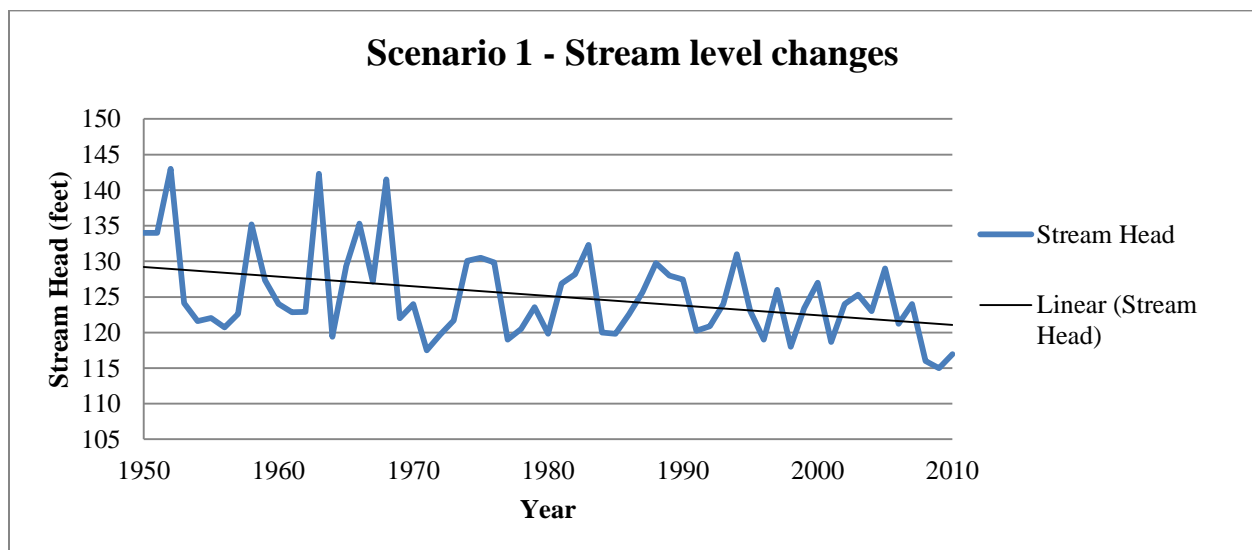


Figure 51: ABM Scenario 1 results – changes in stream level in the absence of regulations

The decline in stream level could be partially cushioned due to the leveling out of water use observed in the Scenario 1 results, see Figure 36. Farmer's behavior, which is based primarily on physical relationships, did not drive them to continuously increase water use, so stream levels did not decline at as dramatic of a rate. Using irrigation scheduling as a

management strategy may, thus, help to control over-pumping per acre as well as contribute to streamflow restoration.

4.9 Behavior Factor

In the different scenarios we can see different dynamics in the average farmer behavior factor through time, see Figure 52. In both scenarios with no regulation change, the behavior factor is fairly constant and increases steadily through time. This increase is most likely due to improvements in irrigation application and consequently, crop yield, which is one driver for increases in the behavior factor. In the other three scenarios and the historical simulation, we can see the timing of behavior change corresponding to regulation changes. The differences in peak values also follow with the idea that the behavior factor increases steadily through time - the early timed regulations result in the lowest peak in the behavior factor, the historical simulation result in the middle peak and the late regulations produce the highest peak in the behavior factor. This dramatic shift in behavior in response to regulation change can be understood as one of the drivers behind the threshold observed in Scenarios 1, 2 and 3.

