Essays on land use modeling and water scarcity

By

Amer Al-Sudani

B.S., University of Baghdad, 1993
M.S., University of Baghdad, 1998
M.A., Kansas State University, 2016

AN ABSTRACT OF A DISSERTATION

Submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2021

Abstract

Agriculture represents a major use of land across the globe. Half of the world's habitable land is used for agriculture. In addition, water is an essential factor for life on the planet. Besides being key to human survival, water for irrigation is considered the primary factor for raising the productivity of lands around the world. About 20% of the world's croplands are irrigated, but they produce around 40% of the global crop supply. Thus, farmers' decisions with regards to water use in the face of water scarcity is an important topic with economic and environmental implications. Agricultural land decisions are affected by economic factors (e.g., output and input prices) and environmental factors (e.g., climate, soil characteristics, water quality, water availability, ecology). Government policies can have direct and indirect impacts on farmers' cropping patterns and land use decisions. Water scarcity is a significant constraint on l and use and crop production in the Great Plains. The primary source of irrigation water in Kansas is the High Plains aquifer (HPA), which underlies about 175,000 square miles, in parts of eight states. The HPA has been extensively used for agricultural irrigation in Kansas began in the 1930s and 1940s. Prolonged pumping from this aquifer has led to declining water levels, especially in the southwestern part of the aquifer. Decreases in aquifer levels between 2000 and 2017 ranged from 5 feet to more than 80 feet in southwestern Kansas.

The overall purpose of this dissertation is to examine the impact of agricultural land use in Kansas in the context of water scarcity, biofuel expansion, and government policy. The study area is the HPA in Kansas using field-level and county-level data set. Results from these studies provide important contributions to estimation of acreage response and land-use change to water scarcity; the impact of ethanol market expansion on local irrigation decisions; and more robust estimation using a more flexible land use modeling based on land use budgeting. Results of the study are of

interest to policy makers, watershed managers, agricultural producers and other Kansas stakeholders interested in land-use and irrigation decisions studies.

The first essay is an attempt to examine the effects of water scarcity on crop acreage shares using a multinomial logit (MNL) statistical framework to model land use of major irrigated crops (alfalfa, corn, sorghum, soybeans, and wheat) in the Kansas HPA. We estimate county level and regional level acreage share elasticities with respect to a number of water scarcity variables. Generally, most of the elasticity's signs are consistent between the county- and regional-level. However, regional-level elasticities are slightly higher in magnitude than elasticities in other studies that do not focus specifically on irrigation. Our results show that water deficit, depth to water, natural gas prices, and quantity of water authorized for extraction have an effect on irrigated crop acreage share at the county- and regional-level.

The second essay proposes to demonstrate that a more generalized version of the MNL framework, the nested multinomial logistic (NMNL) statistical framework for modeling land use can provide a flexible model to address a multi crop and multi land use response for assessment of the impacts on land use from economic and non-economic factors. First, we show that NMNL acreage share models can be derived from well-defined profit maximizing behavior under specific assumptions. Second, we show that the NMNL acreage share model can provide a multi-crop and multi-land use econometric modeling framework that can be used to estimate unconditional, conditional and group acreage share elasticities that allow for the assessment of direct and indirect effects of explanatory factors on land use decisions and allocation. The model is illustrated using an empirical example of farmer land use allocation between irrigated cropland, non-irrigated cropland, and non-cropland categories.

The third essay aims to examine local irrigation decisions of agricultural producers in the Kansas portion of the HPA in response to ethanol market expansion. To identify the effects of ethanol expansion on local irrigation decisions, we examine field-level data on irrigation water use, total irrigated acreage, and irrigated crop decisions for the years 2000-2018. Specifically, we measure the response of three irrigation decisions: (i) irrigated acreage (extensive margin), (ii) irrigation per acre (intensive margin), and (iii) total water use (total effect) to the location and production capacity of an ethanol plant. We adopt proximity of 25KM and 50KM neighborhood of field from ethanol plant as treatment group to capture the impact of ethanol plant location and capacity on irrigation behavior of fields. We estimate that ethanol plants increase total water use by 12.36 acre-ft and 9.12 acre-ft per field when a new plant is built within 25KM and 50KM neighborhood distance, respectively. In addition, we estimate that a 1 million gallon per year increase in ethanol capacity leads to about a 0.26 and 0.19 acre-ft increase in total water use per field for 25KM and 50KM neighborhood, respectively. Approximately 13% of total response in total water use is due to increases in irrigated acreage. Furthermore, we estimate that a 1 million gallon per year increase in ethanol capacity increases irrigated corn by 0.07 and 0.09 acre per field for 25KM and 50KM neighborhood, respectively.

