Essay in Environmental Spillover of US Crop Insurance on Surface Water, Agricultural and Geographical Effects on Surface Water Impairment, and A Hypothetical Irrigation Game in Madison Co., TN

A Dissertation Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

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December 2018

"He giveth, and giveth, and giveth again." -Annie J. Flint

Acknowledgments

I would like to express my sincere immeasurable gratitude to my super adviser Dr. English, Burton C., for his patience listening to my broken english, encouragement to finish the works, for his way of coaching by answering my question with question which develops my curiosity, also for his trust, grace, compassion, guidance and wisdom. I would also like to thank him for the life lessons that I have learned during the weekly meeting which are more valuable than any knowledge I have gained in class.

I would also like to express my profound appreciation to Dr. Clark, Christopher D., and Dr. Lambert, Dayton M., for their support, guidance, critics, and willingness to let me sit in their offices, hours after hours asking too many questions about microeconomics and econometrics.

Special thanks to Dr. Carruthers, Celeste K., and Dr. Hodges, Donald G., for their comments and suggestions on my dissertation.

I would also like to thank my office mates and friends in Knoxville who endure this phd life together. It has been a great camaraderie.

Last but foremost, to *Bapak*, *Mama*, Hilda, Hellen, Krisboa, and Herbert, thank you for the encouragement and prayers.

Abstract

Essay in ‘Environmental Spillover of US Crop Insurance on Surface Water’ investigates the spillover effect of the premium subsidy change in crop insurance to the surface water impairment. A two-step IV-GMM with SHAC optimal weighting matrix is used in the estimation. Data for the empirical evidence are from EPA, Risk Management Agency, National Agricultural Statistics Service, and US Census Bureau are used. The estimation results suggest an increase in premium subsidy and/or indemnified losses could lead to an increase in insured acres. However, the increase in insured acres may not significantly worsen the condition of impaired waters.

Essay in ‘Agriculture and Geographical Effects on Water Impairment Condition’ investigates the impact of agriculture and geographical effects on water impairment condition by assembling county-aggregated huc-12s water impairment data and county agricultural data. Number of farms, number of animal units, farm-size, and agricultural-designated waters are used as agricultural indicators. County elevation and geographical position from equator are used as geographical indicator. Using IV approach, this study finds that higher number of farms and animal units could worsen water impairment condition. However, larger farm-size is associated with less change in water impairment. County located on predominantly higher elevation tends to have larger agricultural-designated waters which subsequently worsen the water impairment. There is also evidence that county’s geographical position is significant in explaining county’s progression in water impairment.

Essay in ‘A Hypothetical Irrigation Game in Madison Co., TN,’ examines the condition that could lead to groundwater overdraft due to competition among farmers where weather condition dictates optimal water allocation. Using a dated response function and Madison County, TN., weather data from Jackson Weather Station, the simulation results indicate

that when pumping cost is relatively low, the risk averse farmer would allocate more water than risk neutral farmers including during wet months. The result implies that the overdraft problem in southeastern region might exist if most farmers in the region are risk averse and pumping cost are very low. Thus, the sense of competition of water extraction might lead to groundwater overdraft even though the region has high precipitation.

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Chapter 1

Introduction

The primary aim of US Agricultural policy is to assure the continuance of agricultural production (Tolley et al. 1938[59]). To meet those objective, policy instruments have been enacted (e.g., federal crop insurance, commodity loans to farmers) resulting in an expansion of the agricultural sector (Young et al. 2000[72]). The expansion may carry spillover effects to surface water quality and to water resource availability. This dissertation considers this broad issue in three essays.

The first essay titled 'Environmental Spillover of US Crop Insurance on Surface Water' examines the spillover effect of the change in crop insurance premium subsidy to the surface water impairment. The background of this first essay is that an increase in crop insurance subsidy may cause farmers to convert more land into cropland (Wu 1999[70], Goodwin et al. 2013[24], Claassen et al. 2016[8]) which could subsequently increase the surface water impairment. In this first essay, a system of equations is used to portray the relationship between changes in crop insurance subsidy, changes in insured acres, and changes in impaired waters at county level. Using data from EPA (water impairment geospatial information), Risk Management Agency, USDA (crop insurance data), National Agricultural Statistics Service, USDA (agricultural land in acres, number of livestock), and US Census Bureau (population growth), a two step Instrumental Variables-Generalized Method of Moments (IV-GMM) with spatial heteroskedasticity and autocorrelation covariance (SHAC) optimal weighting matrix is used to estimate the system of equations

The second essay of this dissertation is titled 'Agricultural Sector and Geographical Difference Effects on Water Impairment Condition'. The objective of the second essay is to provide general empirical evidence of agriculture sector on water impairment in US (Carpenter et al. 1998[5], Parry 1998[43]) and to examine how geographical difference across counties affect the water impairment condition. In this second essay, the county geographical feature is represented by elevation, and county's geographical position. The county's geographical position from equator is expected to capture the climatic or weather differences across counties (Frakes 1972[20]). Number of farm operations, animal units, farm-size and agricultural-designated waters are used as agricultural sector indicators that could affect the water impairment. The agricultural-designated waters are assumed to be endogenous, thus, Instrumental Variables approach is used to estimate the regression model.

The third essay of this dissertation is titled 'A Hypothetical Irrigation Game in Southeastern US: Madison Co., TN.' as irrigated land continues to increase in southeastern region of US (Mullen et al. 2009[40]). Groundwater overdraft might exist due to competition even though the region has high precipitation (Evett et al. 2003[17]) and the groundwater table is replenished annually. The objective of this essay is to evaluate conditions that could lead to groundwater overdraft as a result of competition among farmers. This essay assumes that there are two identical farmers that compete for an aquifer for irrigation. The analysis is done under four scenarios of per-acre inch water pumping cost and two scenarios altering risk preference.

Chapter 2

Environmental Spillover of US Crop Insurance on Surface Water

2.1 Introduction

To increase insurance participation, the US Congress has restructured the US Crop Insurance Program (Glauber et al. 2004[22]; Goodwin et al. 2004[25]; Woodard et al. 2012[68]). On August 13, 2015, the Congressional Research Service produced a report concerning the public cost of the crop insurance program. One of the main concerns was that the subsidized insurance premium exceeded farmers out-of-pocket costs to adequately protect themselves. If the claim is true and farmers are rational agents, then there must exist increasing insurance participation after the amendment took effect. As the participation rate increases, the insured farmers‘ production decision would likely affect surface water condition.

Subsidized crop insurance may induce changes in the production decision. In general, the changes can be categorized into two schemes (Claassen et al. 2016[8]). First, farmers could activate more acres into cropland (Wu 1999[70]; Goodwin et al. 2013[24]; Claassen et al. 2016[8]). Second, farmers could change farming practices by changing input decisions (Quggin et al. 1993[47]; Horowitz et al. 1993[32]; Smith et al. 1996[55]; Wu 1999[70]; Goodwin et al. 2004[25]; Walters et al. 2012[65]; Goodwin et al. 2013[24]; Claassen et al. 2016[8]).

Several early works have discussed the subsequent effect of federal crop insurance on the environment, including on groundwater nutrient content, soil structure, land use change, nitrogen run off, and sedimentation. Goodwin et al. (2003) analyzed the effects of crop insurance on soil loss ([23]). They used two stage least square and county level data from USDA's National Resources Inventory database describing soil erosion, soil structure, and land use pattern. From the results, they found that subsidized crop insurance decreases soil losses. However, the magnitude of the effect is small. Walters et al. (2012) investigated the impact of crop insurance on acreage allocation and its subsequent impact on soil erosion at producer level ([65]). They used crop insurance data from Risk Management Agency, USDA and soil indicator data from National Nutrient Loss and Soil Carbon Database. Using panel data regression method, they found that crop insurance significantly affects the acreage allocation. However, the empirical evidence suggests that the impact of insurance-induced acreage allocation on soil erosion is small and ambiguous across regions. Claassen et al. (2016) investigated the impact of crop insurance on land use change and crop choices in the Corn Belt region data, and its subsequent impact on nitrogen run off, soil content and sedimentation ([8]). They used the latent class logit models to estimate the effect of crop insurance on land use and crop choices. And then, used the estimated coefficients to simulate the impact of land use change and crop choices on the environmental indicators. From the results, they found that crop insurance has an impact on crop choice and crop ration. However, they also found that crop insurance has small impact on land use change from non-cropland to cropland. Thus, they concluded that crop insurance has no substantial impact on the environment.

The aforementioned works measured the environmental impact on the basis of soil quality and only provided empirical evidence for a particular region. Therefore, to add to the literature, this paper measures the environmental spillover of crop insurance program on the surface water impairment and provides empirical evidence across US using more than 2,000 counties as observations.

In this paper, the spillover effect of the change in crop insurance premium subsidy to surface water impairment through the change of insured acres is examined. Crop insurance data at county level and water impairment data at hydrological unit code level-12 (HUC-12) are used in the analysis. The huc-12 level geospatial data of water impairment are aggregated to a county level using 2010 US County Shapefile. Since the water impairment data are in cross-section form but, the crop insurance data are in longitudinal form, the crop insurance variables are evaluated by using annual average growth. Additional variables such as animal units, population growth, agricultural land, and agricultural-designated waters are also used in the analysis.

A system of two equations is used to portray the relationships between the changes in subsidized crop insurance, the changes in insured acres, and the changes in water impairment. The first equation captures the relationship between the changes in crop insurance policy (e.g., premium subsidy) to the changes in insured acres. The second equation captures the relationship between the changes in insured acres to the changes in water impairment condition. A two-step Instrumental Variables - Generalized Method of Moments (IV-GMM) is used to estimate the system of equations. Due to water impairment data aggregation, an unknown heteroskedasticiy and autocorrelation (SHAC) problem across spatial units is expected (Lambert et al. 2016[36]). To address the issue, this paper adopts the Lambert's et al. (2016) SHAC variance-covariance estimator to develop an optimal weighting matrix in the IV-GMM estimation ([36]). The estimation results suggest that the changes in premium subsidy leads to significant increase in insured acres. More type of losses that are indemnified lead to larger insured acres. However, the results show that these additional insured acres do not significantly worsen the condition of impaired waters.

2.2 Conceptual Framework

Insured Acres and Subsidy

Several earlier works have discussed the extensive-effect of subsidized crop insurance on acreage of cropland. Goodwin et al., (2004) tested the effects of subsidized crop insurance program on acreage allocation decision for corn and soybean in the Corn Belt and the Northern Great Plains region [25]. Using a system of equations portraying the endogenous production decision of farmers, they found that expansion of insurance premium subsidy significantly associated with expansion of acreage cropland. Goodwin et al., (2013) estimated acreage response function to changes in premium subsidy rate using county-level planted acreage from NASS, USDA and five-year historical averages of the insurance premium subsidy rate data for corn, soybeans, cotton, and wheat from RMA, USDA [24]. Using Ordinary Least Square estimation, they found that higher subsidy rates and higher participation in the previous year are significantly associated with an increase in cropland acreage. Claassen et al. (2016) integrated economic and biophysical models to measure the impact of subsidized federal crop insurance on land use decision and cropping patters in Corn Belt region at parcel level [8]. Using latent class logit models, they found that in Corn Belt region, the subsidized federal crop insurance had impact on crop choice and crop rotation, but no substantial impact on land conversion from non-cropland to cropland.

The literature infers that the subsidized crop insurance may or may not cause an additional acreage to the preexisting cropland. However, the literature indicates that there exists a crop insurance-induced change on the preexisting cropland. It suggests that the change at least happens to the acreage land which is already insured. Therefore, the relationship between the changes in insured acres and the changes in premium subsidy can be specified as:

$$A = h(s, z) \tag{2.1}$$

where A denotes cropland, s denotes subsidy per-enrolled acres, and z denotes a vector of other exogenous variables that could also determine the insured acres (e.g., insurance indemnity). The marginal effect of the changes in premium subsidy on cropland can be derived by taking the total derivative of equation (2.1). The total derivative can be specified into:

$$dA = \frac{\partial h}{\partial s} \, . \, ds \ + \frac{\partial h}{\partial z} \, . \, dz \tag{2.2}$$

where $\frac{\partial h}{\partial s}$ is the coefficient of interest indicating the marginal effect of insurance premium subsidy to insured acres.

Water Impairment and Insured Acres

Changes in agricultural land use is perceived to have an impact on surface water quality (Sharpley et al. 1994[53]; Allan et al. 2004[1]; Foley et al. 2005[19]; Tang et al. 2005[58];

Lubowski et al. 2006[37]). Assuming all agricultural land are insured, then, the relationship between the changes in surface water condition, w, and the changes in insured agricultural land, A, can be specified as:

$$w = g(A, x) \tag{2.3}$$

where the total derivative and the marginal effect of the changes in agricultural land can be specified into:

$$dw = \frac{\partial g}{\partial A} \,.\, dA \;\; + \; \frac{\partial g}{\partial x} \,.\, dx \tag{2.4}$$

$\boldsymbol{x}$ denotes exogenous variables that explain the waterbody condition such as population growth, and livestock related variable within a region.

If the changes in premium subsidy substantially alter the insured cropland within a region, then, presumably there is a spillover effect of the changes in premium subsidy to the waterbody condition. This relationship is captured by substituting equation (2.2) into (2.4). Substituting equation (2.2) into (2.4) results in the reduced form of the structural equations.The coefficient $\frac{\partial g}{\partial A} \times \frac{\partial h}{\partial s}$ from the reduced form captures the spillover effect of the changes in the premium subsidy to the changes in waterbody condition.

2.3 Data

The data used in this study are from various publicly-accessible sources. These data can be categorized into three groups which are water impairment data, crop insurance data, and agricultural and demographic data. Water impairment data are from Environmental Protection Agency (EPA) database. Crop insurance data are from Risk Management Agency (RMA), USDA database. Agricultural and demographic data are from United States Census Bureau and National Agricultural Statistics Service (NASS), USDA.

Water Impairment Data

Federal Clean Water Act section 305(b) requires each state to biennially monitor and assess the quality of its waters. Each state has to assess and assigns its huc-12 waters as ‘good’, ‘impaired’, or ‘threatened’ given the designated use (e.g., agricultural activity, industrial, recreation, etc.). EPA compiled states' past reported assessment as geospatial database which is titled as '305(b) Waters As Assessed' (EPA 2017b[16]). EPA also compiled national baseline data of impaired water which is titled as '2002 Impaired Waters Baseline' (EPA 2017a[15]). EPA developed the '2002 Impaired Waters Baseline' database to create a consistent measure of progress of the nation's water impairment. The '305(b) Waters As Assessed' contains data from cycle year 2002 to 2012. Whereas, the '2002 Impaired Waters Baseline' contains impaired waters information from baseline year 1998 to 2004.

EPA data records (Appendix: Figures A.1 and A.2) indicate that there is no time variation in water impairment data for each state. With this limitation, this study measures a one-time change of water impairment at the county level. The measurement is done by taking the difference of impaired waters (km) from baseline year record and cycle year record within each county. The 2010 US county shapefile from US Census Bureau is used to identify the county location of each segmented huc-12. Using Arc-GIS software package, the huc-12 data are intersected with the 2010 US county shapefile. These huc-12 level data are aggregated into county level resulting 2,811 counties. Table 2.1 summarizes the number of counties depending on county's baseline and cycle year. From this merged-dataset, two variables are generated, county level percentage change of impaired water and county level ratio of total agricultural-designated waters to total water length.

Table 2.1: Number of county as represented by the water impairment data

cycle		2002	2004	2006	2008	2010	2012	Total
baseline	1998				4	47	21	72
	2000				2	28	124	154
	2002	41	108	43	60	920	1,406	2,578
	2004					1	6	7
Total		41	108	43	68	995	1,551	2,811

Source: county-aggregated 2002 Impaired Waters and 305(b) Waters As Assessed

This study assumes that the changes in impaired waters is an accumulative effect from what happens in agriculture. Therefore, this study only observes counties that have at least five-year gap between baseline year and cycle year. From 2,811 counties, there are only 2,419 counties that meet the criteria. The impaired waters data of 2,419 counties are merged with county level data of crop insurance, agricultural land data, total animal units data, and population growth data.

Insured Acres, Premium Subsidy, Insurance Indemnity

Crop insurance data are collected from the summary of business reports of Federal Crop Insurance (RMA USDA 2017[50]). The summary of business reports contains information of total insured acres, number of policies sold, the total value of insurance liability, insurance premium, subsidy, indemnity amount, and loss-ratio percentage for each county/state/agricultural district/crop type/insurance policy/coverage level. For the purpose of this study, there are three variables that are used in the analysis. These variables are the total insured acres, total amount of subsidy, and total amount of indemnity at county level.

These crop insurance data have different data structure from the water impairment data. The water data is in cross-sectional structure, whereas the crop insurance data is in longitudinal structure. To accommodate this difference, the crop insurance variables are evaluated at growth level (%) for each county, unconditional to the type of insurance, coverage level, and crops. The growth is the average of annual growth within the gap period (baseline year and cycle year) of water impairment data. For example, Baldwin County, Alabama has 2002/2012 gap period in its water impairment data. Therefore, the crop insurance variables of Baldwin County, AL., are evaluated at average annual growth (%) between 2002-2012. Another example, Preston County, West Virginia, has 1998/2010 gap period in its water impairment data. Therefore, for the Preston County, WV., the crop insurance variables are evaluated at average annual growth (%) between 1998-2010. This crop insurance data are merged with the county-aggregated impairment data resulting in 2,193 observations. The summary statistics of percentage change of impaired waters and annual average growth of crop insurances variables are presented in Table 2.2.

Ratio of Agricultural Land, Ratio of Animal Units, Population Growth

In this paper, several other exogenous variables that are used as instrumental variables are agricultural land density (i.e., ratio of agricultural land to county size), animal units density

Table 2.2: Crop Insurance, Population, Agriculture, and Water Impairment

County level variables	Mean	Std.	Min	Max
[1]Crop Insurance variables:				
[2]net reported acres (%Δ)	.0242	.1107	-1.0898	1.4031
[2]subsidy amount (%Δ)	.1555	.1146	-1.5182	.9739
[23]indemnity amount (%Δ)	.0695	.3876	-5.1879	4.3029
Demographic & agricultural statistics variables:				
[5]population annual avg. growth (%)	.1300	.2026	-.3640	.5705
[6]county area (km2)	2,253.05	284.34	222.56	51,947.24
[7]annual avg. of ag.-Land ratio	.1014	.1610	.0000	.9641
[8]annual avg. of animal-unit ratio	.1043	.2782	.0000	5.8786
[9]Water impairment variables:				
impaired water (%Δ)	268.78	406.50	0.00	7,767.31
water length (km)	462.39	675.23	.0018	12,858.87
ratio of agricultural-purposed water	.0915	.1642	.0000	1.0000
Number of observation: 2,139 counties				

[1]Data comes from Crop Insurance Business Reports by Risk Management Agency, USDA.

[2]The variables are in average unconditional to crop/insurance type.

[3]Total insurance indemnity over total premium.

[4]Data from Census Bureau of United States.

[5]Mean of annualized average from the 1999-2000 and 2000-2010.

[6]Data from National Agricultural Statistics Service, USDA.

[7]Mean of agricultural land ratio from census 1997, 2002, 2007, and 2012.

[8]Data from WATERS as Assessed and 2002 Impaired Water Baseline from EPA.

(i.e., total number of animal units to county size), and population growth. The agricultural land density is used as instrumental variable to the growth of insured acres (Goodwin et al. 2004[25]) and the percentage change of impaired waters. Whereas, animal unit density and population growth are used as additional exogenous variables to explain the variation of the percentage change of impaired waters (Cropper et al. 1994[10]; Vorosmarty et al. 2000[63]; Hoorman et al. 2008[31]).

The county's agricultural land data are collected from 1997-2012 US Census of Agriculture, USDA National Agricultural Statistics Service (USDA 2017[12]), whereas the total available land data are collected from US Census Bureau. For each census year (i.e., 1997, 2002, 2005, and 2012), the ratio of agricultural land to total available land is calculated for each census year. In the estimation, this study uses the average of the ratios from all census year. The total animal units are calculated from total livestock (i.e., dairy cattle, calves, swine, and sheep or lambs) in each county. County's total livestock data are collected from 1997-2012 US Census of Agriculture (USDA 2017[12]). To calculate total animal units for each county, this study follows the definition of animal units by the Office of Wastewater Management, EPA [14]. Based on the EPA's definition, a single animal unit is determined by multiplying the number of animals for each species to a constant factor of each species. In the estimation, this study uses the county average ratio of total animal units to land from every census year data.

The population growth data are collected from US Census Bureau. US Census Bureau provides 10 year growth, G, from 1990 to 2000, or from 2000 to 2010. This study assumes that annual growth, g, is constant. Therefore, annual average growth rate is solved from logical relation between annual average population growth and 10-year population growth. The relation can be described as:

$$Pop_0(1+g)^{10} = Pop_0(1+G) \tag{2.5}$$

$$g = (1+G)^{\frac{1}{10}} - 1 \tag{2.6}$$

where Pop_0 denotes for population at year 1990 or at year 2000, g denotes for annual average population growth, and G denotes for 10-year population growth. The average of calculated annual growths in 1990-2000 and 2000-2010 is used as the approximation of annual average growth for each county.

These variables are merged to the county-aggregated water impairment data and the crop insurance data. From data managing process, there are 2,139 counties of observation covering 45 states. The summary statistics of these variables are presented in Table 2.2.

2.4 Econometric Model and Results

2.4.1 Econometric Model

The percentage change of impaired waters in each county is used as the approximation of environmental indicator. As mentioned in the literature and explained in the conceptual framework section, the percentage change of impaired waters is assumed to be affected by the changes in insured acres. The changes in insured-acres itself is assumed to be explained by the changes in premium subsidy (Goodwin et al. 2003[23]; Claassen et al. 2016[8]), the changes in insurance indemnity (Makki et al. 2001[38]), and the agricultural land density within a county (Goodwin et al. 2004[25]). This study also uses several other exogenous variables to explain the percentage change of impaired waters. These exogenous variables are population growth (Cropper et al. 1994[10]; Vorosmarty et al. 2000[63]), the ratio of total length of agricultural-designated waters to the total length of waters within a county (Puckett et al. 1995[46]), the animal units density (Hoorman et al. 2008[31]), and the interaction between the ratio of agricultural-designated waters and the animal unit density. The relationships between these variables are represented by a system of equations:

$$\%\Delta acres_i = \beta_1 \%\Delta subsidy_i + \beta_2 \%\Delta indemnity_i + \beta_3 ag.land_i + \beta_0 + u_1 \tag{2.7}$$

$$\begin{aligned} \%\Delta impaired_i = {} & \gamma_1 \%\Delta acres_i + \gamma_2 \%\Delta population_i + \gamma_3 useratio_i \\ & + \gamma_4 auratio_i + \gamma_5 useratio_i \times auratio_i + \gamma_0 + u_2 \end{aligned} \tag{2.8}$$

where,

· $\%\Delta acres_i$ denotes the growth of insured acres within county i

· $\%\Delta subsidy_i$ denotes the growth of insurance subsidy county i

· $\%\Delta indemnity_i$ denotes the growth of insurance indemnity i

· $ag.Land_i$ denotes the agricultural land density within county i

· $\%\Delta impaired_i$ denotes the percentage change of impaired water within county i

· $\%\Delta population_i$ denotes county i's population growth

· $useratio_i$ denotes the ratio of agricultural-designated waters to the total length of waters within county i

· $auratio_i$ denotes the animal units density within county i.