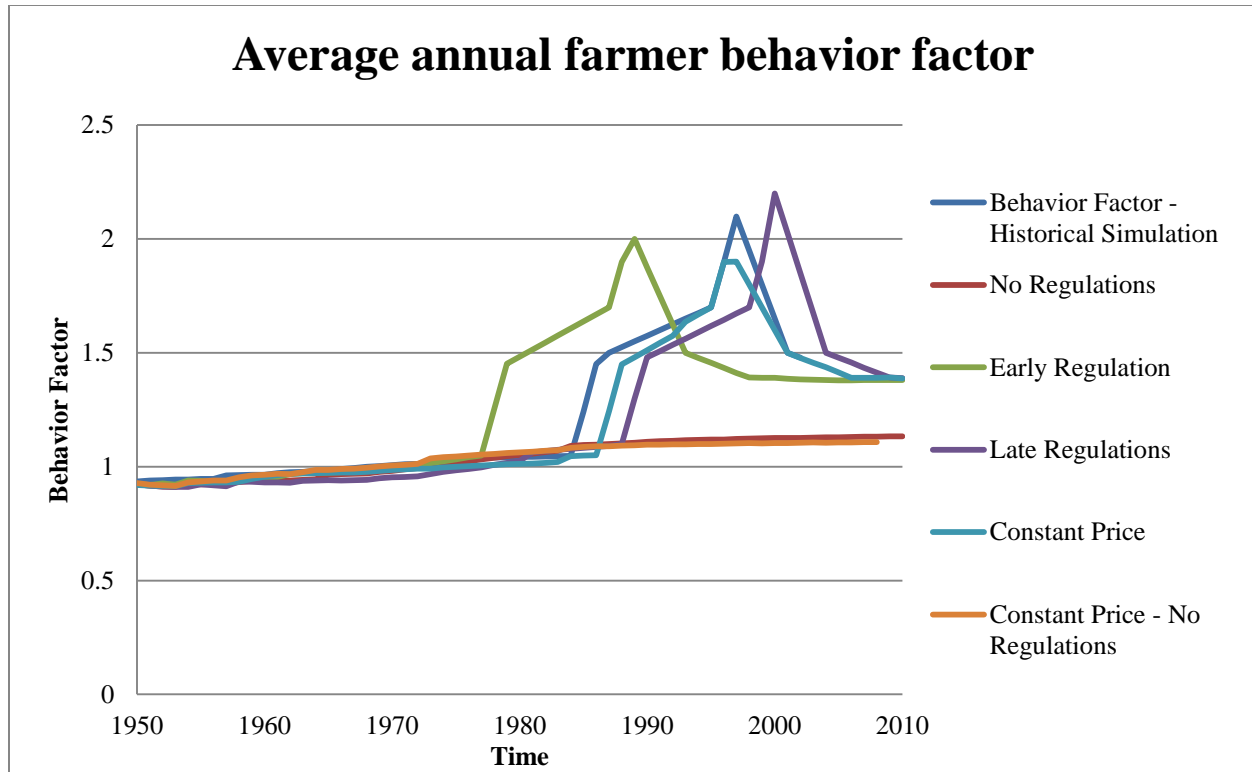


Figure 52: ABM results – behavior factor changes in historical simulation and each scenario

4.10 Key results

In summary, using the coupled ABM we are able to extract key inferences on the drivers of farmer's behavior, the mechanisms behind their reaction to changing regulations, and the importance of more decentralized management strategies. We summarize these inferences organized around the research questions upon which the ABM was formulated.

Q1: What key points or thresholds can we identify and how are they critical to both the human and natural systems involved?

From the three scenarios, we concluded that a behavioral threshold exists at 13.5 in/acre. This regulation change triggered a stronger reaction by farmers than previous restrictions on water use caused. This threshold is highly tied to both physical and social systems and indicates a point in which both systems reach a critical point, as shown in Figure 53. On the social side, this threshold illustrates a point in which farmer behavior strongly reacted to regulatory oversight. On the physical side, we see a point in which the physical needs of the agricultural system are limited by water availability. Further, we can characterize this threshold as one in which farmers become less reactive to the environmental and more reactive to institutional factors. The dramatic increase in the behavior factor observed at this threshold causes this factor to be a more prominent driver of farmer decision making that in the time period before, so environmental variables are less dominant. The peak in the farmer behavior factor occurred in all scenarios at this threshold. This reaction was also found to be sensitive to crop price, as this impacted the farmer's net profit.

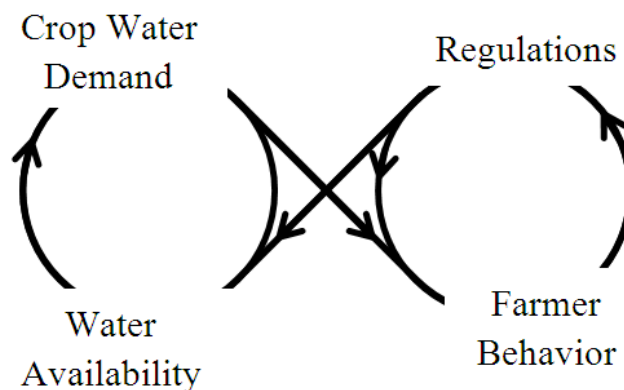


Figure 53: Conceptual coupling point between physical and social systems

Q2: How has regulatory change impacted farmer decision-making?