Essays on land use modeling and water scarcity

By

Amer Al-Sudani

B.S., University of Baghdad, 1993
M.S., University of Baghdad, 1998
M.A., Kansas State University, 2016

A DISSERTATION

Submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2021

Approved by:
Co-Major Professor
Jason S. Bergtold

Approved by:
Co-Major Professor
Gabriel S. Sampson

Copyright

Abstract

Agriculture represents a major use of land across the globe. Half of the world's habitable land is used for agriculture. In addition, water is an essential factor for life on the planet. Besides being key to human survival, water for irrigation is considered the primary factor for raising the productivity of lands around the world. About 20% of the world's croplands are irrigated, but they produce around 40% of the global crop supply. Thus, farmers' decisions with regards to water use in the face of water scarcity is an important topic with economic and environmental implications. Agricultural land decisions are affected by economic factors (e.g., output and input prices) and environmental factors (e.g., climate, soil characteristics, water quality, water availability, ecology). Government policies can have direct and indirect impacts on farmers' cropping patterns and land use decisions. Water scarcity is a significant constraint on l and use and crop production in the Great Plains. The primary source of irrigation water in Kansas is the High Plains aquifer (HPA), which underlies about 175,000 square miles, in parts of eight states. The HPA has been extensively used for agricultural irrigation in Kansas began in the 1930s and 1940s. Prolonged pumping from this aquifer has led to declining water levels, especially in the southwestern part of the aquifer. Decreases in aquifer levels between 2000 and 2017 ranged from 5 feet to more than 80 feet in southwestern Kansas.

The overall purpose of this dissertation is to examine the impact of agricultural land use in Kansas in the context of water scarcity, biofuel expansion, and government policy. The study area is the HPA in Kansas using field-level and county-level data set. Results from these studies provide important contributions to estimation of acreage response and land-use change to water scarcity; the impact of ethanol market expansion on local irrigation decisions; and more robust estimation using a more flexible land use modeling based on land use budgeting. Results of the study are of

interest to policy makers, watershed managers, agricultural producers and other Kansas stakeholders interested in land-use and irrigation decisions studies.

The first essay is an attempt to examine the effects of water scarcity on crop acreage shares using a multinomial logit (MNL) statistical framework to model land use of major irrigated crops (alfalfa, corn, sorghum, soybeans, and wheat) in the Kansas HPA. We estimate county level and regional level acreage share elasticities with respect to a number of water scarcity variables. Generally, most of the elasticity's signs are consistent between the county- and regional-level. However, regional-level elasticities are slightly higher in magnitude than elasticities in other studies that do not focus specifically on irrigation. Our results show that water deficit, depth to water, natural gas prices, and quantity of water authorized for extraction have an effect on irrigated crop acreage share at the county- and regional-level.

The second essay proposes to demonstrate that a more generalized version of the MNL framework, the nested multinomial logistic (NMNL) statistical framework for modeling land use can provide a flexible model to address a multi crop and multi land use response for assessment of the impacts on land use from economic and non-economic factors. First, we show that NMNL acreage share models can be derived from well-defined profit maximizing behavior under specific assumptions. Second, we show that the NMNL acreage share model can provide a multi-crop and multi-land use econometric modeling framework that can be used to estimate unconditional, conditional and group acreage share elasticities that allow for the assessment of direct and indirect effects of explanatory factors on land use decisions and allocation. The model is illustrated using an empirical example of farmer land use allocation between irrigated cropland, non-irrigated cropland, and non-cropland categories.