The coefficient of estimate for the $\%\Delta acres_i$ in equation (2.8) is the coefficient of interest of this study because it captures the spillover effect of the changes in the crop insurance program (e.g., changes in subsidy and indemnity policy) to the changes in water impairment.

Structural Form

In general, the structural form of the system of equations from equation (2.7) and (2.8), can be characterized in a matrix form as (Kmenta 1997[35]):

$$By_i + \boldsymbol{\Gamma x_i} = u_i \tag{2.9}$$

where,

$$y_i = \begin{pmatrix} y_{1i} \\ y_{2i} \end{pmatrix}, \qquad \boldsymbol{x_i} = \begin{pmatrix} \boldsymbol{x_{11i}} \\ \boldsymbol{x_{21i}} \end{pmatrix}, \qquad u_i = \begin{pmatrix} u_{1i} \\ u_{2i} \end{pmatrix}$$

$$B = \begin{pmatrix} 1 & 0 \\ -\beta_{21} & 1 \end{pmatrix}, \qquad \Gamma = \begin{pmatrix} -\boldsymbol{\gamma_{11}} & 0 \\ 0 & -\boldsymbol{\gamma_{21}} \end{pmatrix}$$

$\boldsymbol{y_i}$ is a vector consisting endogenous variables of $\%\Delta acres_i$ and $\%\Delta impaired_i$. Whereas, $\boldsymbol{x_i}$ consists exogenous variables which are $\%\Delta subsidy_i$, $\%\Delta indemnity_i$, $ag.land_i$, $\%\Delta pop_i$, $useratio_i$, and $auratio_i$. u_i represents an error term vector for each equation. Matrix B represents the recursive relationship between the endogenous variables. Matrix Γ contains the estimates for the exogenous variables. For all i (county) = 1, 2, . . ., N, the equation (3.1) can be expressed as:

$$YB' + \boldsymbol{X\Gamma'} = U \tag{2.10}$$

where, Y is an $N \times 2$ matrix, X is a $N \times 7$ matrix, and U is a $N \times 2$ matrix. This study assumes that there exists an unknown form of heteroskedasticity and autocorrelation across counties due to data aggregation of water impairment (Lambert et al. 2016[36]). Therefore, the error terms, U, follows (Kelejian et al. 2007[34]):

$$U = R \cdot \varepsilon \tag{2.11}$$

where $\boldsymbol{\varepsilon}$ is an i.i.d $N \times 2$ matrix of innovation and R is a $N \times N$ non-stochastic matrix with unknown elements (Kelejian et al. 2007[34]).

This study applies a two step linear Instrumental Variables Generalized Method of Moments (IV-GMM) estimation to estimate the regression model. Supposing there exist Z_{1i} and Z_{2i}, which are the $(1 \times L_g)$ vectors of instrumental variables for each equation $g = 1, 2$ in the regression model, under the orthogonality condition of $\mathbb{E}({Z_{gi}}' u_{gi})$ and rank $\mathbb{E}({Z_{gi}}' x_{gi})$=$K$, the $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ solve the linear population moment conditions $\mathbb{E}({Z_{gi}}' u_{gi}) = 0$ (Wooldridge 2010[69]). Therefore, as sample averages are consistent estimators of population moments, the estimator $\hat{\boldsymbol{\beta}}$ and $\hat{\boldsymbol{\gamma}}$ solve:

$$N^{-1} \sum_{i=1}^{N} {Z_{1i}}' \big(y_{1i} - X_{1i}\hat{\delta}_1\big) = 0 \tag{2.12}$$

$$N^{-1} \sum_{i=1}^{N} {Z_{2i}}' \big(y_{2i} - X_{2i}\hat{\delta}_2\big) = 0 \tag{2.13}$$

Given the number of instrumental variables is larger than the number of covariates in the regression model, then, a GMM estimator of $\boldsymbol{\delta}$ is a vector $\hat{\boldsymbol{\delta}}$ that solves the optimization problem (Wooldridge 2010[69]):

$$\min_{\mathbf{d}} \begin{pmatrix} \sum_{i=1}^{N} {Z_{1i}}' \big(y_{1i} - X_{1i}\mathrm{d}_1\big) & 0 \\ 0 & \sum_{i=1}^{N} {Z_{1i}}' \big(y_{1i} - X_{1i}\mathrm{d}_2\big) \end{pmatrix}' \hat{\boldsymbol{W}} \begin{pmatrix} \sum_{i=1}^{N} {Z_{1i}}' \big(y_{1i} - X_{1i}\mathrm{d}_1\big) & 0 \\ 0 & \sum_{i=1}^{N} {Z_{1i}}' \big(y_{1i} - X_{1i}\mathrm{d}_2\big) \end{pmatrix} \tag{2.14}$$

Where $\hat{\boldsymbol{W}}$ is a $(L \times L)$ estimated, symmetric, positive semidefinite weighting matrix. For the first step of the two step IV-GMM estimation, the weighting matrix $\hat{\boldsymbol{W}}_1$ is defined as follows:

$$\hat{\boldsymbol{W}}_1 = \begin{pmatrix} N^{-1} \sum_{i=1}^{N} \; Z_{1i}{}' Z_{1i} & N^{-1} \sum_{i=1}^{N} \; Z_{1i}{}' Z_{2i} \\ N^{-1} \sum_{i=1}^{N} \; Z_{2i}{}' Z_{1i} & N^{-1} \sum_{i=1}^{N} \; Z_{2i}{}' Z_{2i} \end{pmatrix}^{-1} \tag{2.15}$$

Because equation (2.14) expresses the quadratic function of $\mathbf{d}$, thus, by plugging equation (2.15) into equation (2.14), and by aggregating to all i to cancel N everywhere, there exists a unique solution of $\boldsymbol{\delta}$ from the first step estimation:

$$\hat{\boldsymbol{\delta}}_g = [X_g' Z_g (Z_g' Z_g)^{-1} Z_g' X_g]^{-1} X_g' Z_g (Z_g' Z_g)^{-1} Z_g' y_g \;, \qquad g = 1, 2 \tag{2.16}$$

The estimator expressed in equation (2.16) equals the 2SLS estimator (Wooldridge 2010[69]). From the first estimation, $\hat{u}_{1i}$, $\hat{u}_{2i}$, $\hat{u}_{3i}$, $\forall \; i = 1...N$, are derived. Considering equation (2.11), these estimated error terms are not robust to the unknown form of heteroskedasticity and autocorrelation across spatial units. Therefore, the spatial heteroskedasticity and autocorrelation consistent (SHAC) estimator of variance covariance matrix is needed to develop an efficient weighting matrix in order to obtain robust standard error. Wooldridge (2010) characterized the efficient weighting matrix as [69]:

$$\hat{\boldsymbol{W}}_{opt} = \mathbb{E}\big(\boldsymbol{Z_i' u_i u_i' Z_i}\big) \tag{2.17}$$

substituting equation (2.11) into (2.17), then the optimal weighting matrix that is robust to spatial hetereskedasticity and autocorrelation is characterized as:

$$\hat{\boldsymbol{W}}_{opt} = \mathbb{E}\big(\boldsymbol{Z_i' \epsilon_i} R R' \boldsymbol{\epsilon_i' Z_i}\big) \tag{2.18}$$

Lambert et al. (2016) suggested a spatial-temporal robust covariance estimator in a system of multinomial logit equations [36]. Having no knowledge of other studies that demonstrate SHAC estimator in a system of equations with endogenous covariates, this study adopts Lambert's et al. (2016) spatial-temporal robust covariance estimator as the optimal weighting matrix for the second step of the two-step IV-GMM estimation ([36]). Following [36] and using the estimated error terms from the first step estimation $\big(\hat{u}_{1i},\ \hat{u}_{2i},\ \hat{u}_{3i},\ \forall\ i = 1...N\big)$, then, the second step optimal weighting matrix of equation (2.18), $\hat{\boldsymbol{W}}_{opt}$, can be specified into:

$$\hat{\boldsymbol{W}}_{opt} = \begin{pmatrix} \hat{W_{11}} & \hat{W_{12}} \\ \hat{W_{21}} & \hat{W_{22}} \end{pmatrix}^{-1} \tag{2.19}$$

where,

$$W_{opt_{g,f}}\hat{} = N^{-1} \sum_{i=1}^{N} \sum_{j=1}^{N} Z'_{gi} \hat{u}_{gi} K(d_{i,\,j}) \hat{u}'_{fj} Z_{fi}\ , \qquad g, f = 1, 2 \tag{2.20}$$

and,

$$K(d_{i,\,j}) = \begin{cases} k(z) & \text{if } j \in i\text{'s } \textit{neighbor} \\ 0 & \text{otherwise} \end{cases} \tag{2.21}$$

$$k(z) = (1 - z^2)^2 \tag{2.22}$$

$$z = \frac{d_{i,\,j}}{d_n} \tag{2.23}$$

where $K(d_{i,\,j})$ is a square kernel smoothing function to weight spatial pairs between county i and its neighbor county j. Assuming there are $N^{1/4}$ number of neighbors that are spatially dependent ([34]), the $K(d_{i,\,j})$ is a function of distance, $d_{i,\,j}$, between county i and j, and d_n denotes for maximum distance amongst the $N^{1/4}$ neighbors. The distance county i and county j is calculated by using Euclidean distance as described below:

$$d_{i,j} = \sqrt{(latitude_i - latitude_j)^2 + (longitude_i - longitude_j)^2} \tag{2.24}$$

Therefore, re-optimizing equation (2.14) and aggregating equation (2.20) $\forall\, j$ gives rise to a unique solution of δ_{gmm} that is defined as:

$$\begin{aligned}\hat{\delta}_{g\,gmm} = &\left[X_g' Z_g \left(\sum_{i=1}^{N} Z_{gi}{}' \hat{u}_{gi} \boldsymbol{K(d_{i,\,j})} \boldsymbol{\hat{u}_{gj}}{}' Z_{gi}\right)^{-1} Z_g' X_g\right]^{-1} \\ & X_g' Z_g \left(\sum_{i=1}^{N} Z_{gi}{}' \hat{u}_{gi} \boldsymbol{K(d_{i,\,j})} \boldsymbol{\hat{u}_{gj}}{}' Z_{gi}\right)^{-1} Z_g' y_g\ , \qquad \forall\, g = 1, 2\end{aligned} \tag{2.25}$$

where, $\boldsymbol{K(d_{i,\,j})}$ is the $(1 \times N)$ vector of spatial weighting matrix between observation i and all observations, and $\boldsymbol{\hat{u}_{gj}}$ is the $(N \times 1)$ vector of the estimated error terms of equation g from the first step estimation. The results of estimation using SHAC optimal weighting matrix are written under 'Model 1'.

This study also estimates the regression model using the two step IV-GMM estimation assuming no spatial heteroskedasticity and autocorrelation and merely using robust optimal weighting matrix. The results of this estimation are written under 'Model 2'. To have more rigorous analysis, IV-2SLS estimation is also done. The 2SLS estimation results are presented under 'Model 3'. In the 2SLS estimation, the issue of the unknown form of spatial heteroskedasticity and autocorrelation problem is ignored.

Reduced Form

Reduced form estimation is also added to the analysis. The reduced form of estimation can be specified into:

$$\%\Delta impaired_i = \alpha_1 \%\Delta subsidy_i \ + \ \boldsymbol{\delta X} \ + \ \alpha_0 \ + \ u_3 \tag{2.26}$$

$\boldsymbol{X}$ denotes for other exogenous variables (e.g., insurance indemnity growth, ratio of agricultural land, population growth, ratio of animal units, and the ratio of agricultural-purposed waters). Since the reduced form is exactly identified estimation, an Ordinary Least Square estimation with bootstrap standard error ('Model 4') is used to estimate the reduced form.

2.4.2 Results

Structural Form

Table 2.3 component 1 ('Model 1' and 'Model 2') present the estimates of equation (2.7). Equation (2.7) portrays the relationship between the growth of insured acres, growth of premium subsidy, growth of insurance indemnity and the agricultural land ratio. The coefficient of estimate for premium subsidy growth is .6886 and it is highly significant. A one point increase in subsidy growth could lead to an additional increase of insured acres growth equals by .69 point. It infers that higher premium subsidy leads to higher insurance participation. As for indemnity growth and agricultural land ratio, the coefficient of estimates are .0117 (significant at 5% significance level) and .0152 (significant at 10% significance level), respectively. The positive sign of the coefficient for indemnity growth infers that more losses that are indemnified could lead to higher insurance participation which means larger insured acres. The positive sign of the coefficient of estimate for agricultural land ratio infers that county with larger percentage of agricultural land tends to have higher growth of insured acres. However, the agricultural land ratio is not significant factor to the growth of insured acres.

Table 2.3 component 2 ('Model 1' and 'Model 2') present the estimates of equation (2.8). Equation (2.8) portrays the relationship between the percentage change of impaired waters, growth of insured acres, population growth, the ratio of agricultural-designated waters, and the ratio of animal units. The coefficient of estimate for the insured acres growth of equals 1,578.57. This coefficient of estimate indicates the spillover effect of the changes in crop insurance program to the surface water impairment. The estimation results also show that population growth is also positively correlated to the percentage change of impaired water. A county with higher population growth has higher percentage change of impaired waters. The coefficient of estimate for the population growth is 167.12, yet, it is not statistically significant at 10% significance level. The coefficients of the ratio of agricultural-purpose waters (778.75) and the ratio of animal units to land acres (139.81) are also positively correlated to the percentage change of impaired waters. These infers that a county with a higher ratio of agricultural-designated waters and/or higher ratio of animal units to land

Table 2.3: Estimation Results

Estimation		Model 1 (SHAC)	Model 2 (robust)	Model 3 (2SLS)	Model 4 (OLS)
component 1: %Δacres					
intercept		-.085***	-.085***		
		(.007)	(.007)		
%$\Delta subsidy$		.689***	.689***		
		(.039)	(.039)		
%$\Delta indemnity$		.012**	.012**		
		(.006)	(.006)		
$ag.Land$		.015*	.015*		
		(.008)	(.008)		
component 2: %Δimpaired					
intercept		272.859***	272.859***	309.294***	240.621
		(43.5)	(43.5)	(53.4)	(177.6)
%$\Delta acres$		1578.6	1578.6	1220.4	
		(1180.7)	(1180.7)	(1285.2)	
%$\Delta population$		167.1	167.1	120.7	136.6
		(177.9)	(177.9)	(184.7)	(212.9)
$useratio$		778.8	778.8	708.0	717.6
		(490.3)	(490.3)	(519.9)	(521.1)
$auratio$		139.8	139.8	491.8	473.5
		(274.9)	(274.9)	(379.3)	(438.3)
$useratio \times auratio$		-5096.9**	-5096.9**	-6372.4**	-5991.7**
		(2551.8)	(2551.8)	(2838.9)	(3114)
%$\Delta subsidy$					823.3
					(989.3)
%$\Delta indemnity$					36.7
					(109.0)
$ag.Land$					-351.7
					(267.9)
N (county)		2,139	2,139	2,139	2,139
Hansen's J test (p-value)		.2418	.2418		
Wald chi2 test (p-value)				.1140	
F test (p-value)					.3488
s.e. in parentheses	*p<.1 **p<.05 ***p<.01				

Source: author's estimation

acres has higher percentage change of impaired waters. However, these variables are not statistically significant in explaining the variation of the percentage change of impaired waters at 10% significance level. The interaction term between the ratio of agricultural-designated waters and the ratio of animal units is statistically significant at 5% significance level.

The coefficients of estimate and the significance between 'Model 1'/IV-GMM using SHAC optimal weighting matrix and 'Model 2'/IV-GMM using robust optimal weighting matrix are not substantially different. Therefore, the inferences between the two model results are not different. Furthermore, the Hansen's J test p-value indicates that both models, 'Model 1' and 'Model 2' are not misspecified and that the instruments are valid. Even though the magnitude of the coefficients are different, the 2SLS estimation results (Table 2.3 'Model 3') suggest similar inference to the IV-GMM's results in 'Model 1' and 'Model 2'.

Reduced Form

Table 2.3 'Model 4' presents estimation results under the reduced form. an OLS with bootstrap variance-covariance matrix is used to estimate the reduced form. The reduced form estimation results show that the percentage change of insurance subsidy and the percentage change of insurance indemnity are positively correlated with the percentage change of impaired waters. The coefficients of estimate for the percentage change of insurance subsidy and the percentage change of insurance indemnity are 823.33 and 36.73, respectively. However, the coefficients of estimate are not statistically significant. Similar to the structural form estimation, the reduced form estimation results show that the ratio of agricultural-designated waters, the ratio of animal units, and population growth are positively correlated with the percentage change of impaired waters.

2.5 Conclusion

This study provides a empirical evidence of an environmental spillover of the changes in crop insurance program to the changes of water impairment across counties in the United States. The exogenous changes in crop insurance program are represented by the changes in premium-subsidy and insurance indemnity. These changes are assumed to be the cause of an increase in insured acres which indicates an increase in insurance participation. A system of two equations regression model is used to link the relationship between the changes in crop insurance program and the changes of water impairment condition. A two step IV-GMM is used to estimate the system of equations. SHAC optimal weighting matrix is used in the second step of the two step IV-GMM estimation to address an issue of unknown form of heteroskedasticity and autocorrelation between spatial units due to data aggregation of water impairment.

The estimation results suggest that changes in premium could significantly lead to an increase in insured acres. The results also suggest that insurance indemnity growth significantly result in an increase in insured acres. More loss that are indemnified leads to an increase in insurance participation. However, the additional insured acres due to higher premium subsidy and more indemnified losses does not significantly worsen the water impairment. This study also finds that population growth, the ratio of agricultural-purposed waters to total length of waters, and the ratio of animal units to land acres within a county are positively correlated to the changes of impaired waters.

Although this study has addressed its objective, there are several unavoidable limitations. First, water impairment data of the '305(b) Waters As Assessed' may have data collection issues. The water impairment is reported by states' agents, thus, the measurement process might incur subjective perception. Second, the '305(b) Waters As Assessed' data are not well compiled biennially by EPA for every state even though the Clean Water Act requires states have to report biennially to EPA. This limitation forces this study to adjust crop insurance data into a cross section form. Under opposite circumstance, then, panel data analysis could be done that may subsequently result in different conclusion in the significance of spillover effect. While this study uses impairment data as the environmental indicator for surface water, future research may use total pollution loads as the indicator.

Chapter 3

Agricultural and Geographical Effects On Water Impairment Condition

3.1 Introduction

The agricultural sector is perceived to be a major problem when examining surface water impairment in the US (Carpenter et al. 1998[5]; Parry 1998[43]). Eutrophication from phosporus (P) and nitrogen (N), and also livestock manure from agricultural activities are one of sources of the impairment (Carpenter et al. 1998[5]; Parry 1998[43]). Earlier works have provided evidence on the causes of these impairments. However, these studies provided local scale evidence for a particular river, watershed or creek (Turner et al. 1991[60]; Vache et al. 2002[61]; Berka et al. 2001[3]; Renwick et al. 2008[49]) or only provide general descriptive analysis or review of water impairment conditions in US (Cooper et al. 1993[9]; Parry 1998[43]; Padgitt et al. 2000[42]). Therefore, to enrich the literature, this study provides empirical evidence of agricultural sector impact on water impairment in US using geospatial data of county aggregated huc-12s level water impairment information from Environmental Protection Agency (EPA) database. In addition, this study also examines the effect of geographical differences on the variation of water impairment condition across counties.

Number of farm operations, animal units, farm-size and agricultural-designated waters are used as the agricultural indicators to explain the variation of water impairment progression across counties (Sharpley et al. 1994[53], Allan et al. 2004[1]; Foley et al.

2005[19]; Tang et al. 2005[58]; Lubowski et al. 2006[37]) and agricultural-designated waters is assumed to be endogenous. County's elevation range and elevation mode are used as instrumental variables for agricultural-designated waters. County's geographical position from equator is used as indicators for geographical differences that may capture climatic or weather differences across counties (Frakes 1972[20]). A system of equations is developed to portray the relationship between the change in impaired waters, agricultural sector indicators, and county's geographical differences.

This study uses: (1)water impairment related data from Environmental Protection Agency (EPA) database; (2)agricultural census data for number of farms, number of livestock, and agricultural land from National Agricultural Statistics Service (NASS), USDA; (3)and elevation data from Global Land One-km Base Elevation (GLOBE) Project, National Centers from Environmental Information, National Oceanic and Atmospheric Administration (NOAA). The 2010 US County Shapefile is used to link the agricultural census data and geospatial data of water impairment from EPA and elevation data from NOAA and also used to get county's latitude and longitude coordinate.

Using Instrumental-Variables estimation, this study finds that agricultural sector and geographical differences significantly explain the variation of water impairment progression across counties. Higher number of farms and animal units could worsen the impaired waters condition. However, larger farm is associated with less change in impaired waters. County located on predominantly higher elevation tends to have larger agricultural-designated waters which subsequently worsen the water impairment condition. This study also finds that county's geographical position is also significant in explaining the water impairment progression. Even though further explanation on the relationship between county's position and the change in water impairment might be irrelevant, the result suggests that geographical characteristic matters in explaining the progression of water impairment within a county. Thus, these findings may imply that geographical and county's agricultural features can be used as signal for better water quality monitoring at the State level.

3.2 Econometric Model

Existing literature on the empirical evidences of the relationship between agriculture sector and topography and water impairment in US is limited. Turner et al. (1991) measured the changes of phosphorus, silicon, and nitrate concentration over time in the Mississippi River watershed [60]. By providing descriptive statistics of the three chemical concentration, they concluded that water quality changes coexist with the increase use of fertilizer. Vache et al. (2002) examined the effects of agriculture on water quality at the watershed scale and estimate how landscape and changes in crop production might affect water quality [61]. Using SWAT model and Buck and Walnut Creek Watershed data in Iowa, they concluded that reduction in nutrient export coming from Corn Belt area is necessary to restore water quality in the creeks. Berka et al. (2001) linked agricultural intensification practice with the water quality in the Sumas River watershed which is part of the Fraser River Lowland, Washington State and British Columbia [3]. They merged spatial data of agricultural land use changes and intensity from 1964 to 1995, water quality sampling from sixteen stations, farm survey data, and census data within the study area. Using Spearman's rank correlation coefficient, they found that an increase in animal units with fix-base land which leads to increase in manure production is the major source of non-point source pollution in the study area. They also found that higher surplus Nitrogen is associated to lesser dissolved oxygen. Renwick et al. (2008) reported the changes of nutrient loading (i.e., ammonium, nitrate, and soluble reactive phosphorus) in three Corn Belt streams from 1994 to 2006 [49]. Using autoregressive moving average process in the analysis, they concluded that agricultural practices and livestock production are the driving force of the changes in water quality in the Corn Belt streams.