Generally, spatial patterns in farmer behavior also showed that regulations increase heterogeneity in pumping decisions and heighten the impact of an individual's behavior factor. Less restrictions on water use produced more homogeneous behavior patterns that reflected a farmer's physical conditions.

The timing of the point of coupling between the three systems – farmers, institutions and the environment is highly driven by both farmer behavior as well as institutional decision-making. The sensitivity of regulatory agents to changes in streamflow impacted both the timing of regulation change as well as the timing of the threshold discussed above. When regulatory agents enacted regulation change sooner, the farmer behavioral threshold occurred at 13 in/acre; when they responded later, the threshold occurred closer to 15 in/acre. We can recall from the above discussion that this coupling point, or threshold, reflects the switch from farmer decision-making being dominated by environmental variable to being more reactive to institutions as well as the environment. From this, it seems that heightened institutional sensitivity to the environment also increased farmer adherence to the demands of the physical system.

In addition, we can gain some insight on how to adapt management strategies given the results of this model. Generally, stream level declines were found to be mitigated by implementation of regulations. However, the physical components of the decision-making framework could also be used as a guide to limit water use, as modeling results show a natural upper limit in water use. Management strategies which focus more on limiting variations in behavior and focusing on farmer's physical conditions could be successful at mitigating future declines and restoring stream levels.

Q3: What role do physical considerations play in a farmer's actual decision on water use?

In general, the pumping volume appeared to level off naturally around 14.5 – 15 inches per acre in the absence of regulations. Because the farmer decision-making framework was based on physical relationships between soil type, climate and crop growth, at the individual level this quantity of water use was probably the maximum water needed by crops. The multiple scenarios analyzed showed us that in absence of regulations, farmer's behavior more closely followed the needs of the surrounding environment, and the impact of this upper bound on water use was more pronounced. This was also shown in the spatial homogeneity of farmer behavior in the absence of regulations. When institutional regulations become more restrictive on farmers, the impact of individual decision-making was more apparent and the importance of environmental considerations was lessened.

CHAPTER 5

CONCLUSIONS

This research examined the dynamics of farmer behavior on groundwater use, regulatory institutions and decision-making and the feedbacks and response of natural groundwater and surface water systems in the Republican River Basin. We viewed the RRB as a coupled human-nature system and utilized integrated methods, including a coupled physically-based and agent-based model, which drew from hydrology, statistics, sociology, agronomics and economics.

From the statistical analysis we found that spatial covariances between agricultural wells in the Republican River Basin were an important driver for decision-making and could be the result of collaboration between neighboring farmers; and that a consideration of both environmental and social factors is key for understanding farmer's water-use behaviors.

These results were extended to inform the development of the coupled agent-based and physically-based model. This modeling framework was shown to be capable of representing basic relationships between changes in streamflow, water use regulations and farmer's decisions on the timing and amount of irrigation. We concluded that a behavioral threshold exists at 13.5 in/acre in which institutional and social variables may play a larger role in farmer's decision on water use than previously. In addition, we found that the implementation of water use regulations increased the heterogeneity in pumping decisions and heightened the impact of an individual's behavior factor. In absence of regulations, farmer's behavior more closely followed the needs of the surrounding environment. Our results also suggest that management strategies which focus more on farmer's physical conditions could be successful at mitigating future surface water declines and restoring stream levels.

Our use of coupled physically-based and agent-based modeling illustrates the flexibility of the method to functionally integrate several models, particularly when dealing with multiple, interconnected systems. However, all systems involved were highly complex so the model was only able to represent key relationships between the human and natural systems. The framework can still be extended to be better informed by local surveying and research, include more complex physical processes and would benefit from more interaction between social and physical scientists. Coupled models should also be used with caution, though, as each system is limited by the formulation and assumptions of the other - too much simplicity or complexity from one model can largely impact the results from another. Overall, this method offers a unique platform for multiple disciplines to test scientific theories, collaboratively develop model components and build a model capable of providing insights for researchers across disciplines.

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