The third essay aims to examine local irrigation decisions of agricultural producers in the Kansas portion of the HPA in response to ethanol market expansion. To identify the effects of ethanol expansion on local irrigation decisions, we examine field-level data on irrigation water use, total irrigated acreage, and irrigated crop decisions for the years 2000-2018. Specifically, we measure the response of three irrigation decisions: (i) irrigated acreage (extensive margin), (ii) irrigation per acre (intensive margin), and (iii) total water use (total effect) to the location and production capacity of an ethanol plant. We adopt proximity of 25KM and 50KM neighborhood of field from ethanol plant as treatment group to capture the impact of ethanol plant location and capacity on irrigation behavior of fields. We estimate that ethanol plants increase total water use by 12.36 acre-ft and 9.12 acre-ft per field when a new plant is built within 25KM and 50KM neighborhood distance, respectively. In addition, we estimate that a 1 million gallon per year increase in ethanol capacity leads to about a 0.26 and 0.19 acre-ft increase in total water use per field for 25KM and 50KM neighborhood, respectively. Approximately 13% of total response in total water use is due to increases in irrigated acreage. Furthermore, we estimate that a 1 million gallon per year increase in ethanol capacity increases irrigated corn by 0.07 and 0.09 acre per field for 25KM and 50KM neighborhood, respectively.

Table of Contents

List of Figures

List of Tables

Acknowledgements

I would like to first thank my major professors, Dr. Jason Bergtold and Dr. Gabriel Sampson, for the support they have provided as supervisors, researchers, teachers, professionals; and friends. I have learned much from them to improve my ability as a researcher. I had a very hard time during my program, but always I found the support from them to motivate and encourage me to pass the hard situations. Secondly, I would like to thank Dr. Nathan Hendricks for his willingness to provide advice as well as the insightful comments and questions. In addition, I would like to thank the other members of my committee, Dr. Chatura Ariyaratne, Dr. Aleksey Sheshukov, and Dr. Jeffrey Smith for their insightful comments during my defense. I am also would also like to thank Dr. Rich Llewelyn for his assistance in providing and helping with data used in this study. Thank you to Deana Foster, Judy Maberry, Carla Woodward, Terry Teske and the rest of the staff in the department of agricultural economics who helped me during my program. Many thanks to the entire fellow graduate students, who graduated or still in program, who have made my time here at Kansas State enjoyable and memorable. A special thank my friend Taylor Jennings for all her help and support, especially during my hard time.

Finally, I am eternally grateful for the love and support of my wife (Enas) and lovely daughter (Leia), who have helped me through my achievement. Also, I grateful for family in Iraq (My dad, sisters, and brothers). A special grateful for my mom for her moral support and prayers. Finally, I would like to thank everyone I know, who support me in words or actions, it is reminding me to be thankful for those things that truly matter.

Dedication

To my small family (my wife Enas and daughter Leia) and my big family (my parents, sisters, and brothers).

Chapter 1 - Introduction

Agriculture represents a major use of land across the globe. Half of the world's habitable land is used for agriculture. In addition, worldwide, agriculture accounts for 70% of all fresh water consumption. Thus, farmers' decisions with regards to water use in the face of water scarcity is an important topic with economic and environmental implications (Christopher and Shideed 1989; Duffy and Shalishali 1994; Bailey and Womack 1985; Huang and Khanna 2010; Haile et al. 2014; Hodjo et al. 2016; Saddiq 2014). Agricultural land decisions is affected by economic factors (e.g., output and input prices) and environmental factors (e.g., climate, soil characteristics, water quality, water availability, ecology). Government policies can have direct and indirect impacts on farmers' cropping patterns and land use decisions. For example, the Conservation Reserve Program (CRP) and Renewable Fuel Standard (RFS) can have direct and indirect effects on land use. The CRP provides incentives to retire land from production, while the RFS increases demand for grains (e.g. corn and sorghum), which can change cropping patterns and the amount of water used for crop production (Lubowski 2002; Luboweski et. al. 2005; Lubowski et. al. 2008).

Environmental factors, such as climate change and extreme weather can play an important role in determining agricultural land-use. For instance, the level of precipitation and availability of groundwater for irrigation can affect land-use transitions from irrigated to non-irrigated crops. In addition, water availability for irrigation can play an important role in allocating land between different irrigated crops. In addition, farmers might convert cropland into pastureland to enhance soil stability and reduce erosion (Franzluebbers et. al 2000). Land use and land cover plays an important role in global environmental change (Wu 2000; Olesen and Bindi 2002; Kline 2005; Mao et. al. 2011).