Using the agricultural indicators that are already introduced in the existing literature and assuming that the agricultural-designated waters variable is endogenous, this paper estimates a system of equations using elevation variables to instrument the agricultural-designated waters. Instrumental Variables approach is used to estimate the system of equation (Baum et al. 2003[2]; Wooldridge 2010[69];). The system of equations can be specified into:

$$ag.waters_i = \theta_1 elv.range_i \ + \ \theta_2 elv.mode_i + \ \theta_0 \ + \varepsilon_1 \tag{3.1}$$

$$\begin{aligned}\Delta impaired_i &= \beta_1 ag.waters_i + \beta_2 farms_i + \beta_3 animal.units_i + \beta_4 farmsize_i \\ &+ \beta_5 long_i + \beta_6 lat_i + \beta_7 farmsize_i \times long_i + \beta_8 farmsize_i \times lat_i \\ &+ \beta_7 farms_i \times animal.units_i + \beta_8 farms_i \times farmsize_i + \beta_0 + \varepsilon_2\end{aligned} \tag{3.2}$$

where:

· $ag.waters_i$ denotes the length of agricultural-designated waters (km) in county i

· $elv.range_i$ denotes the range of elevation within a county (km)

· $elv.mode_i$ denotes the central tendency of elevation within a county (km)

· $\Delta impaired_i$ denotes the change of the length of impaired waters (km) from baseline year to cycle year

· $farms_i$ denotes the the census year average of the total number of farm operations (count)

· $animal.units_i$ denotes the census year average of total number of animal units (count)

· $farmsize_i$ denotes the average of farm-size within county (acres)

· $long_i$ denotes the county's i longitude coordinate (degree)

· lat_i denotes the county's i latitude coordinate (degree)

Two estimations of the system of equations are conducted using the two step IV-GMM (Wooldridge 2010 [69]). The first estimation model is done without controlling state code (Model 1), and the second estimation is done by controlling the state code (Model 2). IV-two Stage Least Square estimation (IV-2SLS) with robust standard error is also used to estimate the system of equations (Wooldridge 2010 [69]). Similar to IV-GMM, two estimations of IV-2SLS are also done based on controlling the state code (Model 3 and Model 4).

This study also estimates the reduced form of the system of equations using an Ordinary Least Square (OLS) estimation with bootstrapped standard error:

$$\begin{aligned}\Delta impaired_i = {} & \gamma_1 elv.range_i + \gamma_2 elv.mode_i + \gamma_3 farms_i + \gamma_4 animal.units_i + \gamma_5 farmsize_i \\ & + \gamma_6 long_i + \gamma_7 lat_i + \gamma_8 farmsize_i \times long_i + \gamma_9 farmsize_i \times lat_i \\ & + \gamma_{10} farms_i \times animal.units_i + \gamma_{11} farms_i \times farmsize_i + \gamma_0 + \varepsilon_3 \end{aligned} \tag{3.3}$$

Two OLS estimations are done where the first estimation is done without controlling state code (Model 5) and the second estimation is done by controlling the state code (Model 6).

3.3 Data

The data used in this study are from publicly-accessible sources. Water impairment data are from Environmental Protection Agency (EPA) database. Agricultural related data are from National Agricultural Statistics Service (NASS), USDA. Elevation data are derived from Global Land One-km Base Elevation Project, National Centers from Environmental Information, National Oceanic and Atmospheric Administration (NOAA).

Water Impairment and Agricultural-Designated Waters

Each state is required to biennially assess its hydrological unit code-12 (huc-12) waters as 'good', 'impaired', or 'threatened' given the huc-12's designated use (e.g., agricultural activity, industrial, recreation, etc.) and to report the assessment to EPA. Based on past reports, EPA compiled the freshwaters assessment from all states into a database which is titled '305(b) Waters As Assessed' (EPA 2017b[16]). EPA also developed a national baseline database for impaired waters which is titled as '2002 Impaired Waters Baseline' to have a consistent measure of progress for national water impairment condition (EPA 2017a[15]). The '305(b) Waters As Assessed' contains data from cycle year 2002 to 2012. Whereas, the '2002 Impaired Waters Baseline' contains impaired waters information from 1998 to 2004.

Because of the way the water impairment data compiled (Appendix: A.1 and A.2), the analysis is conducted under cross-section form since the database does not show time variation of impaired water condition for each state. Therefore, this study measures a one-time changes of water impairment condition for each county. The change of impaired water is calculated by taking the difference of impaired waters (km) between baseline year (EPA 2017a[15]) and cycle year (EPA 2017b[16]) within each county. The 2010 US county shapefile from US Census Bureau is used to identify the county location of each huc-12 freshwaters. Based on the 2010 US County Shapefile, data are aggregated at county level. The summary statistics of county level data for the change in water impairment (km) and the agricultural-designated waters (km) are presented on Table 3.1.

Table 3.1: Agriculture, Elevation, Geographical Position, and Water Impairment

County level variables	Mean	Std.	Min	Max
[1,2]farm operations (count)	346.04	302.70	1.50	4,747
[1,2]animal units (count)	38,686.25	122,038	.5333	3,170,719
[1,2]agricultural land (acres)	70,699	164,661	6	2,020,777
[1,2]farm size (acres)	437.74	1668.75	.02	29150
[3]elevation range (km)	422.77	635.81	4	4,391
[3]elevation mode (km)	373.92	451.45	-75	3,333
[4]agricultural-designated waters (km)	49.72	149.38	.00	3344.10
[5]Δimpaired waters (km)	69.40	269.10	-2,788.47	3,876.07
[6]longitude (degree)	-91.85	11.83	-159.71	-67.61
[6]latitude (degree)	38.52	4.75	19.60	48.84
Number of observation: 2,646 counties				

[1]Data from National Agricultural Statistics Service, USDA

[2]Data is the average from census year 1997, 2002, 2007, and 2012

[3]Data from The Global Land One-km Base Elevation Project by NOAA

[4]Data from 305(b) Waters As Assessed NHDPlus Indexed Dataset with Program Attributes

[5]Mean of agricultural land ratio from census 1997, 2002, 2007, and 2012

[6]2010 US County Shapefile

Number of Farms, Farm-size, Animal Units, Elevation, and County's Coordinate Location

Counties' number of farms data are collected from 1997-2012 US Census of Agriculture (USDA 2017[12]). Since the analysis is done in cross-section form, this study uses the average of number of farm operations from all census year. Farm-size data at county level are calculated by taking the average of county's agricultural land divided by county's number of farms for each census year.. The county's agricultural land data are also collected from 1997-2012 US Census of Agriculture (USDA 2017[12]). Total animal units data across counties are calculated from total livestock (i.e., dairy cattle, calves, swine, and sheep or lambs) in each county. County's total livestock data are collected from 1997-2012 US Census of Agriculture (USDA 2017[12]). To calculate total animal units for each county, this study follows the definition of animal units by the Office of Wastewater Management (EPA 1992[14]). Based on the EPA's definition, a single animal unit is determined by multiplying the number of animals of each species to a constant factor of each species. In the estimation, this study uses the average of the ratios of total animal units to land from every census year data.

The elevation data are derived from the Global Land One-km Base Elevation Project (GLOBE) database by National Centers for Environmental Information of NOAA (Hastings et al. 1999[28]). The north-America part of the GLOBE data are overlaid with the 2010 US County shapefile from Census Bureau to have the statistical summary of county level elevation data. In addition, county's coordinate information are derived from US County 2010 Shapefile from US Census Bureau ([6]).

These variables are merged to the county-aggregated water impairment data. From the data managing process, there are 2,646 counties of observation covering 45 states. Table 3.1 displays the summary of statistics for all variables used in the estimation.

3.4 Results and Discussion

'Model 1' of Table 3.2 shows the IV-GMM estimation results for the structural form (equation 3.1 and 3.2) without controlling the state code. Component 1 of 'Model 1' shows the estimation results for equation (3.1). The equation displays the relationship between agricultural-designated waters and county's elevation indicators.

The results show that county's elevation range and elevation mode significantly explain the agricultural-designated waters at 1% significance level. The coefficients of estimate for elevation range and mode are .0175 and .1022, respectively. The results infer that county

Table 3.2: IV-GMM Estimation Results

	IV-GMM (Model 1)	IV-GMM (Model 2)
component 1 (Eq.3.1): ag. desg. water		
intercept	3.6128	3.1346
	(4.4713)	(4.3985)
elevation range	.0175***	.0177***
	(.0059)	(.0059)
elevation mode	.1022***	.1052***
	(.0151)	(.0150)
component 2 (Eq.3.2): Δ*impaired*		
intercept	-77.2457	666.9891**
	(69.0207)	(327.6216)
ag. desg. water	.6950***	.7406*
	(.2355)	(.4245)
farms	.1020***	.1009***
	(.0219)	(.0216)
animal units	.0003***	.0001
	(.0001)	(.0000)
farmsize	-.1569***	-.1172*
	(.0458)	(.0706)
long.	2.5593***	8.0655**
	(.5514)	(3.9790)
lat.	8.1896***	-.9502
	(1.2785)	(3.5647)
$farmsize \times long.$	-.0016***	-.0010
	(.0005)	(.0008)
$farmsize \times lat.$	-.0002	.0005
	(.0006)	(.0005)
$farms \times animal.units$	-3.18e-07**	-2.204e-07
	(.0000)	(.0000)
$farms \times farmsize$	-.0002*	-.0001
	(.0000)	(.0000)
$i.\ state - fips$	No	Yes
N (county)	2,646	2,646
Hansen's J test (p-value)	.3066	.3627
s.e. in parentheses	*p<.1 **p<.05	***p<.01

Source: author's estimation

with wider range of elevation and/or located on predominantly high elevation has larger waters that are designated for agricultural activities.

Component 2 of 'Model 1' shows the IV-GMM estimation results for equation (3.2). Equation (3.2) portrays the relationship between change in impaired waters and agricultural-designated waters, farms, animal units, farm-size, county's distance to Prime Meridian location, and the interactions term of the explanatory variables. The estimation results show that agricultural-designated waters, number of farms, and animal units are positive and significant in explaining the change in impaired waters at 1% significance level. The coefficients of estimate for agricultural-designated waters, number of farms, and animal units are .6950, .1020, and .0003, respectively. The results infer that larger agricultural-designated waters (km), and/or higher number of farms, and/or higher number of animal units within a county could worsen the water impairment condition. In contrast to agricultural-designated waters, number of farms, and animal units, coefficient of estimates for farm-size indicates that higher farm-size is correlated to lower change in impaired waters. The coefficient of farm-size is -.1886 and it is significant at 1% significance level. The estimation results also show that the coefficient of estimates for county geographical position (lat., long) is highly significant at 1% significance level. The coefficient estimate for county's longitude is 2.5593 and for county's latitude is 8.1896. Without further rationalizing the relationship, this result infers that geographical difference across counties represented by county coordinate position is substantial in explaining county's progress on water impairment.

The coefficients of estimates from 'Model 1' for interaction terms between farm-size and county's longitude coordinate ($farm - size \times longitude$), and between number of farms and animal units ($farms \times animal.units$) are significant at 5% significance level. The coefficients for the three interaction terms are .0016, -4.1e-07, and -.0002, respectively. The Hansen's J Test for 'Model 1' is not significant at alpha 1% (p-value: .3066). This results that the model are not miss-specified and all the instrumental variables are valid.

'Model 2' of Table 3.2 shows the IV-GMM estimation results for the structural form (equation 3.1 and 3.2) by controlling the state code or adding the state-code as instrumental variables. There are no substantial differences in magnitude, significance, and inferences of estimation results for equation (3.1) between 'Model 1' and 'Model 2'. As for equation (3.2) estimation, the results from 'Model 2' do not show differences in inferences from 'Model 1'. However, the significance results from 'Model 2' show different conclusion from 'Model 1'. In contrast to 'Model 1', the coefficients of estimates from 'Model 2' for animal units, latitude, the interaction term between farm-size and longitude, and, the interaction term between number of farms and farm-size are not significant in explaining the change in impaired waters at 10% significance level. Also, in contrast to 'Model 1', the intercept of change in impaired water are positive and highly significant. The Hansen's J Test for 'Model 2' is not significant (p-value: .3643) indicating the model are not miss-specified and all the instrumental variables are valid.

Table 3.3 shows the 2SLS estimation results for the system equations (equation 3.1 and 3.2). The 2SLS estimation results may show differences in magnitude and significance conclusion from the IV-GMM estimations. However, the inferences from 2SLS estimation results do not show any differences in inferences from the IV-GMM estimations. The R-squared-s from 2SLS estimation for 'Model 3' (without state code) and 'Model 4' (with state code) are .1239 and .4684, respectively. For 'Model 3' and 'Model 4', the Wald chi2 test shows that altogether the explanatory variables significantly explain the change in impaired waters at 1% significance level.

Table 3.4 presents the OLS estimation results for the reduced form, equation (3.3). The equation (3.3) displays the relationship between the change in impaired waters with elevation range, elevation mode, number of farms, number of animal units, farm-size, county's geographical position (lat., long.,), and the interaction terms (e.g., $farm - size \times long.$, $farm - size \times lat.$, $farms \times animal.units$, and $farms \times farmsize$).

Without controlling the state code ('Model 5'), the estimation results show that elevation mode, number of farms, animal units, farm-size, county's geographical position, and the interaction term between farm-size and county's longitude coordinate are significant in explaining the change in impaired waters at 5% significance level. The coefficients of estimates for elevation mode, number of farms, and animal units are .0676, .0919, and .0002, respectively. These infer that being predominantly located on higher elevation from the sea level and/or having higher number of farms, and/or higher number of animal units, worsen county's water impairment. The coefficients of estimate for farm-size is -.1789 indicating

Table 3.3: 2SLS Estimation Results

	2SLS (Model 3)	2SLS (Model 4)
component 1 (Eq.3.1): ag. desg. water		
intercept	3.8165	3.8165
	(4.4744)	(4.4744)
elevation range	.0171***	.0171***
	(.0059)	(0059)
elevation mode	.1035***	.1035***
	(.01518)	(.01518)
component 2 (Eq.3.2): Δ*impaired*		
intercept	-68.9279	696.3022**
	(70.4575)	(329.0573)
ag. desg. water	.7689***	.6925
	(.2521)	(.4276)
farms	.1029***	.0981***
	(.0219)	(.0219)
animal units	.0003***	.0001
	(.0001)	(.0000)
farmsize	-.1531***	-.1292*
	(.0466)	(.0715)
longitude	2.5358***	8.2103**
	(.5531)	(3.9936)
latitude	7.8399***	-1.3156
	(1.3439)	(3.5815)
$farmsize \times long.$	-.0016***	-.0011
	(.0005)	(.0008)
$farmsize \times lat.$	-.0002	.0005
	(.0006)	(.0005)
$farms \times animal.units$	-3.50e-07**	-2.01e-07
	(.0000)	(.0000)
$farms \times farmsize$	-.0002*	-.0001
	(.0001)	(.0001)
$i.\ state - fips$	No	Yes
N (county)	2,646	2,646
Wald chi2 (p-value)	.0000	.0000
R-squared	.1239	.4684
s.e. in parentheses	*p<.1 **p<.05	***p<.01

Source: author's estimation

Table 3.4: OLS Estimation Results

	OLS (Model 5)	OLS (Model 6)
estimation (Eq.3.3): Δimpaired		
intercept	-74.014	380.5877
	(68.5954)	(296.1864)
elevation range	.0177	.0280
	(.0145)	(.0203)
elevation mode	.0676***	.0096
	(.0234)	(.0345)
farms	.0919***	.1120***
	(.0240)	(.0220)
animal units	.0002**	.0001
	(.0001)	(.0001)
farmsize	-.1789**	-.2059***
	(.0841)	(.0753)
longitude	2.9029***	4.1471
	(.6139)	(3.1571)
latitude	9.0246***	-9.2351
	(1.1522)	(4.0410)
$farmsize \times longitude$	-.0019**	-.0020**
	(.0009)	(.0008)
$farmsize \times latitude$	-.0005	.0002
	(.0009)	(.0007)
$farms \times animal.units$	-1.75e-07	-1.22e-07
	(.0000)	(.0000)
$farms \times farmsize$	-.0001	-.00004
	(.0000)	(.0000)
$i.\ state - fips$	No	Yes
N (county)	2,646	2,646
Wald chi2 (p-value)	.0000	.0000
R-squared	.0633	.4283
s.e. in parentheses	*p<.1 **p<.05	***p<.01

Source: author's estimation

larger farm-size could worsen water impairment. The coefficients of estimation for county's geographical position (lat., long.,) are 9.0246 and 2.9029, respectively.

'Model 6' table 3.4 shows the reduced form estimation results where state-code is controlled. The results show that there are no differences in inferences for the coefficients of estimates for all the explanatory variables. However, the significance of several coefficients changes. Under 'Model 6', only the coefficients for number of farms, farm-size, and the interaction term between farm-size and county's longitude coordinate are the only coefficients that are significant at 5% significance level. The R-squared-s for 'Model 5' and 'Model 6' are .0633 and .4283, respectively. Based on the Wald chi2 test for both models, 'Model 5' and 'Model 6', altogether the explanatory variables well explain the change in impaired waters.

3.5 Conclusion

This study provides general empirical evidence of the relationship between impaired waters with agricultural sector and/or geographical differences across counties in United States. Number of farms, number of animal units, farm-size, and agricultural-designated waters are assumed to be the indicators for agricultural sector. The agricultural-designated waters are assumed to be endogenous and well explained by county's geographical feature, such as county's elevation range and mode.

A system of two equations regression model is used to link the relationship between the explanatory variables and the changes of impaired waters at county level. Two step IV-GMM and 2SLS are used to estimate the system of equations. The estimation results suggest that higher number of farms and/or higher number of animal units could worsen water impairment. However, larger farm-size is associated with less change in impaired waters. Furthermore, county predominantly located on higher elevation tends to have larger agricultural-designated waters and subsequently worsen the water impairment. County's geographical position (Lat., Long.,) is also highly significant in explaining the variation of change in impaired water across counties. A reduced form estimation is also done to identify the direct relationship between elevation and the change in impaired waters. Using OLS with bootstrapped standard error, the reduced form estimation without state fixed effect infers that county's elevation significantly explains the change in impaired waters. County located on higher elevation is associated with higher change in impaired waters. These findings may imply that geographical characteristics (elevation and geographical position) and county's capacity to carry agricultural production (number of farms, animal units, and farm-size) can be used as signal for better water quality monitoring at the state level.

While this study uses total change in length of impaired waters (km) for body of waters condition, future research could use estimates of water quality, such as total maximum daily loads for different types of nutrients that are related to agricultural pollution.

Chapter 4

A Hypothetical Irrigation Game in Madison County, Tennessee

4.1 Introduction

Sustained production from irrigated cropland plays a major role to meet the increasing demand for food and bio-energy in the United States (US) (Chiu et al. 2009[7]; Schaib et al. 2012[52]). In southeastern region of the US, irrigated land has increased over the past decades in spite of its relatively high amount of precipitation (Mullen et al. 2009[40]). In Tennessee, irrigated land has grown 84% from 2007 to 2012 (US Department of Agricultures Census of Agriculture 2012). This may indicate that even with high precipitation during the growing season, irrigation systems are still needed to assure water sufficiency for crop production (Mullen et al. 2009[40]). If irrigated land continues to grow and assuming that groundwater is the only source of irrigation, then, the follow up question would be whether southeastern farmers should be concerned with the possibility of facing a groundwater overdraft problem in the region.

Literature has shown that most groundwater overdraft issues occur in the western part of US (Weatherford et al. 1982[66]; Harou et al. 2008[26]; Harter et al. 2015[27]; Medellin et al. 2015[39]). Urbanization and extensive irrigation during drought season are perceived as the major cause of the groundwater overdraft in the western region (Weatherford et al. 1982[66]; Medellin et al. 2015[39]). Seemingly, the southern region of US gradually has started to experience similar problem. Evett et al. (2003) examined the expansion of irrigation in the mid south region of US, such as eastern Arkansas, that has caused aquifer overdraft ([17]). They found that 85% of irrigation water in Arkansas is sourced from groundwater and that 20% of aquifers in Arkansas are under the condition of overdraft. However, not covered in the article is that whether the groundwater overdraft is as a result of optimizing water use for crop yield production or whether a result of competition among farmers for groundwater extraction causing farmers to overuse the groundwater for crop production (Hess et al. 2007[29]). If the former is the case, then, groundwater overdraft is unlikely to happen in the crop region that has high precipitation. However, if the latter scenario is the case, then, growing irrigated land, even in a humid region, may lead to groundwater overdraft in the future.

Several earlier works have discussed irrigation water competition among farmers due to the condition that groundwater possesses natural characteristic of common pool resources which is substractability[1]. Negri (1989) formulated a mathematical analysis using optimal control theory to explain an individual farmer's optimizing decision on groundwater withdrawal given a pumping cost externality[2] and a strategic externality[3] in a groundwater game [41]. He concluded that farmer's water withdrawal is optimized when the value of marginal unit of water in production equals the value of a marginal unit of water as a stock. He also concluded that a farmer may behave strategically[4] if the farmer somehow could observe a rival farmers decision. Similar to Negri, Provencher & Burt (1993) discussed farmers decision on water withdrawal assuming the farmer is risk neutral at the beginning period, but risk averse at the terminal point [45]. They assumed that crop production is a function of both surface and groundwater. They introduced the concept of risk externality that could occur in the groundwater game. Risk externality is derived from the notion that

[1]The use of resource by one agent reduces the available quantity of the resource for other agents use (Walker & Gardner, 1992[64])

[2]Pumping cost externality arises from the yield substractability characteristics. Meaning, other things being equal, individual groundwater extraction can lower the water table, thus, it increases rivals pumping cost (Negri, D., 1989 [41]; Rubio & Casino, 2001[51]).

[3]As for strategic externality, it results from the non-exclusion characteristics. With undefined property rights, groundwater users may behave competitively to each other (Rubio & Casino, 2001[51]).

[4]Strategice behavior is defined as a decision-making process that considers the actions and/or reactions of other economic agents (Tadelis 2013[57]).

income risk of all farmers is affected by total amount of groundwater stock available for future pumping. Each additional unit of available groundwater stock lowers the income risk of all farmers by increasing the buffer against risk provided by total amount of available stock for future pumping. By optimizing total irrigation net returns at the beginning period and expected utility at the terminal period subject to total groundwater carried over from the beginning period, they concluded that (1)risk preference of individual farmer and income distribution of farmers determine the speed of groundwater exploitation; (2)assuming all farmers are risk averse, the groundwater withdrawal will not converge to social optimal solution; and (3)differences in risk aversion may lead to condition where more risk averse farmers transfer risk to the relatively less risk averse farmers. Empirical research by Pfeiffer et al. (2012) supported Negri (1989) and Provencher et al. (1993). Pfeiffer et al., (2012) developed a theoretical model for private and social optimal extraction decision and also empirically estimated the magnitude and the extent of interaction between neighboring farmers, resulting from groundwater extraction behavior [44]. For the theoretical model, they used continuous time profit maximization problem subject to the equation of motion for water stock. For the empirical evidence, the authors used spatial instrumental variable approach and used Kansass Water Information Management and Analysis System and US Geological Surveys (USGS) data. From the analysis, they concluded that (1)based on theoretical model, inability to completely capture groundwater causes over-extraction; and (2)there exists strategic response among neighboring farmers due to physical connectivity between wells. These aforementioned studies seem to indicate that strategic behavior among farmers who share the same aquifer would lead to groundwater overdraft issue (Hess et al. 2007[29]).

To enrich the literature, this paper investigates an individual farmer's optimal water withdrawal and individual farmer's strategic behavior given other identical farmer's decision where monthly weather variability (e.g., precipitation and evapotranspiration) during growing season dictates the optimal water allocation. This study develops a simple dated crop response function which portrays the relationship between crop yield and weather variability. The monthly optimizing water allocation is solved using static optimization and backward induction. The results from these two optimization methods are used as the monthly upper and lower bound for farmer's decision during the irrigation game. The game is assumed to be between two identical risk neutral corn farmers or two identical risk averse corn farmers. This study assumes four scenarios of per-acre inch marginal pumping cost to examine different decisions given different rates of marginal pumping cost. For the game numerical simulation, this paper uses historical weather data, precipitation and evapotranspiration, for Jackson Experiment Station in Madison County, Tennessee (USGS 2017[21]). Also, this paper uses corn growing production assumptions based on University of Tennessee Extension Budget (Smith et al. 2017[54]).

From the game simulation, this study finds that if the marginal rate of pumping cost is relatively low a risk averse farmer would allocate more water than risk neutral farmers. In contrast to risk neutral, a risk averse farmer always negatively reacts to the opponent farmer. A risk neutral farmer would reduce the amount of allocated water when the return hits zero, given opponent farmer's action. Farmers, both risk averse and risk neutral, would still allocate some amount of water during relatively wetter season. However, during this wet season, a risk neutral farmers would allocate less water than a risk farmer. If the marginal rate of pumping cost is relatively high, the risk averse farmer would choose not to irrigate at all during the season. In terms of total allocation of water for the whole growing season resulted from the monthly game equilibrium, a risk averse farmer allocate more water than the total of yield optimizing water allocation. In contrast to the risk averse, a risk neutral farmer would allocate less than the yield optimizing total water allocation. These results may infer that an overdraft problem in southeastern region might not exist if most farmers are predominantly risk neutral farmers and/or the rate of marginal pumping cost is relatively high. On the other hand, if most farmers in southeastern region are risk averse, with low rate of marginal pumping cost, then, the sense of competition of water extraction could lead to groundwater overdraft problem even though the region has high precipitation.

4.2 Framework of the Game

4.2.1 Production Function

Suppose corn farmers depend on monthly rainfall and irrigation for corn production. If the rainfall meets the corn's monthly water requirement, then, farmers probably are not irrigating their corn land. Suppose all other inputs of production are optimized conditional to soil water adequacy condition. Therefore, every month, a farmer aims to optimize irrigation water given the rainfall rate and crop's evapotranspiration in each month (Stewart et al. 1982[56]). To portray farmer's objective function, this paper borrows a concept of a simple dated crop response function (Rao et al. 1988[48], Yaron et al., 1983[71]). The function portrays the relationship between the crop yield and time based soil moisture condition during crop planting season. The function is defined as (Yaron et al. 1983[71]):

$$Y = Y_{max} \cdot a_1 \cdot a_2 \cdot ... \cdot a_t \cdot ... \cdot a_T \tag{4.1}$$

$$a_t = f(w_t) \tag{4.2}$$

and

$$w_{t+1} = w_t + x_t + pr_t - ea_t \tag{4.3}$$

subject to total available water of an aquifer for irrigation for every time t,

$$Q_{t+1} = Q_t - x_t \tag{4.4}$$

where:

· Inputs other than water (e.g., fertilizer, seeds) are optimized conditional on the amount of allocated water,

· Y is total production at the end of the season,

· Y_{max} is maximum potential crop yield,

· a_t is a coefficient of crop response function to the soil's water adequacy or soil's moisture at time t and $0 < a_t \leq 1$,

· w_t is soil moisture at time t,

· x_t is quantity of water applied for irrigation at time t,

· pr_t is precipitation or rainfall at time t,

· ea_t is actual evapotranspiration at time t,

· Q_t is total available water in the aquifer at time t,

If it is assumed that farmers maintain soil moisture from time to time, or in other words, $w_{t+1} = w_t$, thus, equation (4.3) can be transformed into equation (4.5):

$$ea_t = x_t + pr_t \tag{4.5}$$

Since precipitation is a random natural event, to maintain soil moisture, farmers' control variable, x_t, affects the actual evapotranspiration condition that subsequently affects the coefficient of the crop response function (Yaron et al. 1983[71]). Therefore, given consistent soil moisture, the coefficient of crop response function, a_t, can be described as:

$$a_t = f(ea_t) \tag{4.6}$$

However, Yaron et al. (1983) do not provide the explicit function of crop response coefficient. Therefore, to have well identified response function, this paper adopts the water adequacy ratio function from Hogg and Vieth in 1976 (English et al. 1977[13]). Hogg and Vieth explained that crop yield is determined by a water adequacy ratio which is a function of actual evapotranspiration and potential evapotranspiration (English et al. 1977[13]). Assuming that the coefficient of the crop response function, a_t equals to the water adequacy ratio, this paper transforms equation (4.6) into equation (4.7) (English et al. 1977[13]):

$$a_t = \frac{ea_t}{ep_t} \tag{4.7}$$

where ([13]),

$$ep_t = pe_t \cdot coef_t^{pe} \tag{4.8}$$

Thus, substituting (4.5), and (4.8) into equation (4.7), the a_t can be defined as,

$$a_t = \frac{x_t + pr_t}{pe_t \cdot coef_t^{pe}} \tag{4.9}$$

where,

· ep_t is potential evapotranspiration (acre-inch) at time t at the location of the cropland

· pe_t is pan-evaporation at time t at the location of the cropland

· $coef_t^{pe}$ is coefficient of pan evaporation at time t at the location of the cropland

Furthermore, Howell et al. (1998) examined the relation of corn growth pattern and soil moisture or soil water adequacy [33].They concluded that as corn reach maturity over time, the crop's water requirement continues to decreasing [33]. Therefore, matured corn need less soil moisture. Or in other words, the impact of water to corn growth decreases as corn plant gets mature. Therefore adding the concept introduced in Howell et al. (1998) to the dated crop response (4.1), this paper transforms equation (4.1) into:

$$\frac{Y}{Y_{max}} = a_1 \cdot a_2^{\beta} \cdot ... \cdot a_t^{\beta^{t-1}} \cdot ... \cdot a_T^{\beta^{T-1}} \tag{4.10}$$

where, β $(0 < \beta \leq 1)$ makes sure that the impact of the water adequacy ratio to crop growth decreases over time even when the value of a_t is constant. Taking the log on both sides, the equation (4.10) is transformed into:

$$log\ \frac{Y}{Y_{max}} = log\ \{a_1 \cdot a_2^{\beta} \cdot ... \cdot a_t^{\beta^{t-1}} \cdot ... \cdot a_T^{\beta^{T-1}}\} \tag{4.11}$$

$$y = \sum_{t=1}^{T} \beta^{t-1} log\ a_t \tag{4.12}$$

where y can be considered as total impact of crop water requirement over time to yield .

Substituting equation (4.9) into (4.12), and also assuming precipitation is a random natural event. This paper assumes that individual farmer i's optimal water application for crop yield is solved by optimizing:

$$\max_{\{x_{i,t}\}_1^T} \sum_{t=1}^{T} \beta^{t-1} \cdot log\left(\frac{x_{i,t} + \tilde{pr}_t}{pe_t \cdot coef_t^{pe}}\right) \tag{4.13}$$

subject to,

$$Q_{t+1} = Q_t - \sum_{i=1}^{I} x_{i,t} \tag{4.14}$$

The constraint displayed by equation (4.14) allows farmers to compete in irrigation if the available water in the aquifer is limited. It is expected that a single farmer decision on water application changes as competition in water availability enter an individual farmer's optimization.

4.2.2 Optimal Water Application

The simulation starts from a condition where farmers do not have to compete for water in aquifer, but farmers face limited available of water, applying both static and dynamic optimization to solve for farmer's yield optimizing water withdrawal for each month. Static optimization is used when an individual farmer solves the optimal water application all at once for all t.

Static Optimal Solution

Supposing farmer solves optimal water application all at once, and given the constraint of water availability, Q_0. Therefore, farmer faces a constraint:

$$\sum_{t=1}^{T} x_t + Q_{T+1} = Q_0 \tag{4.15}$$

This constraint indicates that total applied water from irrigation during growing season has to be equal to the initial volume of water in the aquifer minus the the water volume after the growing season. Using the static optimization concept, the farmer optimization problem from equation (4.13) with the constraint equation (4.15) is solved using Lagrangian:

$$\mathcal{L} = \sum_{t=1}^{T} \beta^{t-1} \cdot log\left(\frac{x_t + \tilde{pr}_t}{pe_t \cdot coef_t^{pe}}\right) + \lambda\left(Q_0 - \sum_{t=1}^{T} x_t - Q_{T+1}\right) \tag{4.16}$$

or,

$$\mathcal{L} = \sum_{t=1}^{T} F_t(\cdot) + \lambda\left(Q_0 - \sum_{t=1}^{T} x_t - Q_{T+1}\right) \tag{4.17}$$

the first order condition,

$$[x_1] \qquad \frac{1}{x_1 + \tilde{pr}_1} = \lambda \tag{4.18}$$

till, $\cdots$

$$[x_T] \qquad \beta_{T-1} \cdot \frac{1}{x_T + \tilde{pr}_T} = \lambda \tag{4.19}$$

$$[\lambda] \qquad \sum_{t=1}^{T} x_t + Q_{T+1} = Q_0 \tag{4.20}$$

The first order conditions show that the marginal benefit of water application to the crop's yield across time are equal to each other.

Backward Induction - Dynamic Optimal Solution

Burt et al. (1963) discussed the advantages of dynamic optimization in farm management since many farms management decisions could be framed into multistage process [4]. In the paper, they used the case of planting time decision of wheat in Great Plains region. They used dynamic optimization for the wheat production case because rainfall dictates the wheat planting time in the region. To solve the multistage optimization problem, the principle of optimality/Bellman's equation was used. By adopting this method, the Bellman's equation for this study's yield optimizing water allocation problem can be specified into:

$$f_{T+1}(Q_{T+1}) = 0 \tag{4.21}$$

$$f_T(Q_T) = \max_{x_T \in \ (0,Q_T)} \left\{ log\Big(\frac{x_T + \tilde{pr}_T}{pe_T \cdot coef_T{}^{pe}}\Big) + \beta \cdot f_{T+1}(Q_{T+1}) \right\} \tag{4.22}$$

$$f_{T-1}(Q_{T-1}) = \max_{x_{T-1} \in \ (0,Q_{T-1})} \left\{ log\Big(\frac{x_{T-1} + \tilde{pr}_{T-1}}{pe_{T-1} \cdot coef_{T-1}{}^{pe}}\Big) + \beta \cdot f_T(Q_T) \right\} \tag{4.23}$$

$$f_{T-2}(Q_{T-2}) = \max_{x_{T-2} \in \ (0,Q_{T-2})} \left\{ log\Big(\frac{x_{T-2} + \tilde{pr}_{T-2}}{pe_{T-2} \cdot coef_{T-2}{}^{pe}}\Big) + \beta \cdot f_{T-1}(Q_{T-1}) \right\} \tag{4.24}$$

till,$\cdots$

$$f_1(Q_1) = \max_{x_1 \in \ (0,Q_1)} \left\{ log\Big(\frac{x_1 + \tilde{pr}_1}{pe_1 \cdot coef_1{}^{pe}}\Big) + \beta \cdot f_2(Q_2) \right\} \tag{4.25}$$

where $Q_{t+1} = Q_t - x_t \ \forall \ t \ = T, T, ..., 1$, and $Q_{T+1} = 0$. $f_t(Q_t)$ denotes for the objective function of every stage/month t given stage variable or water availability Q_t in each month t. Under this condition, a time/planning horizon equals to the stage condition. For every month t, the optimality conditions are:

$$\frac{\partial f_t}{\partial x_t} = \frac{1}{x_t + \tilde{pr}_t} + \beta \cdot \frac{\partial f_{t+1}(Q_{t+1})}{\partial x_t} \quad = 0, \tag{4.26}$$

$$\frac{\partial f_t}{\partial Q_t} = \frac{\partial log\Big(\frac{x_t(Q_t) + \tilde{pr}_1}{pe_1 \cdot coef_1{}^{pe}}\Big)}{\partial Q_t} + \beta \cdot \frac{\partial f_{t+1}(Q_{t+1})}{\partial Q_{t+1}} \cdot \frac{\partial Q_{t+1}}{\partial Q_t} \tag{4.27}$$

The results from the static and the dynamic optimization are used as the monthly upper and lower bound of the individual farmer's individual decision in the irrigation game.

4.2.3 Hypothetical Irrigation Game between Two Farmers

Groundwater possesses natural characteristics of common pool resources which are substractability of yield and difficulty of exclusion (Walker et al. 1992[64]). With these characteristics, extraction by an individual pumper may create externalities to other pumpers. Two earlier works discuss that pumping cost is one of the externalities (Negri 1989[41]; Rubio et al. 2001[51]). These earlier works assume that a farmer's water extraction affects the stocks or the depth of an aquifer that is shared among finite number of farmers.

Consequently, a farmer's water extraction indirectly increases other farmers' water extraction cost.

For the purpose of this study, suppose the irrigation cost of individual farmer i is directly a function of farmer j's water extraction. Thus, this assumption can be characterized into:

$$cost_{i,t} = b \ \cdot (x_{i,t} + x_{j,t}) \cdot x_{i,t}, \tag{4.28}$$

and a farmer's revenue function can be formulated into:

$$rev_{i,t} = price_{t+1} \ \cdot idx \cdot exp \left(\ log(Y_{max}) + log\left(\frac{x_{i,t} + \tilde{pr}_t}{pe_t \cdot coef_t^{pe}}\right)\right) \tag{4.29}$$

where:

- $cost_{i,t}$ is for total water allocation cost for farmer i at month t,
- b is for marginal cost of lifting per acre-inch of groundwater,
- $x_{i,t}$ is for total water allocated by farmer i at month t,
- $x_{j,t}$ is for total water allocated by farmer j at month t,
- $rev_{i,t}$ is for monetary value of water allocation in month t for farmer i,
- $price_{t+1}$ is for crop's farm price at month $t+1$,
- idx is for growth index of the crop at the end of month t,

From the formulation of the cost and revenue function at month t, it can be inferred that the game for each month t is static. However, a farmer's monthly water allocation determines the farmer's profit at the of growing season because farmer would continue to maintain the crops and eventually harvest the crops at the month of $T+1$. Therefore, the equilibrium condition of every game in each month affect the following months' profit function. Thus, a farmer i's profit function, π, in each month t can be formulated into:

$$\pi_{i,t} = rev_{i,t} - cost_{i,t} - b \cdot \Sigma_{n=1}^{n=t-1}(x^{\star}_{i,n} + x^{\star}_{j,n}) \cdot x^{\star}_{i,n} \ , \quad \forall \ t = 1, ..., T \tag{4.30}$$

where the $x^{\star}_{i,n}$ and $x^{\star}_{j,n}$ denote for the Nash-Cournot water allocation for farmer i and j resulting from the game in previous months.

Assuming identical risk neutral farmers i and j, then a Nash-Cournot equilibrium must satisfy conditions (Varian 1992[62]):

$$\frac{\partial \pi_{i,t}}{\partial x_{i,t}} = 0, \quad and \quad \frac{\partial \pi_{j,t}}{\partial x_{j,t}} = 0, \quad \forall \;\; t = 1, ..., T \tag{4.31}$$

This study also considers a circumstance where the game happens between two risk averse farmers who maximize their utility function and uses logarithmic utility function to portray risk averse farmers' irrigation decision (Hildreth et al. 1982[30]). Therefore, a Nash-Cournot equilibrium conditions for the risk-averse farmers are:

$$\frac{\partial ln(\pi_{i,t})}{\partial x_{i,t}} = 0, \quad and \quad \frac{\partial ln(\pi_{j,t})}{\partial x_{j,t}} = 0, \quad \forall \;\; t = 1, ..., T \tag{4.32}$$

The comparison between risk neutral farmers' game and risk averse farmers' game may indicate the severity of groundwater extraction. Furthermore, this study also use four scenarios of marginal cost of water lifting, b, to infer the deviation of the severity of water extraction under the existence of competition given high rate of precipitation in southeastern region.

4.3 Data: Madison County, TN

The Madison Co., TN is located in the west part of Tennessee which comprises 1,443 km^2 with 46.5% of the land are agricultural land with 71% of that is corn for grain, soybeans, cotton, upland cotton, and wheat are the major crops (USDA 2017[12]). And, corn land is the largest in acres among the major crops (USDA 2017[12]). Considering this condition, this study assumes that agents in the irrigation game are corn farmers. Several information that are needed for numerical solution of the hypothetical irrigation game are weather data during corn growing season (e.g., precipitation data, pan-evapotranspiration) and corn production assumptions (e.g., maximum yield per acre of corn production, corn price). The precipitation data for Madison County are collected from Jackson Experimental Station, TN

(USGS 2017[21]). Table 4.1 shows the record of monthly precipitation in Madison County area from 2007 to 2016. The pan evapotranspiration data for Jackson Experimental Station,

Table 4.1: Precipitation record (inches) of Madison County, TN., from 2007-2016

stats	April	May	June	July	Aug.	Sept.
max	11.12	8.34	10.95	7.38	6.41	7.30
min	1.42	.86	2.71	1.76	.77	.79
avg.	5.79	5.10	5.01	4.96	3.53	4.08
s.d.	3.73	2.59	2.46	1.69	1.87	2.30

Source: [1]USGS 2017[21]

TN., are collected from National Oceanic and Atmospheric Administration Technical Report (Farnsworth et al. 1983[18]). Whereas, monthly coefficients of evapotranspiration for corn production are taken from English et al. (1977)[13].

Table 4.2: Pan-evapotranspiration & coef., evapotranspiration on corn's growth

Item	Unit	April	May	June	July	Aug.	Sept.
[1]pan-evapotranspiration	inches	5.94	7.16	7.83	7.84	6.96	5.57
[2]coef., evapotranspiration	constant	.28	.57	.88	.99	.97	.80

Source: [1]Farnsworth et al. 1983[18], [2]English et al. 1977[13]

In this numerical solution, this study assumes that the Tennessee corn growing season starts in April to September (USDA 1997[11]). Monthly growing days are used to calculate the effect of irrigated water to corn's monthly growth index. The monthly growth index is used to calculate the monthly monetary value of irrigated water as explained in the individual farmer optimization model. The growth index calculation can be specified into (English et al. 1977[13]):

$$idx_t = \frac{\sum_{n=1}^{t-1} g_n + \sum_{n=1}^{t} g_n}{2 \cdot \sum_{k=1}^{6} g_k} \tag{4.33}$$

where, idx_t denotes for the unadjusted growing index for the t-th month of the season and g_n denotes for the number of growing days of the n-th month. Monthly corn prices are used

Table 4.3: National unadjusted monthly corn prices record ($) from 1960-2015

stats	May	June	July	August	Sept.	Oct.
max	6.97	6.97	7.14	7.63	6.89	6.78
min	1.02	1.03	1.04	0.99	1.01	0.96
avg.	2.54	2.56	2.54	2.50	2.42	2.34
s.d.	1.34	1.34	1.36	1.40	1.26	1.19

Source: NASS 2017[12]

to calculate the monthly monetary value of irrigated water on corn's growth, this study uses historical data of national unadjusted monthly prices which are collected from the National Agricultural Statistics Service, USDA. Figure 4.3 presents the monthly price movement and the statistics of corn price for month of April till October since 1960 to 2015.

The monetary value of irrigated water at month m are based on the one month ahead $m+1$ of corn price as mentioned in the irrigation game model. Therefore, this study only uses monthly corn price data from May to October.

As it is mentioned, there are four scenarios of marginal cost of lifting water. These scenarios are $2, $4, $8, and $32. The $2 scenario comes from the estimated per-acre-inch cost of pumping water in California, and the $4 scenario comes from the estimated per-acre-inch cost of pumping water in Hawaii (Wichelns 2010[67]). Whereas, the $8 and $32 per-acre-inch scenarios are assumed.

4.4 Results

4.4.1 Optimal water allocation

The static optimization results show the same level of irrigation water allocation from April to September which equals .99 acre-inch. In contrast, the backward induction optimization suggests various level of irrigation water allocation for every month. Figure 4.1 shows the optimal water allocation and water stock for each month from static optimization and backward-induction optimization.