Water is an essential factor for life on the planet. Besides being key to human survival, water for irrigation is considered the primary factor for raising the productivity of lands arround the world. About 20% of the world's croplands are irrigated, but they produce around 40% of the global crop supply (Fernández et. al. 2009). In the U.S., About 63.5 million acres were irrigated in 2015. Total irrigation withdrawals were 118 billion gallons per day, which accounted for 64% percent of total freshwater withdrawals. About 52% of the total irrigation withdrawals come from surface water, while 48% come from groundwater (Dieter 2018). In Kansas, groundwater is the source of water for 98% of all irrigated fields (Hendricks and Peterson, 2012). Land use decisions can have a direct impact on groundwater use and availability.

The primary source of irrigation water in Kansas is the High Plains aquifer (HPA), which underlies about 175,000 square miles, in parts of eight states (McGuire, 2014). Extensive use of the HPA for agricultural irrigation in Kansas began in the 1930s and 1940s (Sampson and Perry, 2019). Prolonged pumping from this aquifer has led to declining water levels, especially in the southwestern part of the aquifer (Buchanan et. al., 2001). Decreases in aquifer levels between 2000 and 2017 ranged from 5 feet to more than 80 feet in southwestern Kansas (fig. 1.1). Furthermore, the most common irrigated crop is corn. Estimated irrigated corn acreage has increased over the last 20-year period, and accounts for 43% to 60% of yearly total irrigated acreage. In addition, corn is among the most water intensive crops in Kansas, with an average use of 1.2 acre-feet of water per acre (Kenny and Juracek 2013).

Government policies can play a significant impact in land and water use change. In 2007, Congress created the renewable fuel standard (RFS) program with the intent to reduce greenhouse gas emissions and expand the nation's renewable fuels sector, while reducing reliance on imported oil (NRC 2012). The biofuel industry relies mainly on corn production. Nearly 5.5 billion bushels of corn were used for ethanol production in 2018 (ERS, 2019). Corn acreage has increased substantially in Kansas since passage of the RFS. The increase in biofuel production from legislation led to concerns about food availability and environmental impacts (Hausman et al. 2012). From 2006 to 2007 total corn acreage increased by 550,000 acres (i.e., a 16.5% increase). Approximately half the increase in corn acreage was met with expansions in irrigated production (USDA-NASS). Moreover, most of ethanol industry overlying the HPA in Kansas. The number of ethanol plants also increased from 3 to 12 biofuel plants from 2001 to 2017. The resulting increase in biofuel production led to increasing demand for corn.

The purpose of this dissertation is to examine the impact of agricultural land use in Kansas in the context of water scarcity, biofuel expansion, and government policy. The specific objectives are to:

1. Examine how water scarcity impacts irrigated crop acreage decisions along different dimensions using an acreage response framework based on the multinomial logit framework.;
2. Develop an acreage response modeling framework based on the nested logit framework and land budgeting in the context of water scarcity; and
3. Quantify the impact of ethanol market expansion due to to the RFS mandate on irrigation decisions along different margins.

The study area is the HPA in Kansas using field-level and county-level data set. Results from these studies provide important contributions to estimation of acreage response and land-use change to water scarcity; the impact of ethanol market expansion on local irrigation decisions; and more robust estimation using a more flexible land use modeling based on land use budgeting. Results of the study are of interest to policy makers, watershed managers, agricultural producers and other Kansas stakeholders interested in land-use and irrigation decisions studies. The dissertation is comprised of three essays, which are outlined below.