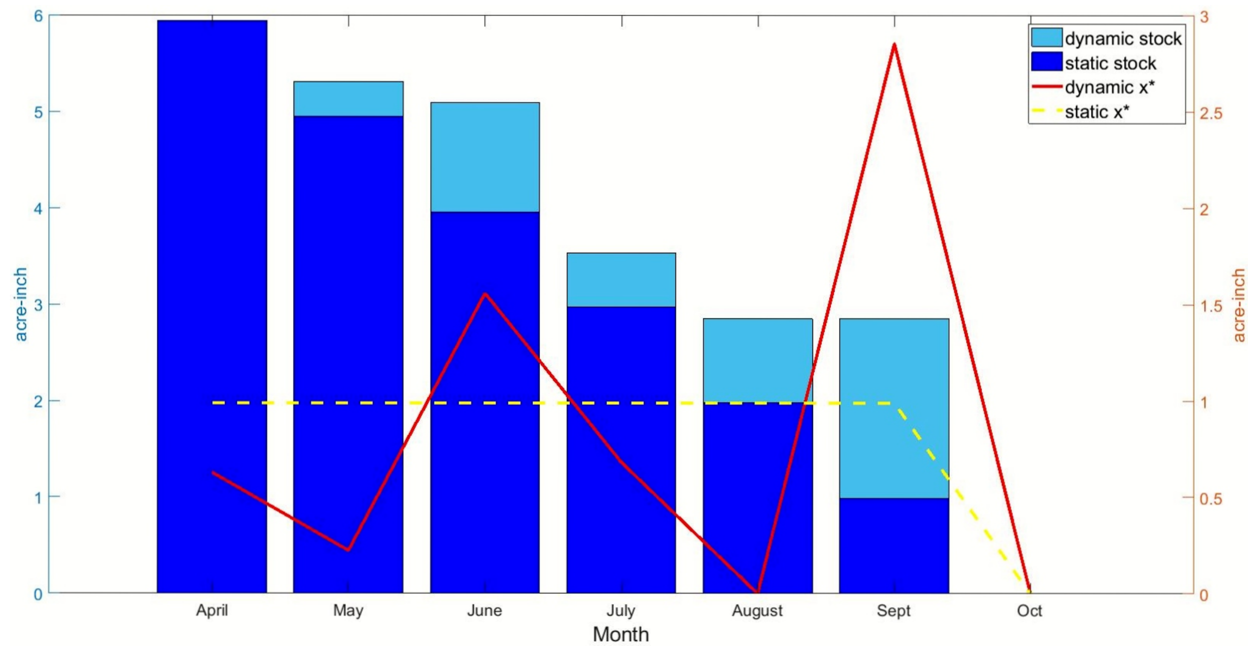

Figure 4.1: Yield optimizing water allocation and water stock during irrigation seasons

From the backward-induction optimization, in April, May, June, July, August, and September, the yield optimizing water allocation for irrigation equals to .63, .22, 1.56, .68, 0, and 2.85 acre-inch, respectively. Backward-induction optimization results are aligned with the precipitation level in every month. The results suggest that farmer would allocate more water in June and dry month of September and not allocate any amount of water relatively wetter month of August. Compare to other months, based on the historical precipitation data, September has the higher probability to hit lowest rate of precipitation, whereas August has the higher probability to hit highest rate of precipitation. Even though both optimization suggests different level of water allocation, the total amount of allocated water for the whole season from both optimization is equal to each other. For the whole irrigation season, the total amount of allocated water is equal to 5.94 acre-inch which is lower than the predicted amount of water allocation by UT Extension Specialist, 7.2 acre-inch (Smith et al. 2017[54]).

As mentioned earlier, the optimal water allocation results are used as the lower and upper bound of farmer i's decision in the irrigation game at different scenarios of per-acre inch irrigation cost (\$2, \$4, \$8, and \$32) and given farmer j's possible water allocation ranging from 0 to 7.2 acre-inch (Smith et al. 2017[54]).

4.4.2 Irrigation Game

Figure 4.2 shows the farmer i's April best responses for different scenario of per-acre-inch irrigation cost (\$2, \$4, \$8, and \$32) given farmer's choices of water allocation.

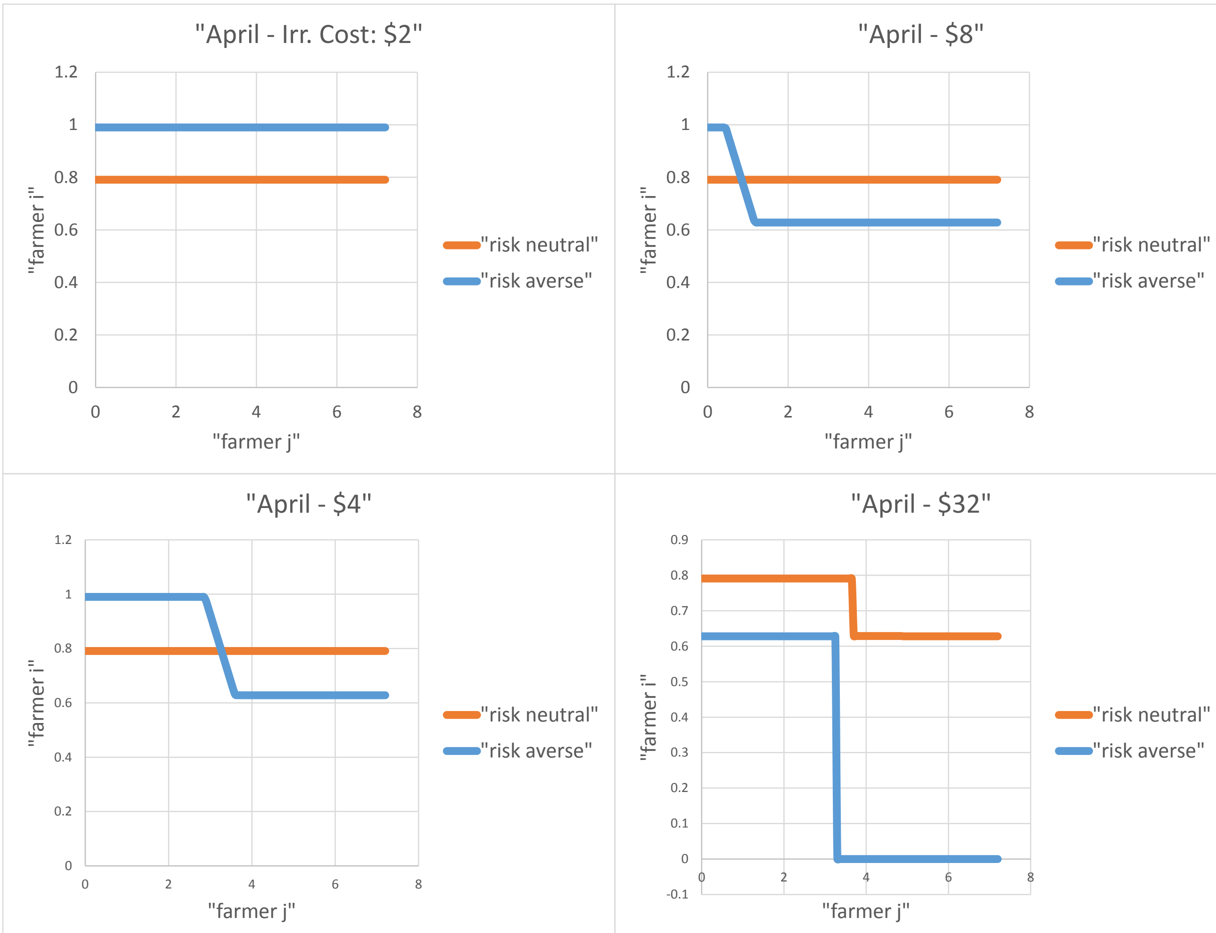

Figure 4.2: Farmer i's April best response given farmer j's choices & irrigation cost

If farmer j decides not to irrigate, a risk averse farmer i would allocate more water than a risk neutral farmer i. If farmer j does not irrigate in April, a risk neutral farmer i would allocate .79 acre-inch of water for irrigation, whereas a risk-averse farmer i would allocate .99. However, if the rate of marginal pumping is very expensive a risk averse farmer i would allocate less water than a risk averse i. At a \$32 of rate marginal pumping cost, without competition from a risk averse farmer j, a risk averse farmer i would allocate 0.63 acre-inch and a risk neutral would still allocate .79 per-acre inch in April. At this rate of marginal pumping cost, the risk neutral farmer i would reduce the amount of allocated water once the April earnings starts hitting lower bound of profit due to increasing irrigation cost. Figure 4.3 shows April earnings of a risk-neutral farmer i and a risk averse farmer i for every combination of decision made by both farmers.

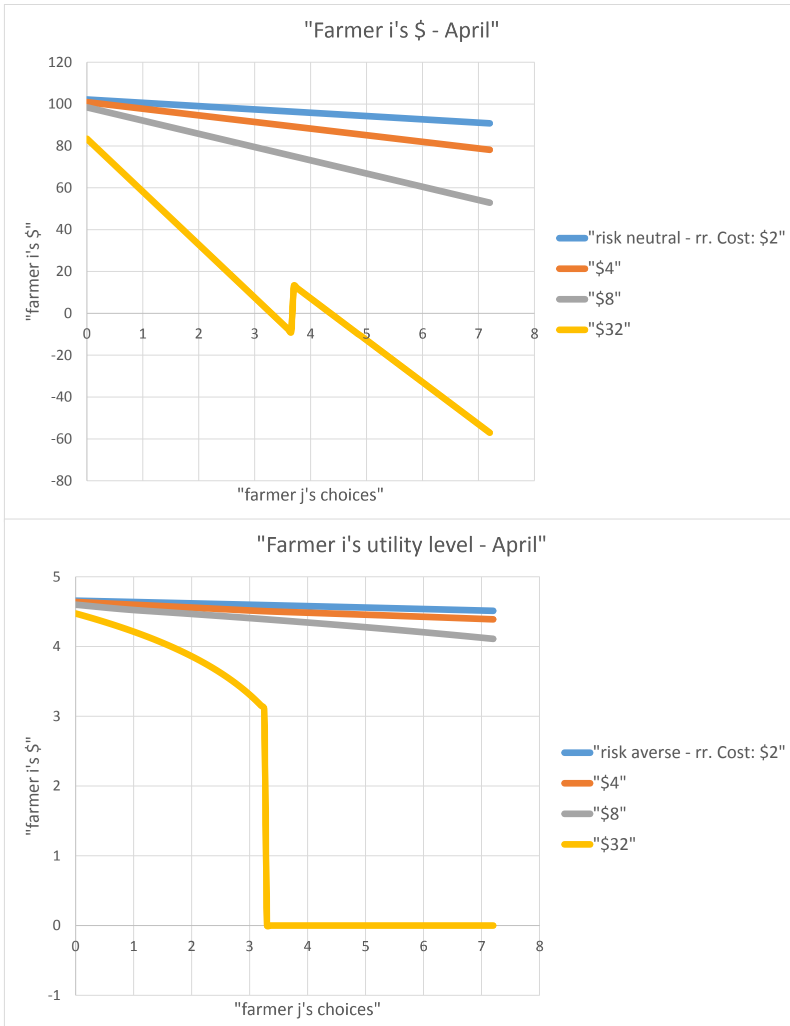

Figure 4.3: Farmer i's April returns (\$) given farmer j's choices & irrigation cost

Different from the risk neutral farmer, a risk averse farmer i always reacts to every farmer j's responses for different rates of marginal pumping cost (Figure 4.2). A risk averse farmer i would keep reducing the water allocation as farmer j keep adding the water allocation. As expected, the earnings of farmer i is negatively correlated with farmer's j decision on water allocation.

Assuming identical risk preference between farmer i and farmer j, then, the April game equilibrium condition between risk neutral farmers equals .79 per-acre inch for any given rates of marginal pumping cost. Figure 4.4 shows the graphs of equilibrium conditions of April irrigation game for risk neutral and risk averse farmers. The April equilibrium for risk averse farmers stays at 0.99 per-acre inch given a \$2 and a \$4 rate of marginal pumping cost. The equilibrium for risk averse farmers decreases to 0.8 per-acre inch when the rate of marginal pumping cost increases to \$8. The equilibrium for risk averse farmers continues to decrease to a level of 0.6 per-acre which is lower than the equilibrium of risk neutral farmers when the rate of marginal pumping cost reaches \$32.

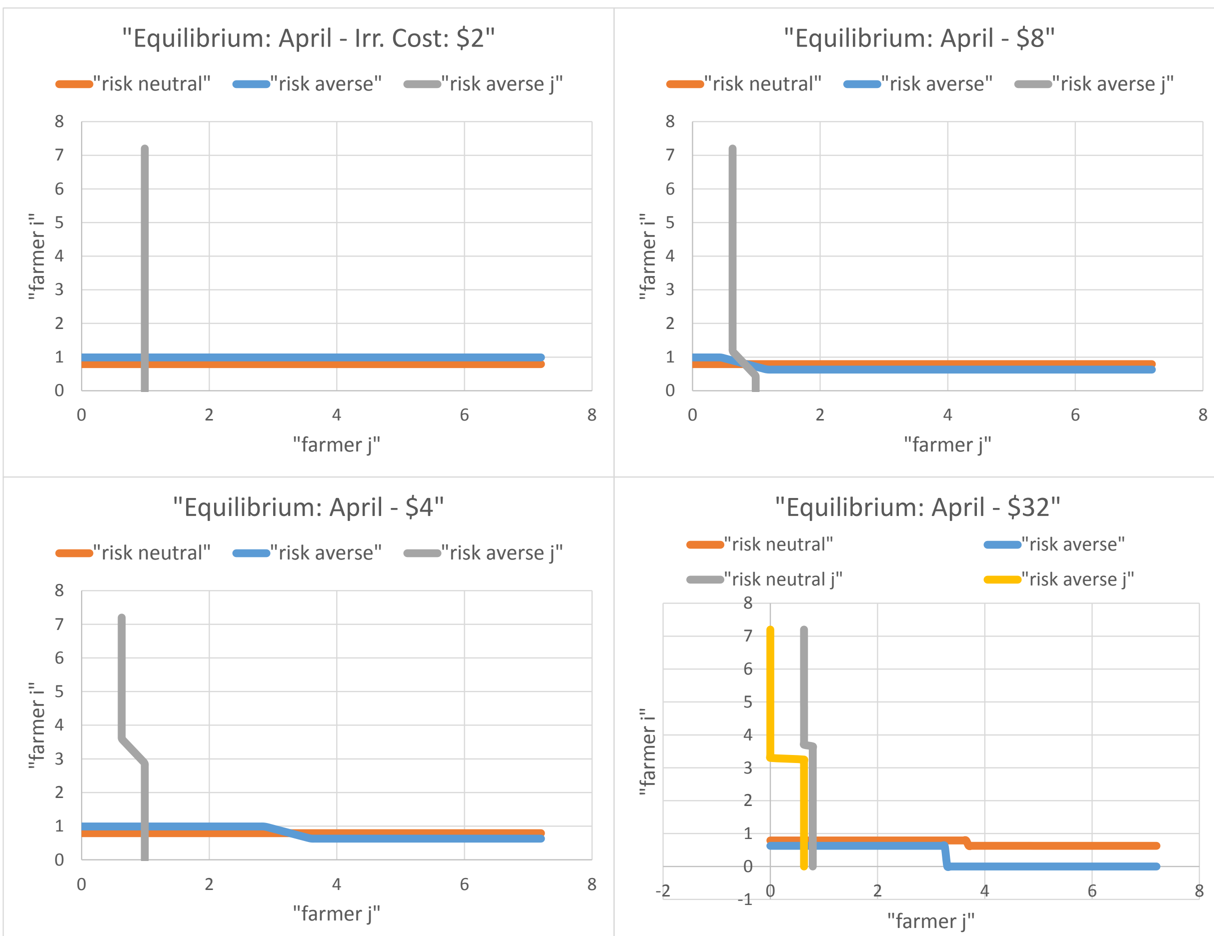

Figure 4.4: April's equilibrium

Similar inferences are shown in May (A.5), June (A.8), July (A.11), August, and September game (A.16). However, there are several additional inferences that are needed to discuss. First, during relatively wetter month of August, even though the yield optimizing water allocation suggests that farmer could choose to not irrigate (Figure 4.1), the equilibrium conditions in August (Figure 4.5) indicate that farmers, both risk neutral and risk averse, still choose to irrigate.

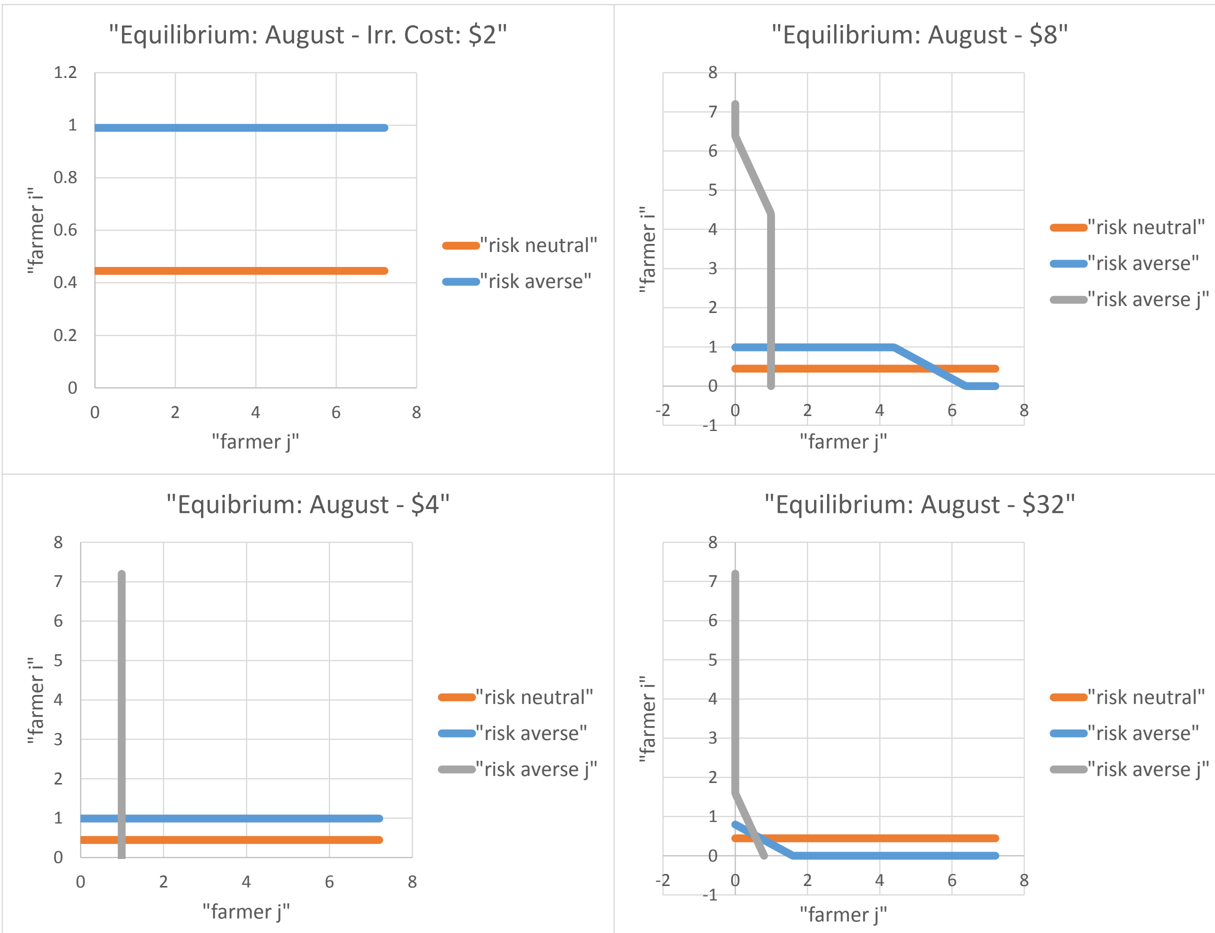

Figure 4.5: August's equilibrium

For the drier month of September (A.16) with low rate of marginal pumping cost, the risk averse farmer always reaches equilibrium at the upper bound of the optimal water allocation. The case does not happen with risk neutral farmers. Second, even though risk averse farmers tend to irrigate more than risk neutral farmers, the equilibrium conditions in every month shows that risk averse farmers irrigate less than risk neutral farmers when the rate of marginal pumping cost is very expensive (e.g., equilibrium in April for $8 and $32 in Figure 4.4). Third, when the rate of marginal pumping cost is relatively low, risk averse farmers continue to allocate more water than the optimal water allocation for the whole planting season. Figure 4.6 shows the total water allocation for the whole growing season resulting from the monthly games' equilibrium for different rates of marginal pumping cost.

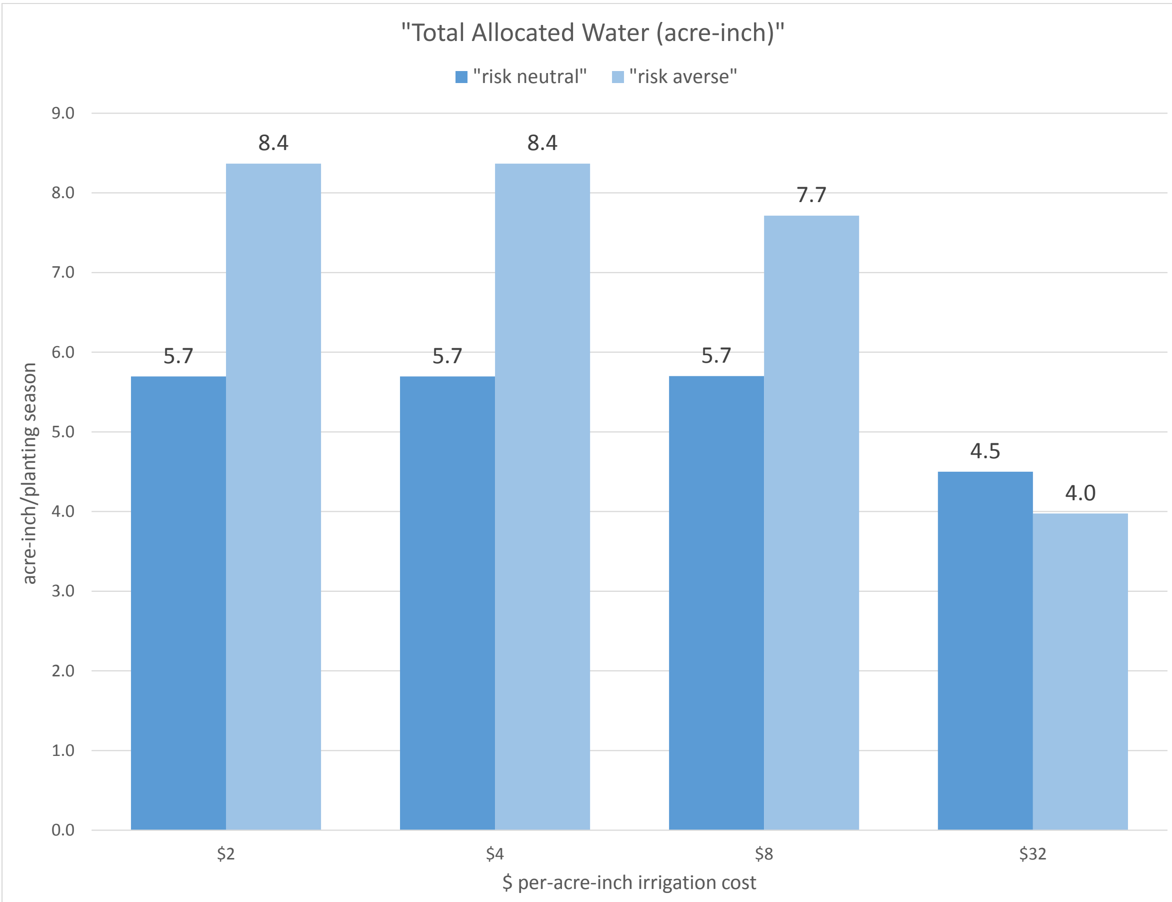

Figure 4.6: Total allocated water for the whole planting season

Given the monthly equilibrium, a risk neutral farmer would allocate 5.7 per-acre inch for the whole planting season for a \$2, \$4, and \$8 per acre-inch of rate marginal pumping cost. The total water allocation for a risk neutral farmer decreases to 4.5 acre-inch when the rate of marginal pumping cost reaches \$32. A risk averse farmer allocates 8.4 acre inch of water for the whole planting season when the rate of marginal pumping cost equals \$2 and \$4. The total amount of water allocation for a risk averse farmer decreases to 7.7 acre-inch when the rate of marginal pumping cost increases to \$8. When the rate of marginal pumping cost increases to \$32, the total amount of water withdrawal is reduced by 50% reaching 4 acre inch which is lower than the risk neutral farmer's total water withdrawal.