1.1 Essay 1: Acreage response of major crops to water scarcity in High Plains Aquifer Kansas

Producers adjust planted acreage in response to water scarcity, prices, market factors, climate, weather, soil characteristics, and government policy, amongst other factors (Christopher and Shideed 1989; Duffy and Shalishali 1994; Bailey and Womack 1985; Huang and Khanna 2010; Haile et al. 2014; Saddiq 2014; Khorshed 2015; Olen et. al. 2015). While the existing literature has examined acreage response to many of these factors, few acreage response studies have dealt with water scarcity and its impact on land use and farmers' acreage allocation decisions with respect to irrigated production. In this essay, we examine the effects of water scarcity on crop acreage shares using a multinomial logit framework (MNL) of major irrigated crops (alfalfa, corn, sorghum, soybeans, and wheat) in the Kansas HPA. We estimate county level and regional level acreage share elasticities with respect to a number of water scarcity variables. Generally, most of the elasticity's signs are consistent between the county- and regional-level. However, regional-level elasticities are slightly higher in magnitude than elasticities in other studies that do not focus specifically on irrigation. Our results show that water deficit, depth to water, natural gas prices, and quantity of water authorized for extraction have an effect on irrigated crop acreage share at the county- and regional-level. Increased water deficit increases crop acreage share, while increased depth to water and natural gas prices decrease irrigated crop acreage shares (due to increasing pumping cost). Increasing the quantity of irrigation of water authorized will increase irrigated crop acreage share especially for corn. In addition, own output price elasticities show a positive significant impact on irrigated crop acreage shares.

1.2 Essay 2: Land-use budgeting and land-use responsiveness to water scarcity, climate, and policy: A nested logit framework

Change in land-use patterns can generate significant economic and environmental impacts. For these reasons, land-use analyses are important for policy makers, providing important implications for policy issues including potential impacts of water scarcity, climate change, soil quality, and conservation on agricultural land-use decisions. Normally, such analyses focus on the response to output and input prices, climate and soil characteristics for a single crop or multi crop analysis. Considering all the possibilities for land-use change, models may require a more flexible approach for land-use in order to adequately assess land use response. A framework of land use compatible with regional water scarcity, climate change, and government programs that more directly takes account of land use planning (through land budgeting) is introduced in this essay. The main objective of this essay is to demonstrate that NMNL acreage share framework can provide a flexible model to address a multi crop and multi land use response for assessment of the impacts on land use from economic and non-economic factors. First, we show that NMNL acreage share models can be derived from well-defined profit maximizing behavior under specific assumptions. Second, we show that the NMNL acreage share model can provide a multi crop and multi land use econometric model that can be used to estimate unconditional, conditional and group acreage share elasticities that allow for the assessment of direct and indirect effects of explanatory factors on land use decisions and allocation.

The model is illustrated using an empirical example of farmer land use allocation between irrigated cropland, non-irrigated cropland, and non-cropland categories. The results show that water scarcity variables, such as energy prices, depth to water, water rights, in addition to energy price amongst others have a significant and direct influence on irrigated land-use decisions, as well as significant and indirect effect on non-irrigated and non-cropland use decisions. The NMNL model provides elasticities estimates that show the direct impact of irrigation water factors on irrigated crops and indirect impacts on non-irrigated crops, CRP, and grassland. Other elasticity estimates show that producers respond significantly to crop prices and other noneconomic factors. These findings are important to policy makers to understand how water scarcity factors can affect other non-irrigated crops and non-cropland land-use.

1.3 Essay 3: Local irrigation decisions and irrigated crop acreage response to ethanol market expansion in the High Plains Aquifer Kansas

Despite a primary goal of government bioenergy policies (e.g., RFS mandate) to improve environmental standards and decrease reliance on oil, such policies can affect groundwater depletion due to changes in farmer's crop choices and irrigation decisions. The U.S ethanol production has grown rapidly due to the RFS mandate. The RFS extended the target amount of biofuel that must be mixed with gasoline sold in the United States to 36 billion gallons by 2022. Recently, the resulting increase in biofuel production led to concerns over food availability and environmental impacts. In this essay, we examine local irrigation decisions of agricultural producers in the Kansas portion of the HPA in response to ethanol market expansion. To identify the effects of ethanol expansion on local irrigation decisions, we examine field-level data on irrigation water use, total irrigated acreage, and irrigated crop decisions for the years 2000-2018. Specifically, we measure the response of three irrigation decisions: (i) irrigated acreage (extensive margin), (ii) irrigation per acre (intensive margin), and (iii) total water use (total effect) to the location and production capacity of an ethanol plant. We adopt proximity of 25KM and 50KM neighborhood of field from ethanol plant as treatment group to capture the impact of ethanol plant location and capacity on irrigation behavior of fields. We estimate that ethanol plant increase total water use by 12.36 acre-ft and 9.12 acre-ft per field when a new plant is built within 25KM and 50KM neighborhood distance, respectively. In addition, we estimate that a 1 million gallon per year increase in ethanol capacity leads to about a 0.26 and 0.19 acre-ft increase in total water use per field for 25KM and 50KM neighborhood, respectively. Approximately 13% of total response in total water use is due to increases in irrigated acreage. Furthermore, we estimate that a 1 million gallon per year increase in ethanol capacity increases irrigated corn by 0.07 and 0.09 acre per field for 25KM and 50KM neighborhood, respectively.