4.5 Conclusion

Irrigated land in the southeastern US is expected to increase as the demand for food and bio-energy increases in the US. With irrigated land continues to grow and assuming that groundwater is the only source of irrigation, then, groundwater overdraft problem could happen in southeastern region even though with high precipitation condition. The literature have examined many cases of strategic behavior of farmers in regards groundwater game in western region of US. However, the discussion about irrigation game in the southeastern part of US where weather variability dictates individual's farmer irrigation decision is limited.

This study uses a dated crop response function which portrays the relationship between corn yield and soil moisture which is determined by precipitation and potential evapotranspiration. Using weather data from Jackson Experimental Weather Station located in Madison County, TN., and several assumptions on corn production, this study develops a hypothetical game of irrigation between two corn farmers. This study also compares the game between two identical risk neutral corn farmers and the game between two identical risk averse farmers.

The optimization results suggest that if the irrigation cost is low enough, then, the risk averse farmer would allocate more water than risk neutral farmers. In the irrigation game between two identical risk averse farmers, individual farmer would react to opposite farmer's actions. The reactions between the risk averse farmers are negatively correlated. In contrast, a risk neutral farmer would allocate the same level of water despite of the opposite farmer's action until the farmer's net return hits the lower bound of monthly profit. When the net return hits the lower bound of profit, a risk neutral farmer would reduce the amount of water extraction. During the wet season, even though yield optimizing water extraction suggests that a farmer could choose not to irrigate, farmers would still allocate some amount of water. During wet months, a risk neutral farmers would allocate less water than a risk averse farmer. Based on equilibrium conditions, if the marginal pumping cost is relatively low, then, the total allocation of water for the whole growing season by a risk averse farmer is larger than the yield optimizing total water allocation. In contrast to the risk averse, a risk neutral farmer would allocate less than the yield optimizing total water allocation.

These results may infer that the overdraft problem in southeastern region might not exist if most farmers are predominantly risk neutral farmers. On the other hand, if most farmers in southeastern region are risk averse, then, the sense of competition of water extraction with low cost of irrigation could lead to groundwater overdraft even though the region has high precipitation.

Chapter 5

Conclusion

This dissertation consists of three essays on water resource issues. The first essay examines the spillover effect of the subsidy change in crop insurance to the surface water impairment. The first essay analysis suggests that an increase in premium subsidy and/or indemnified losses could lead to an increase in insured acres. However, the additional insured acres does not mean significantly worsen the condition of impaired waters. The results seemingly consistent with the literature. However, better publicly accessible data of water impairment by EPA might be necessary for future research.

The second essay of this dissertation provides a general empirical evidence of agriculture sector on water impairment in US and examines how geographical difference across counties affect the water impairment condition. Using Instrumental-Variables estimation, this study finds that agricultural sector and geographical differences significantly explain the variation of water impairment progression across counties. Higher number of farms and animal units could worsen the impaired waters condition. However, farms with larger size is associated with less change in impaired waters. County located on predominantly higher elevation tends to have larger agricultural-designated waters which subsequently worsen the water impairment condition. This study also finds that county's geographical position is also significant in explaining the water impairment progression. Even though further explanation on the relationship between county's geographical position and water impairment might be irrelevant, the result suggests that geographical characteristic matters in explaining the progression of water impairment within a county. Thus, these findings may imply that geographical and county's agricultural features can be used as signal for better water quality monitoring at the State level.

The third essay of this dissertation develop and simulate a hypothetical irrigation between two identical farmers, risk averse and risk neutral type farmers, where weather variability dictates the optimal decision of water allocation. The hypothetical irrigation game indicates that when pumping cost is relatively low, the risk averse farmer would allocate more water than risk neutral farmers. During relatively wet season, even though yield optimizing water allocation suggests that farmer could choose not to irrigate, farmers would still allocate some amount of water. In general, when the marginal pumping cost is relatively low, the total allocation of water for the whole growing season by a risk averse farmer is larger than the total of yield optimizing water allocation. Findings from the third essay imply that with low marginal pumping cost, the overdraft problem in southeastern region might exist if most farmers in the region are risk averse. Then, the sense of competition of water extraction could lead to groundwater overdraft even though the region has high precipitation.

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Appendices

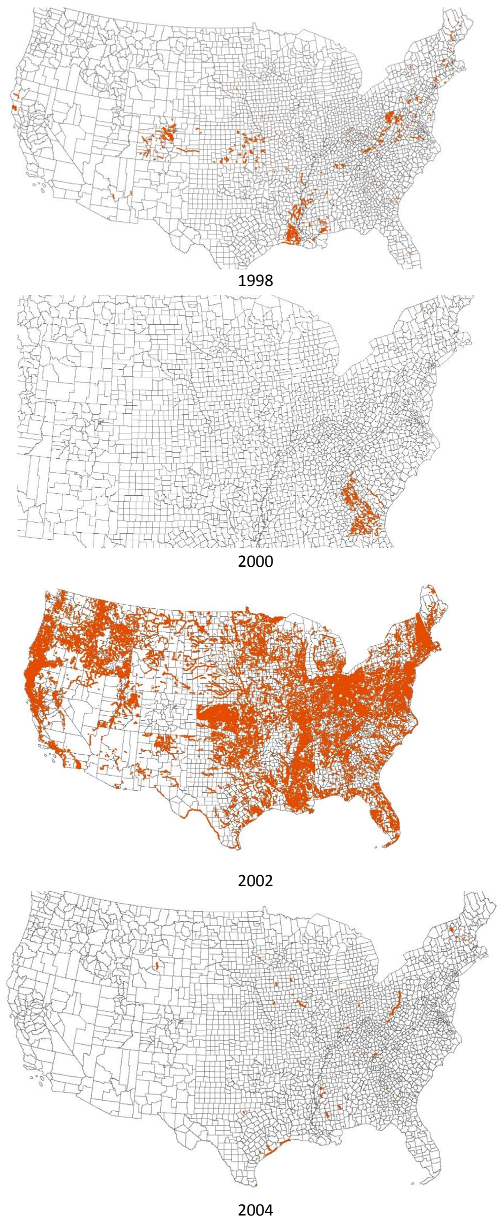

Figure A.1: EPA 2002 Impaired Waters Baseline by Year

Notes: EPA developed the 2002 Impaired Waters Baseline to create a consistent measure of progress of the nation's water impairment. Based on the figure A.1, not all states have the same baseline year. Several states conducted initial measurement of impaired waters in 1998, 2000, or in 2004. The 2002 Impaired Waters Baseline data are collected from EPA website for Watershed Assessment, Tracking & Environmental Results System geo-spatial database.

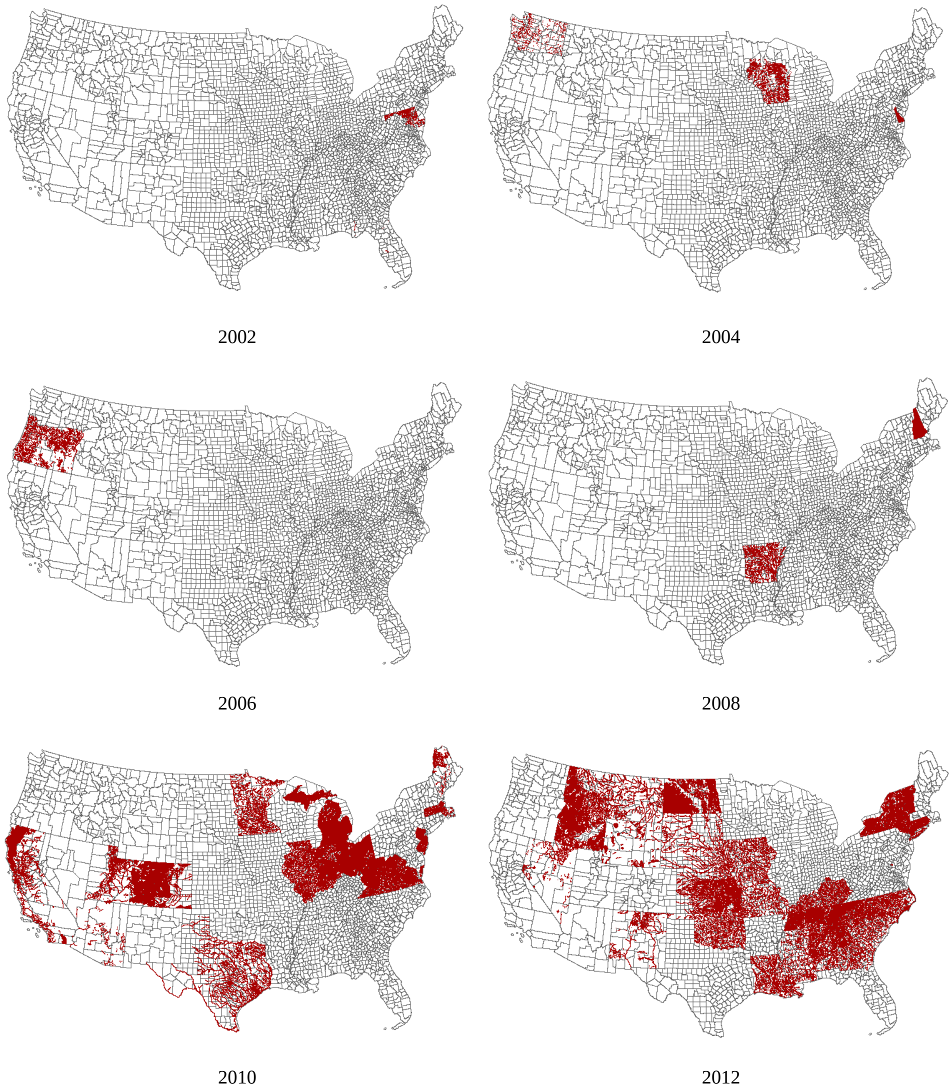

Figure A.2: EPA 305(b) Waters As Assessed by Cycle Year

Notes: Federal Clean Water Act section 305(b) requires state to biennially monitor the quality of its HUC-12 waters. Each state has to assign its HUC-12 as 'good','impaired', or 'threatened' given the designated use (e.g., industrial, agricultural, etc). EPA compiled the states' past reported assessment as geo-spatial database named '305(b) Waters As Assessed'. However, the database does not have complete biennial reports compilation from every state. Figure A.2 indicates that EPA only published a particular assessment year for each state.

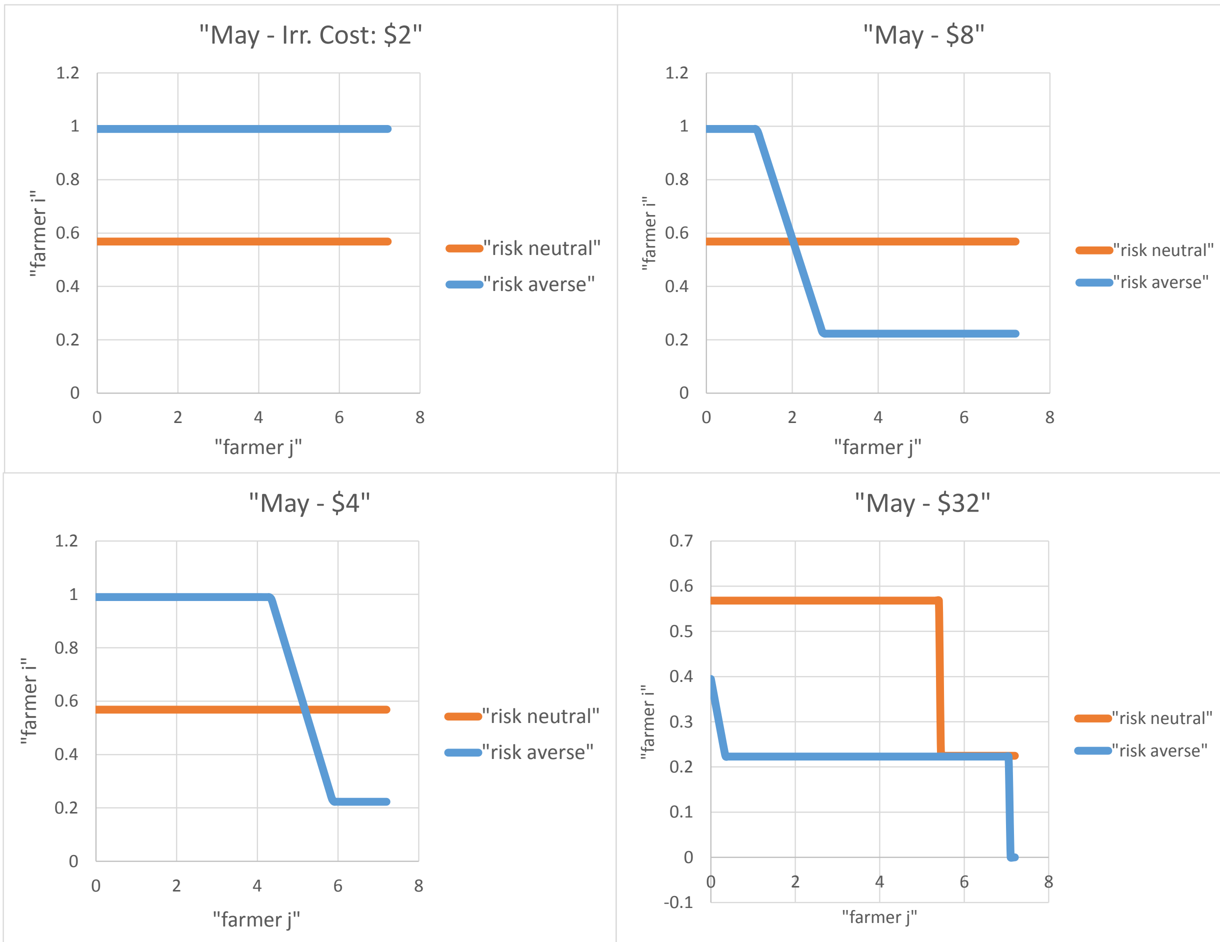

Figure A.3: Farmer i May best response given farmer j's choices & irrigation cost

Notes: Figure A.3 shows Farmer i best response for different marginal pumping rates and given farmer j's choices. The orange line shows the risk neutral farmer i best response and the blue line shows the risk averse farmer i best response. A risk neutral farmer i reacts to the risk neutral farmer j's water extraction when the rate of marginal pumping cost at $32 per-acre inch. In contrast to the risk neutral farmer, a risk averse farmer i always reacts to risk averse farmer j's water extraction except when the rate of marginal pumping cost at the lowest, $2 per-acre inch.

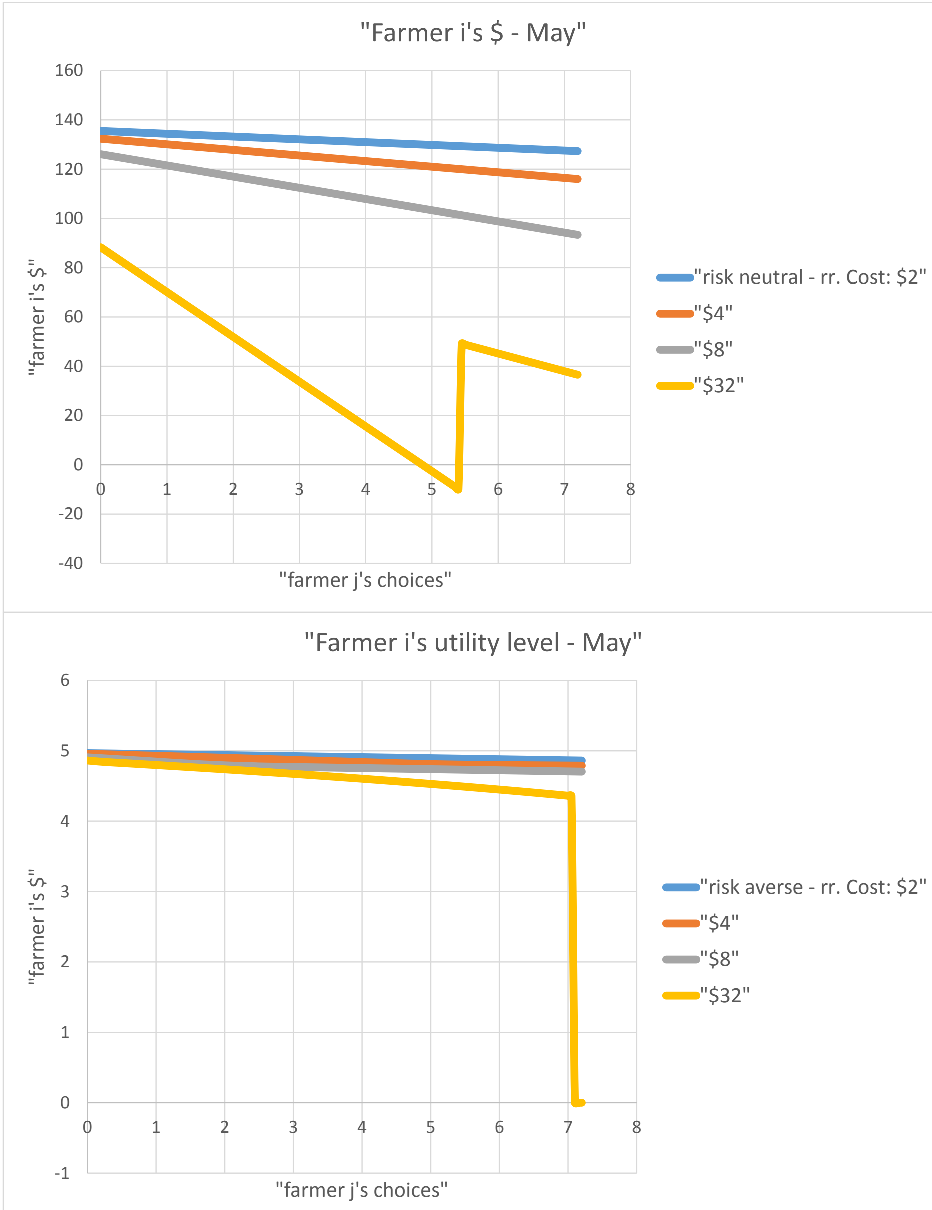

Figure A.4: Farmer i May returns given farmer j's choices & irrigation cost

Notes: Figure A.4 shows Farmer i pay-off given farmer j's choices in May. The upper figure shows the pay-off for a risk neutral farmer i and the lower figure shows the pay-off for a risk averse farmer i. The pay-offs for both types of farmer i decreases as farmer j's water extraction increases.

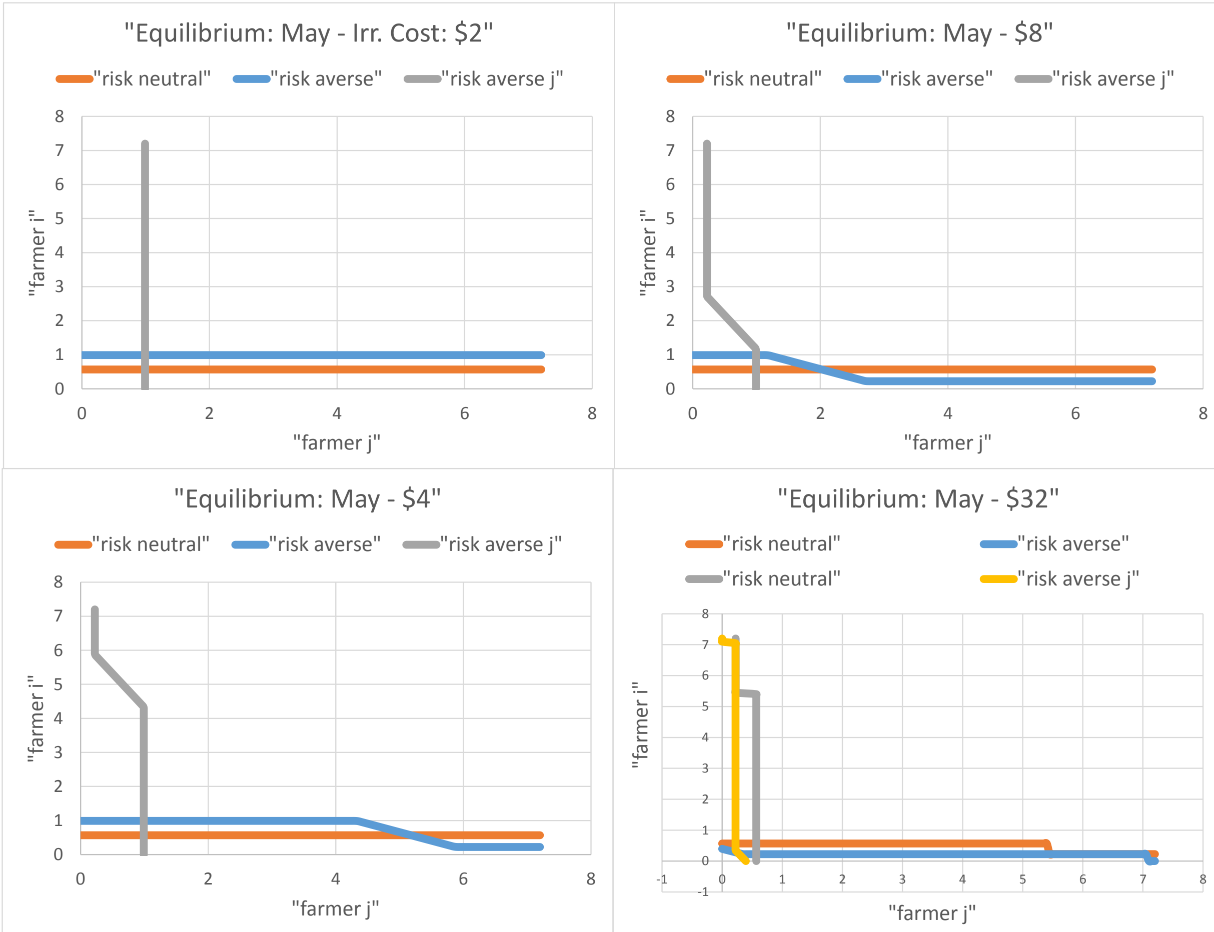

Figure A.5: May equilibrium

Notes: Figure A.5 shows the equilibrium condition of May irrigation game for risk risk neutral farmers and risk averse farmers given different rates of marginal pumping cost. From the figure, it infers when the pumping rate is relatively, the equilibrium from risk averse farmers is always higher than the equilibrium from risk neutral farmers. However, when the marginal pumping cost at $32, the equilibrium from risk neutral farmers is higher from risk averse farmers. At $32 marginal pumping cost, the equilibrium for risk neutral farmers is 0.6 per-acre inch and the equilibrium is 0.3 per-acre inch.

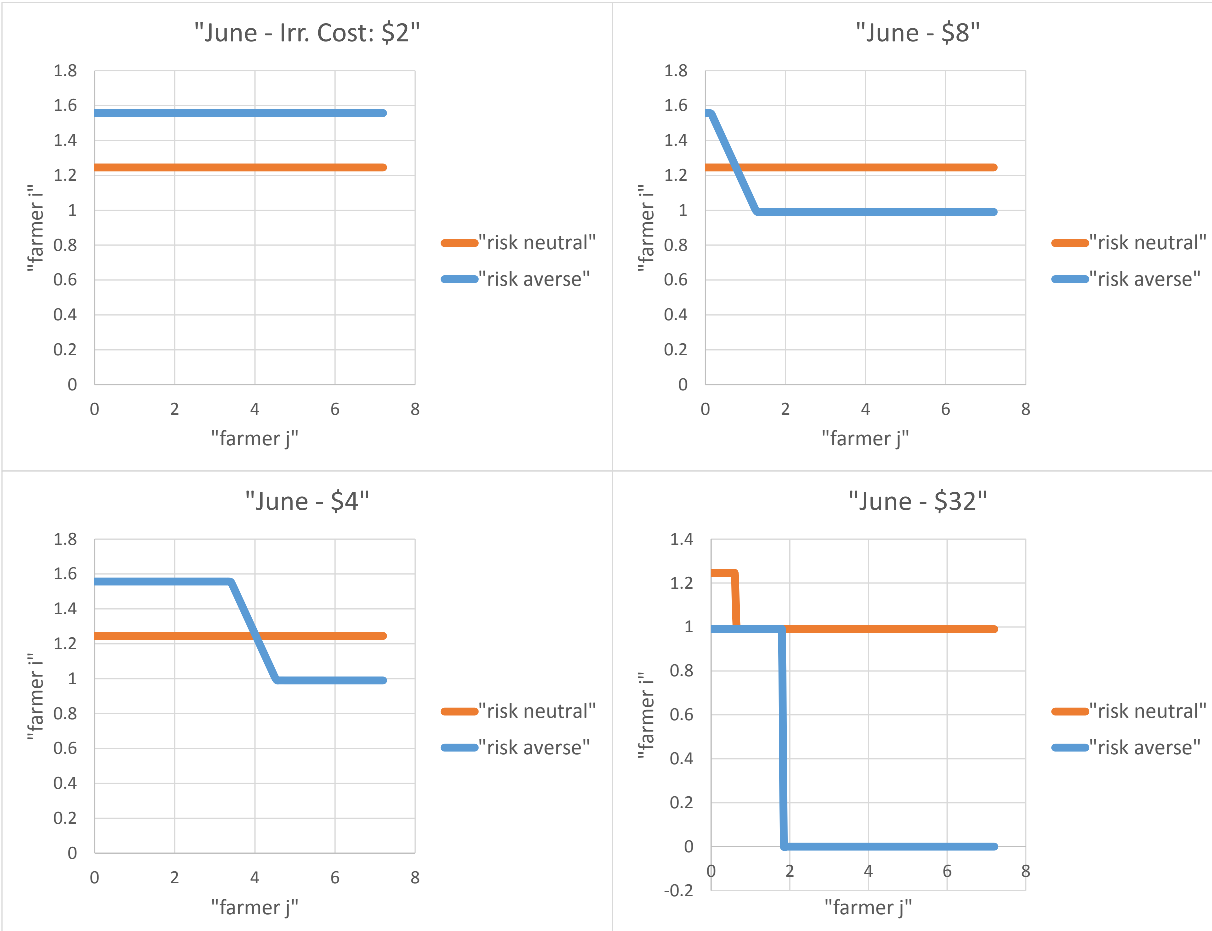

Figure A.6: Farmer i June best response given farmer j's choices & irrigation cost

Notes: Figure A.6 shows Farmer i best response for different marginal pumping rates and given farmer j's choices in June. The orange line shows the risk neutral farmer i best response and the blue line shows the risk averse farmer i best response. If farmer j decides not to irrigate, a risk neutral farmer's water withdrawal equals 1.2 per acre-inch for all scenarios of rate of marginal pumping cost. Different from the risk neutral farmer, if a risk averse farmer j decides not to irrigate, a risk averse farmer i reduces its water withdrawal to 1 per-acre inch from 1.5 per-acre inch when the rate of marginal pumping cost change from $8 to $32.

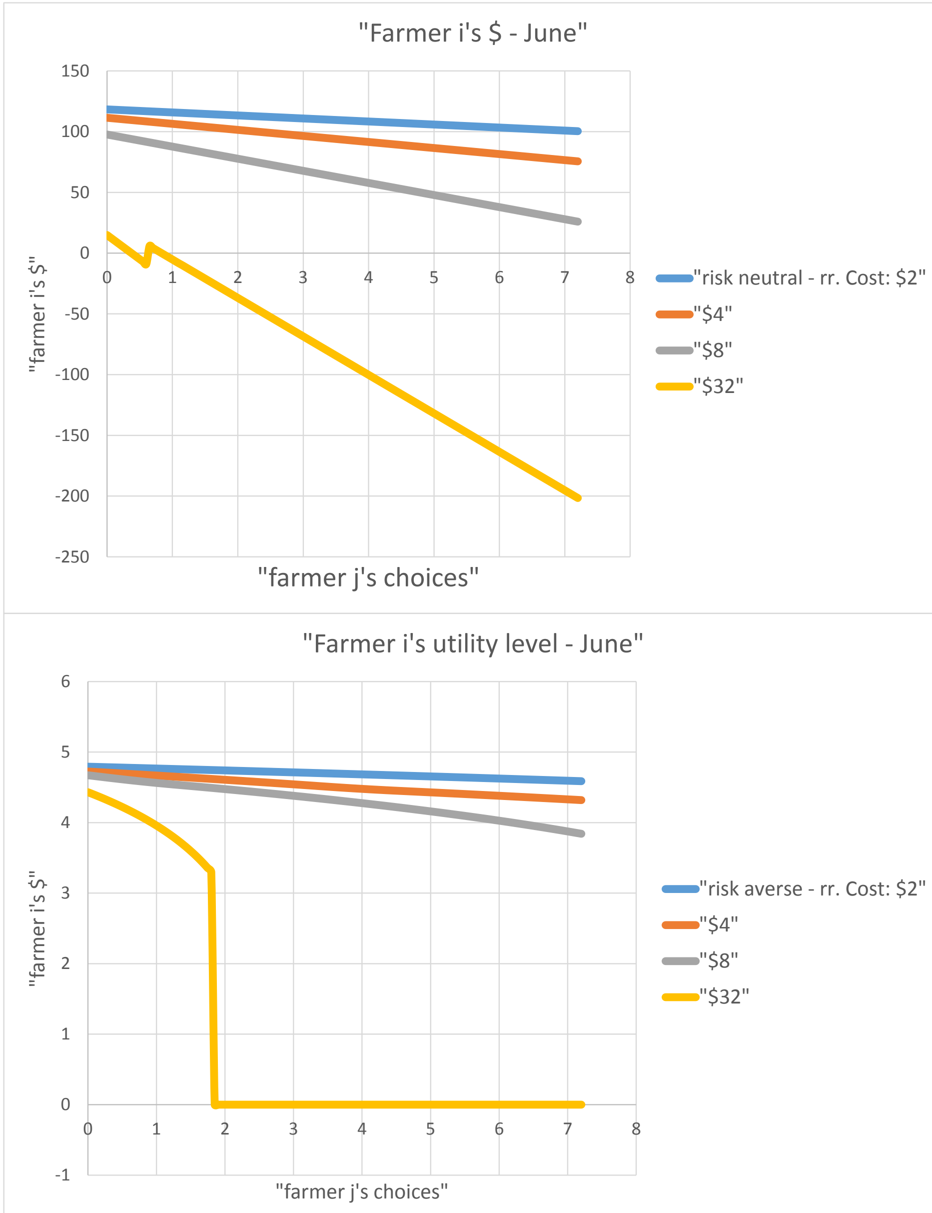

Figure A.7: Farmer i June returns given farmer j's choices & irrigation cost

Notes: Figure A.7 shows Farmer i pay-off given farmer j's choices in June. The upper figure shows the pay-off for a risk neutral farmer i pay-off and the lower figure shows the pay-off for a risk averse farmer i. The pay-offs for both types of farmer i decreases as farmer j's water extraction increases.

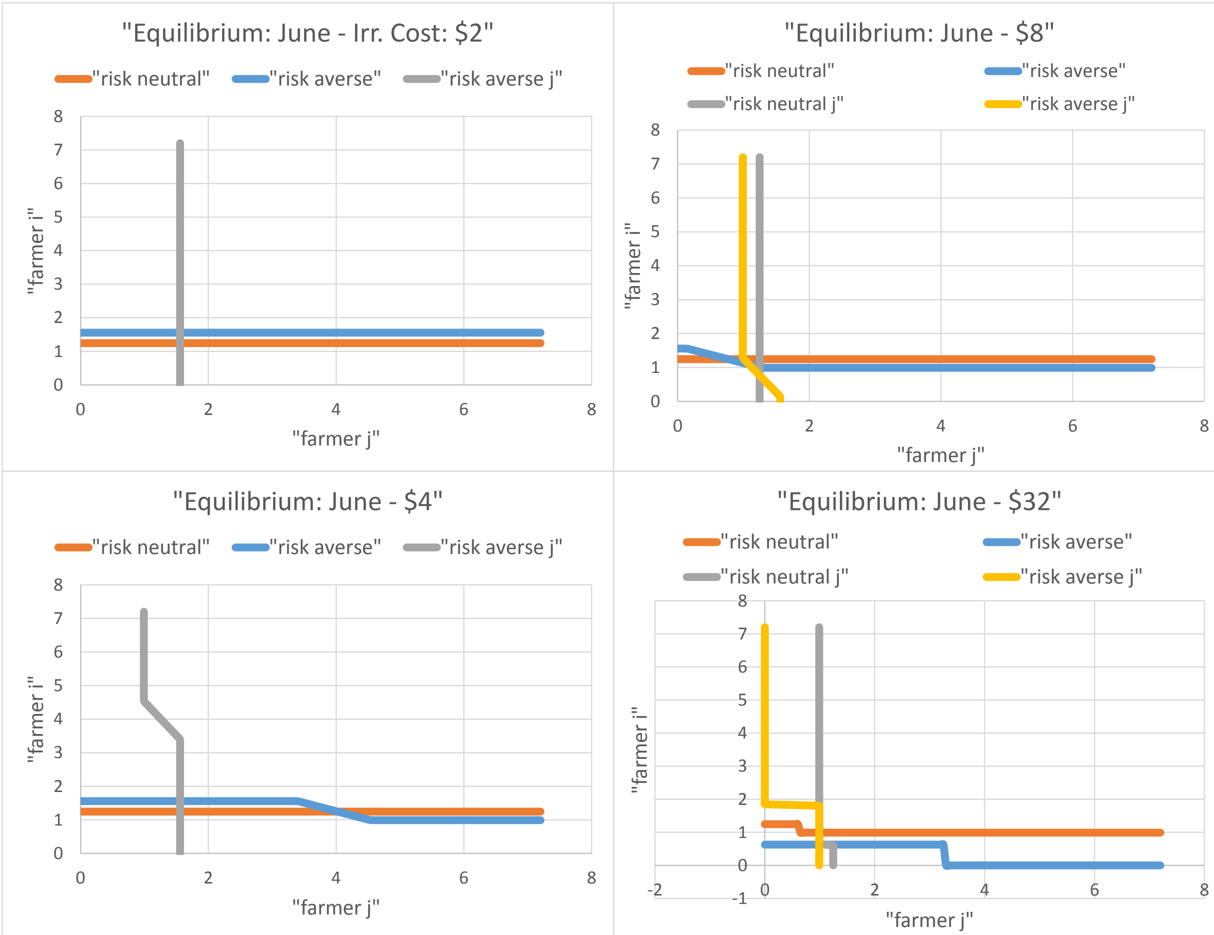

Figure A.8: June equilibrium

Notes: Figure A.8 shows the equilibrium conditions of June irrigation game for risk risk neutral farmers and risk averse farmers given different rates of marginal pumping cost. The equilibrium of the irrigation game when the rate of marginal pumping cost equals \$2 and \$4 is 1.2 per-acre inch for risk neutral farmers and 1.6 for risk averse farmers. At \$8, the equilibrium is 1.2 for risk neutral farmers, and 1 for risk averse farmers. At \$32, the equilibrium is 0.9 per-acre inch for both types of farmer.

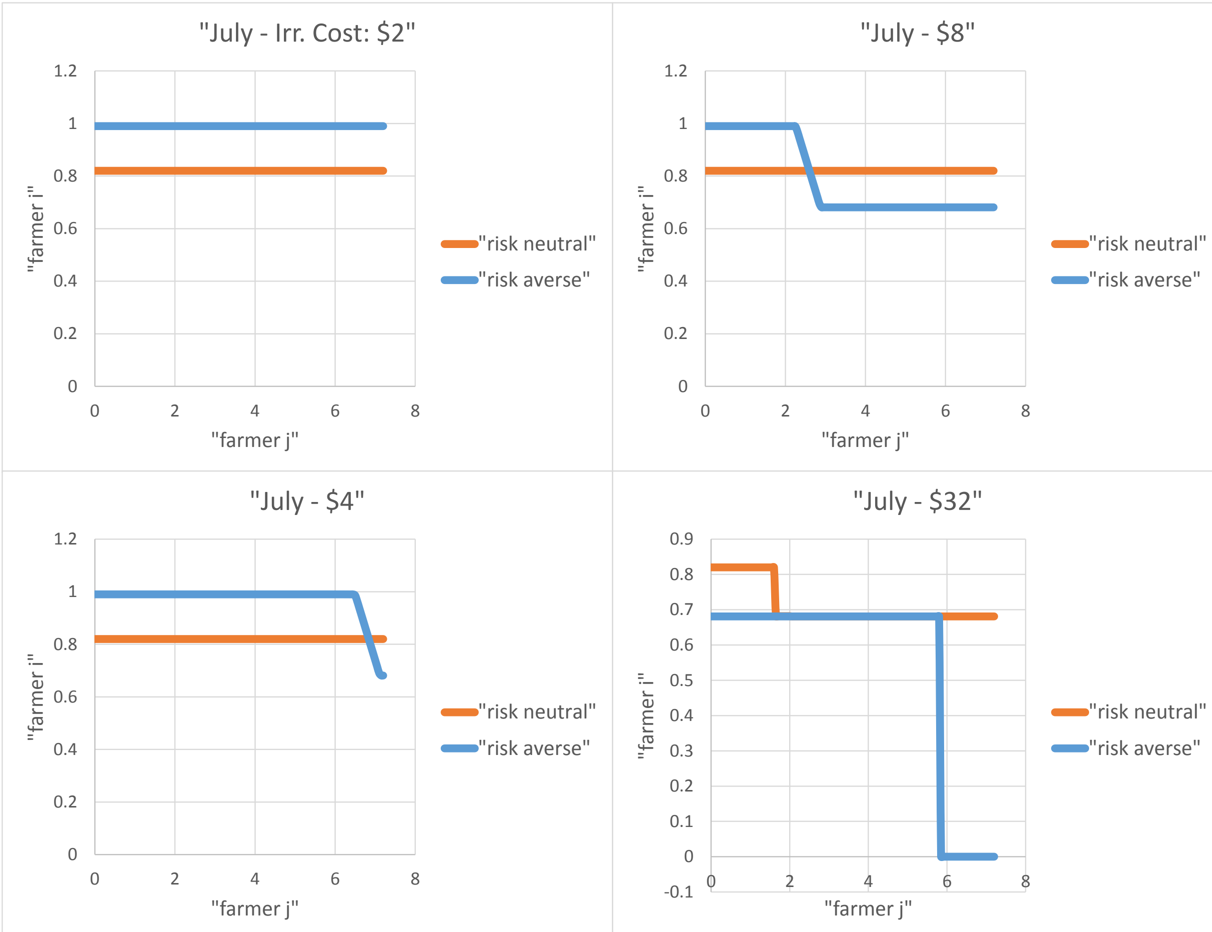

Figure A.9: Farmer i July best response given farmer j's choices & irrigation cost

Notes: Figure A.9 shows Farmer i best response for different marginal pumping rates and given farmer j's choices in July. The orange line shows the risk neutral farmer i best response and the blue line shows the risk averse farmer i best response. If farmer j decides not to irrigate, a risk neutral farmer's water withdrawal equals 0.8 per acre-inch for all scenarios of rate of marginal pumping cost. Different from the risk neutral farmer, if a risk averse farmer j decides not to irrigate, a risk averse farmer i reduces its water withdrawal to 0.7 per-acre inch from 1 per-acre inch when the rate of marginal pumping cost change from \$8 to \$32.

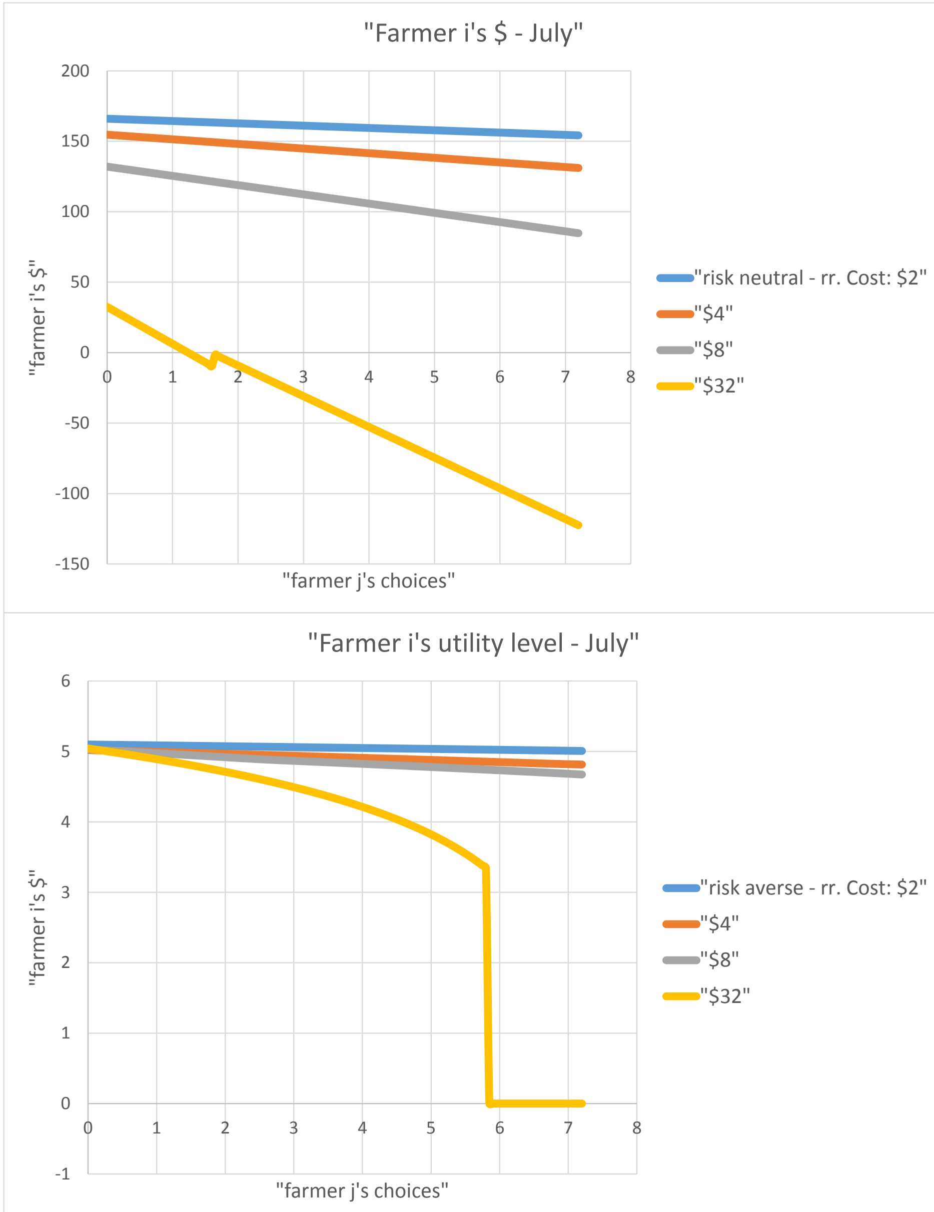

Figure A.10: Farmer i July returns given farmer j's choices & irrigation cost

Notes: Figure A.10 shows Farmer i pay-off given farmer j's choices in July. The upper figure shows the pay-off for a risk neutral farmer i pay-off and the lower figure shows the pay-off for a risk averse farmer i. The pay-offs for both types of farmer i decreases as farmer j's water extraction increases.

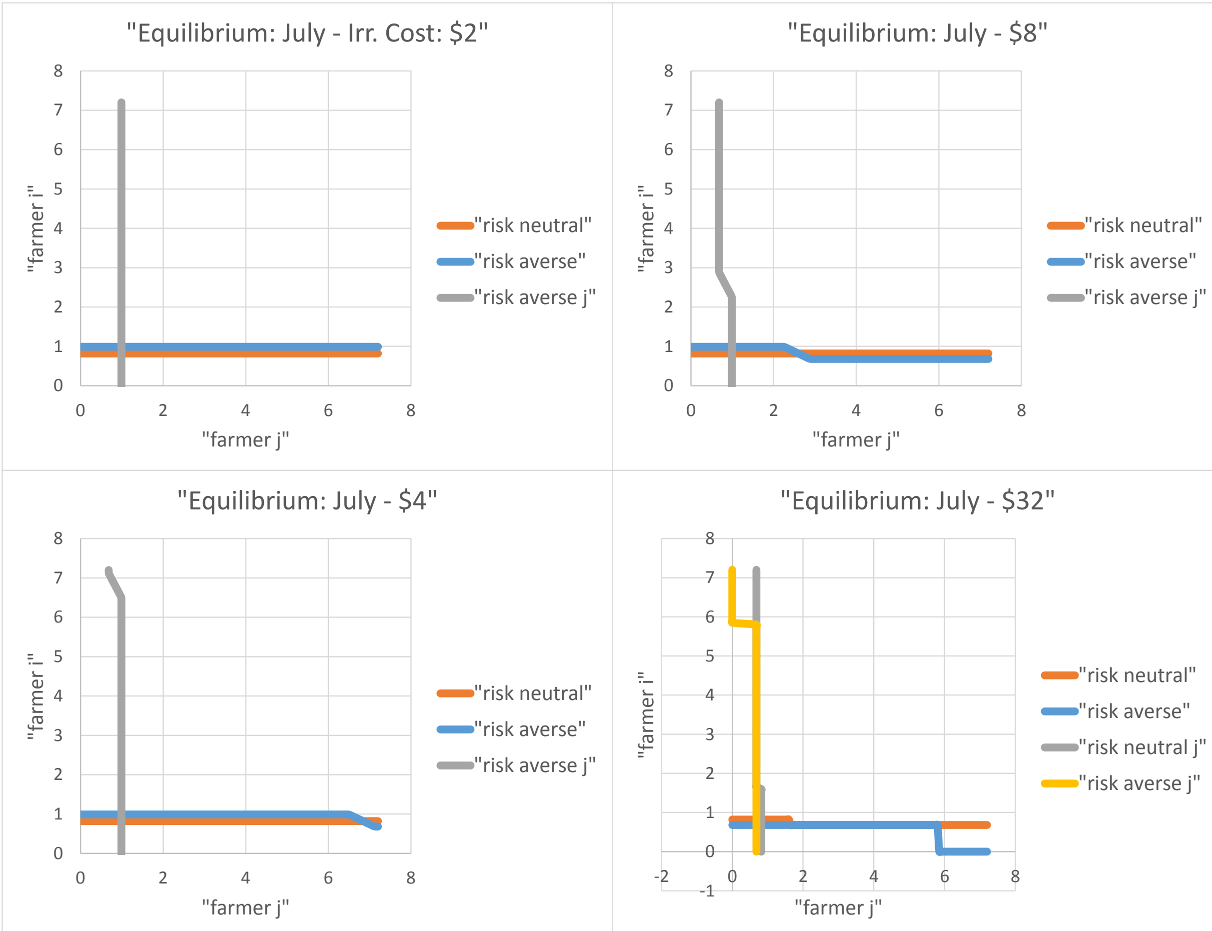

Figure A.11: July equilibrium

Notes: Figure A.11 shows the equilibrium conditions of July irrigation game for risk risk neutral farmers and risk averse farmers given different rates of marginal pumping cost. The equilibrium of the irrigation game when the rate of marginal pumping cost equals \$2, \$4, and \$8 is 0.8 per-acre inch for risk neutral farmers and 1 for risk averse farmers. At \$32, the equilibrium for risk neutral farmers is 0.9 per-acre inch and the equilibrium for risk averse farmers is 0.6 per-acre inch.

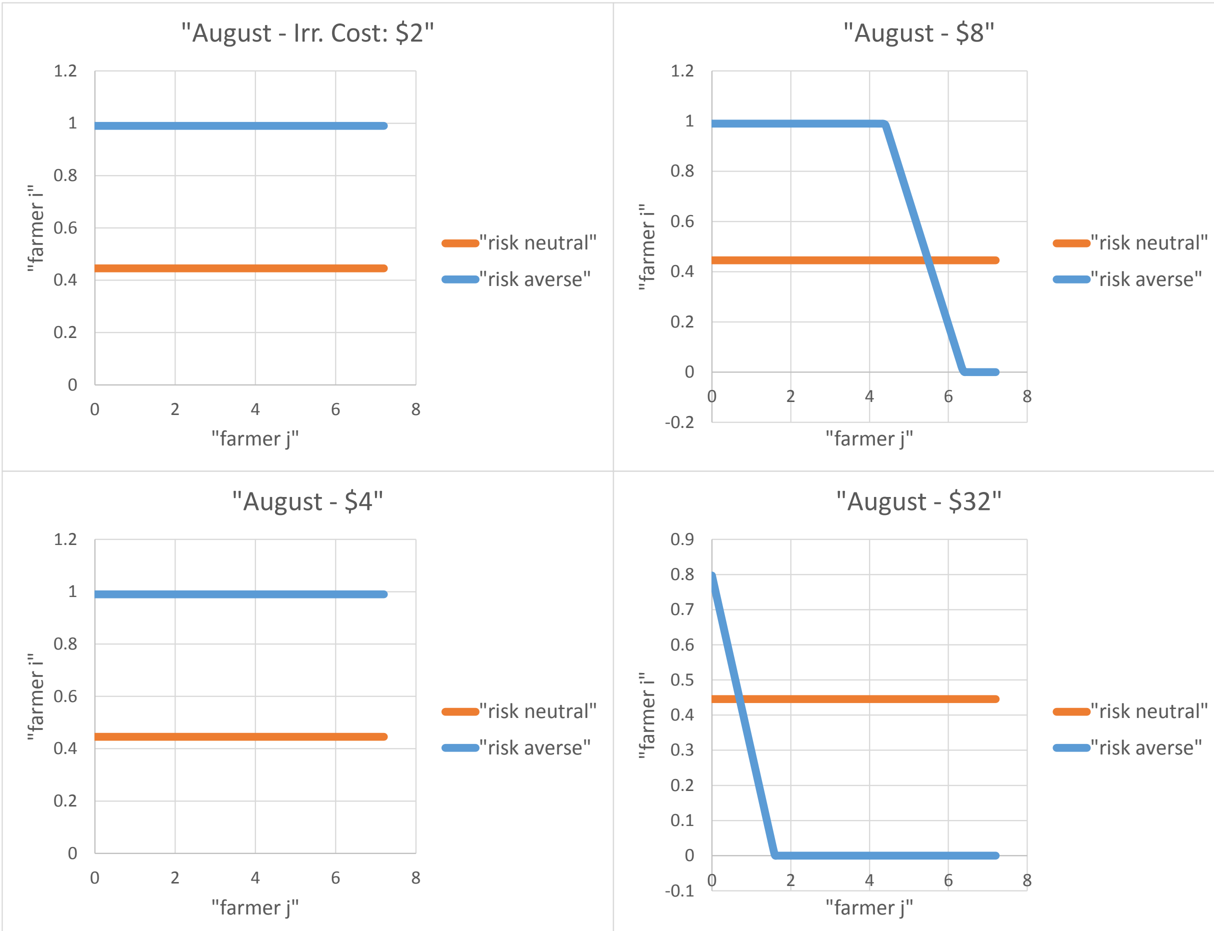

Figure A.12: Farmer i August best response given farmer j's choices & irrigation cost

Notes: Figure A.12 shows Farmer i best response for different marginal pumping rates and given farmer j's choices in August. The orange line shows the risk neutral farmer i best response and the blue line shows the risk averse farmer i best response. In August game, a risk averse farmer i does not react to farmer j's water withdrawal for any given rate of marginal pumping cost. A risk neutral farmer i's water withdrawal stays at 0.45 per-acre inch. A risk averse farmer i reacts to farmer j's water withdrawal for relatively higher pumping cost, \$8 and \$32.

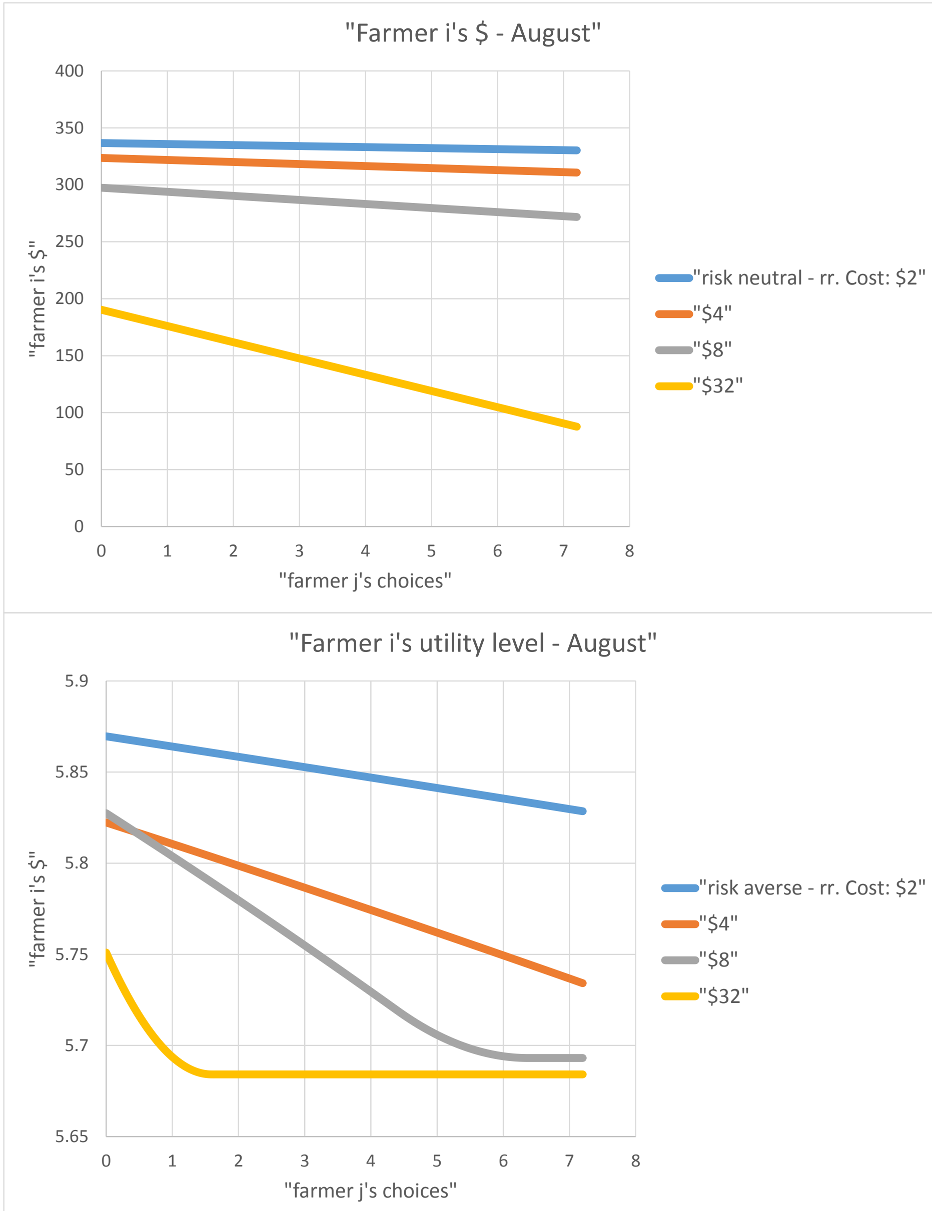

Figure A.13: Farmer i August returns given farmer j's choices & irrigation cost

Notes: Figure A.13 shows Farmer i pay-off given farmer j's choices in August. The upper figure shows the pay-off for a risk neutral farmer i pay-off and the lower figure shows the pay-off for a risk averse farmer i. The pay-offs for both types of farmer i decreases as farmer j's water extraction increases.

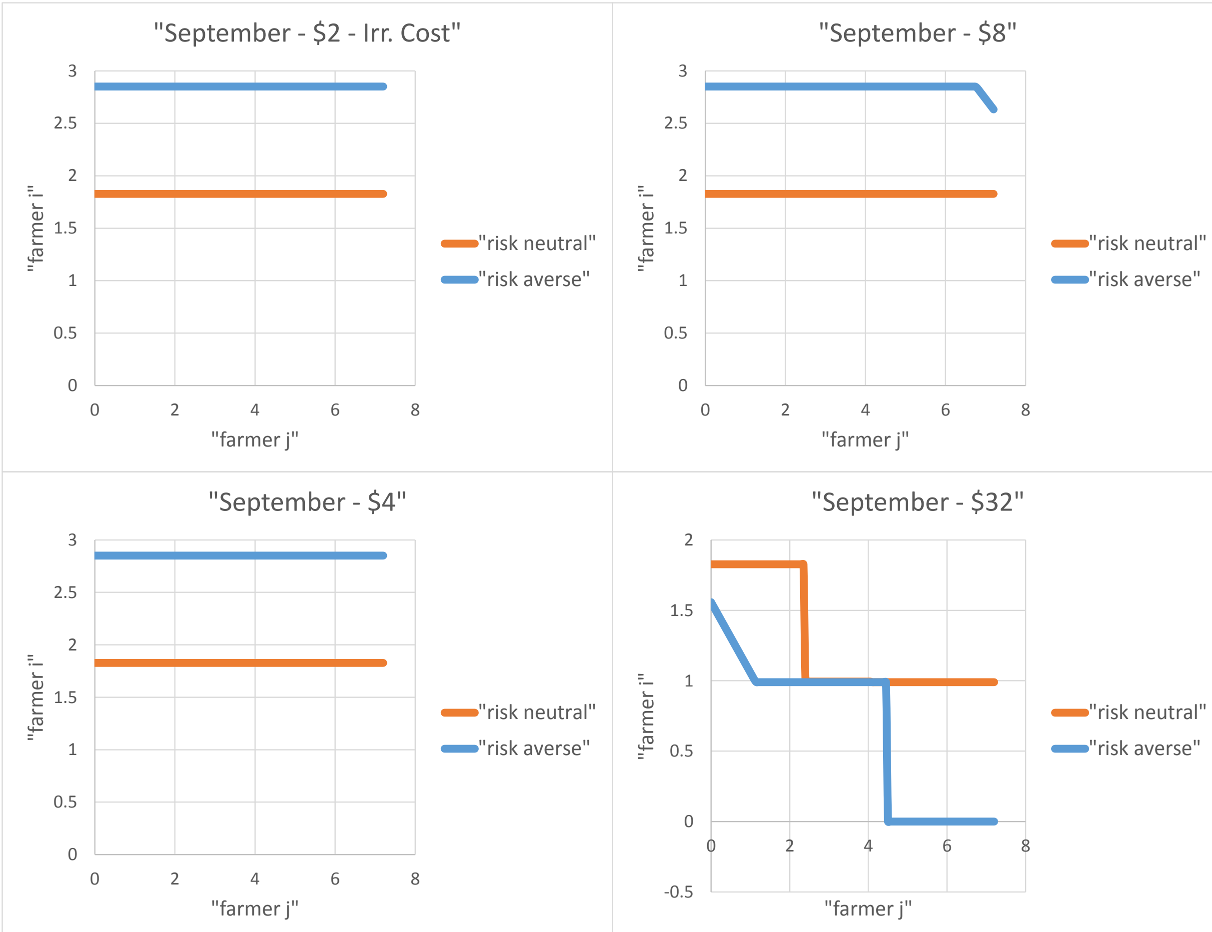

Figure A.14: Farmer i September best response given farmer j's choices & irrigation cost

Notes: Figure A.14 shows Farmer i best response for different marginal pumping rates and given farmer j's choices in September. The orange line shows the risk neutral farmer i best response and the blue line shows the risk averse farmer i best response. In September game, a risk averse farmer i reacts to farmer j's water withdrawal given a $32 of marginal pumping cost. A risk averse farmer i reduces the water withdrawal from 2.9 to 1.6 per-acre inch when the rate of marginal pumping cost increases from $8 to $32 assuming farmer j decides not to irrigate.

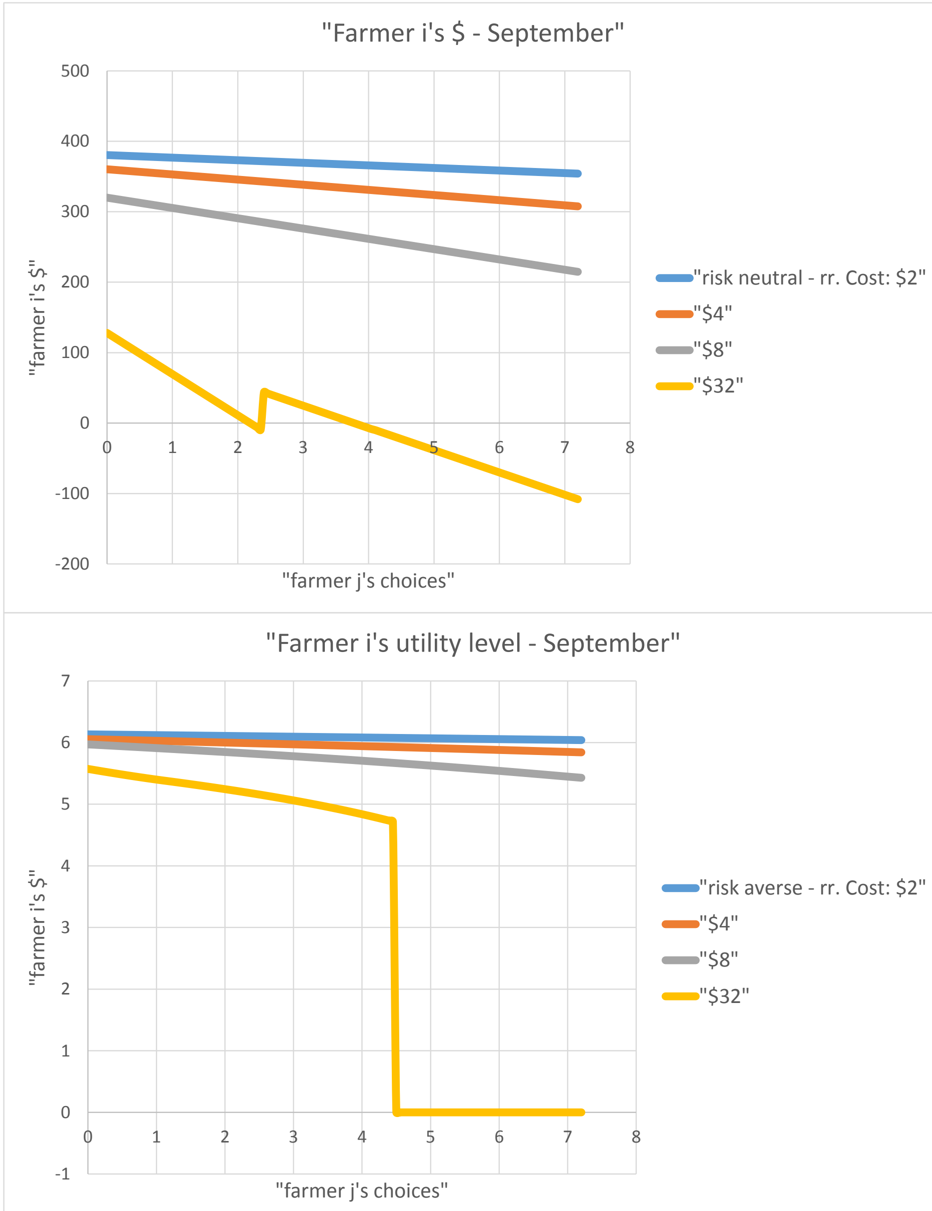

Figure A.15: Farmer i September returns given farmer j's choices & irrigation cost

Notes: Figure A.15 shows Farmer i pay-off given farmer j's choices in September. The upper figure shows the pay-off for a risk neutral farmer i pay-off and the lower figure shows the pay-off for a risk averse farmer i. The pay-offs for both types of farmer i decreases as farmer j's water extraction increases.

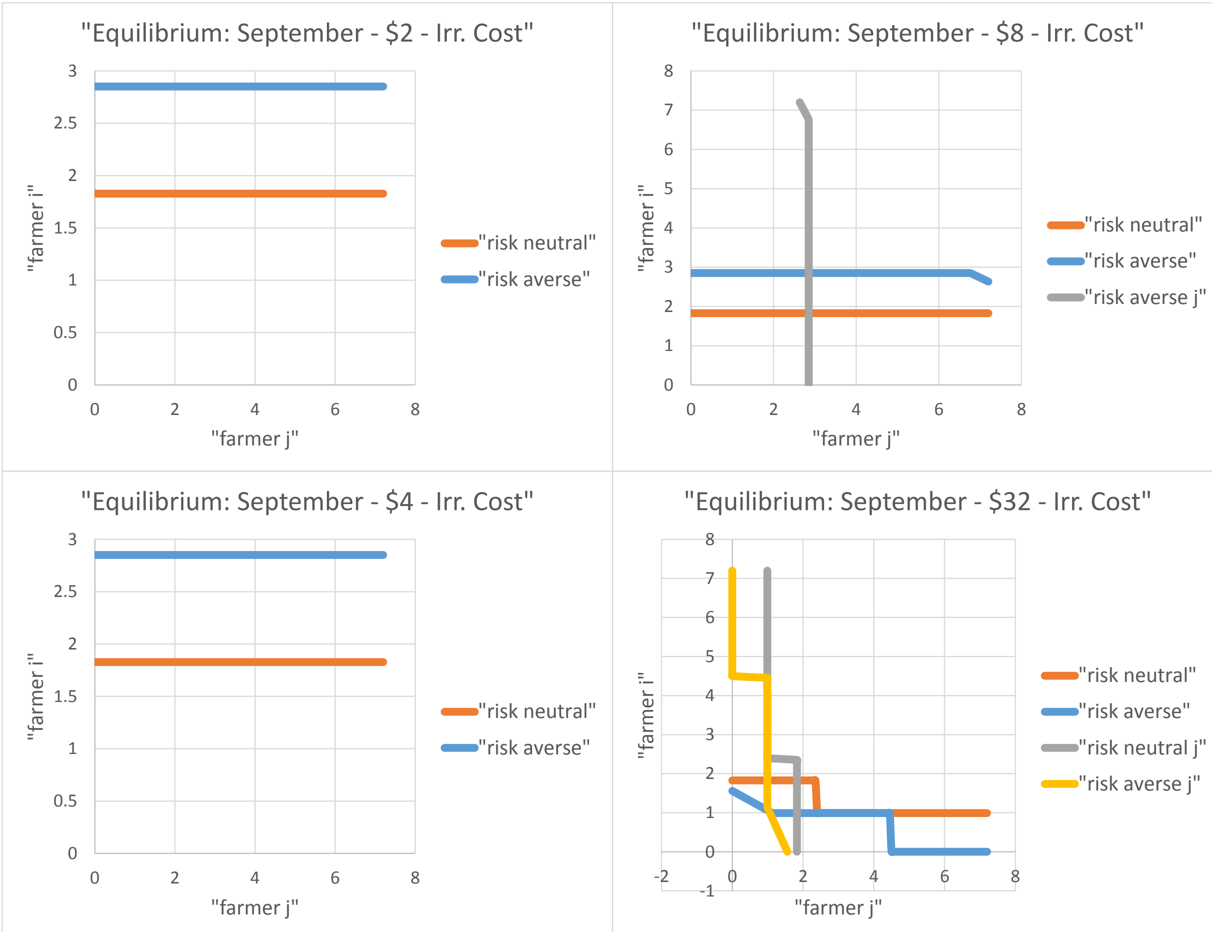

Figure A.16: September equilibrium

Notes: Figure A.16 shows the equilibrium conditions of September irrigation game for risk risk neutral farmers and risk averse farmers given different rates of marginal pumping cost. The September equilibrium for risk neutral farmers equals 1.8 per-acre inch for any given rates of marginal pumping cost. As for risk averse farmers, the September equilibrium equals 2.9 per-acre inch for a $2, $4 and $8 marginal pumping cost. When the rate of marginal pumping cost increases to $32, the September equilibrium for risk averse farmers decreases to 1 per-acre inch.

Vita

Katryn N. Pasaribu was born in Jakarta, Indonesia. She grew up in her hometown. She attended University of Indonesia to study Economics. She had her bachelor degree in 2007. She was awarded USAID scholarship for master program in Applied Economics at University of Wyoming. After completing her master education, in 2014 she started her doctorate education at The University of Tennessee. She earned her Ph.D. degree in Natural Resource Economics in December 2018.