Chapter 2 - Acreage response of major irrigated crops to water scarcity in the High Plains Aquifer Kansas

2.1 Introduction

Water is an essential factor for life on the planet. Increasing world population, economic growth, and expansion of irrigated agriculture are factors driving global demand for water (Liu et. al., 2017). At the global level, enough freshwater is available to meet such demand, but spatial and temporal variations in water demand and availability cause physical water scarcity in many parts of the world (Hoekstra et al., 2012). Water scarcity is a global issue that has significant impacts on agriculture. Every year, water demand increases about 2% due to increases in population and economic growth as reflected by increases in agriculture and industrial production. If this rate of growth continues, global water demand in 2030 will be double what it was in 2005 and will be 40% greater than water supply (Young and Esau, 2013; Liu et. al., 2013). Globally, food and other agricultural products use 70% of freshwater withdrawals from rivers and groundwater (Molden, 2007). In the United States, in 2015 freshwater withdrawals for irrigation accounted for 64 % of total freshwater withdrawals.

There is not a unique definition for water scarcity. However, physical water scarcity is when there is not enough water to meet all human needs, including that needed for ecosystems. Economic water scarcity occurs when there is a lack of investment in infrastructure or technology to withdraw water from different sources, such as rivers and aquifers (Watkins 2006). Water scarcity can be related to a lack of and restricted access to water availability (Damkjaer & Taylor 2017; Liu et. al. 2017; Monzonís et. al. 2015; White 2014; Rijsberman 2006).

Acreage response analysis is an important tool in agricultural policy analysis for land use evaluation. Agricultural land use is significantly impacted by issues such as water scarcity, an important input for agricultural production. Acreage response analysis focuses on acreage responsiveness (land use) to output and input prices, as well as changes in climate and soil characteristics. This type of analysis is incomplete without including water scarcity in the model for regions such as Kansas. Including water scarcity as a factor in acreage response analysis provides a general insight to how this factor can interact with economic and non-economic factors and affect agricultural land use, which captures farmers' revealed agricultural decision-making with regard to land-use.

The objective of this study is to examine the impact of water scarcity on the allocation of agricultural land to irrigated cash crop production in western Kansas over time. This study aims to answer the following questions: (1) How does water scarcity influence farmers' acreage allocation decisions; and (2) What aspects of water scarcity most influence farmers' land use decisions for irrigated crop production? To answer these questions, the study will examine if groundwater depletion and/or irrigation energy costs have affected farmers' acreage allocation decisions. The importance of this study for policy makers in terms of land-use and water-use management is that it can provide information about changes in cropping patterns, in particular water intensive crops responsiveness to groundwater depletion, and to examine its influence on water conservation policies and programs. Furthermore, the study contributes to the literature on acreage response analysis by measuring the impact of water scarcity on irrigated crop acreage decisions through the inclusion of water deficit and irrigation cost function factors, such as energy price and depth to water, instead of using irrigation costs as a single factor that can affect producer's land-use decisions. Second, we estimate county-level and regional-level elasticities for prices and water scarcity variables for each crop to capture whether water scarcity has an impact on producer's land-use decisions for irrigated crops and to capture any heterogeneity in responses across counties.

2.2 Literature Review

In the literature, many acreage response studies recommend including output and input quantities and prices, climate and soil characteristics, and government policies as factors to explain land use change (Christopher and Shideed 1989; Duffy and Shalishali 1994; Bailey and Womack 1985; Huang and Khanna 2010; Haile et al. 2014; Hodjo et al. 2016; Saddiq 2014). Few acreage response studies have dealt with water scarcity and its impact on land use and farmers' acreage allocation decisions.

Deschenes and Greenstone (2007) estimate that climate change will increase annual agricultural profit in the US by $1.3 billion in 2002 or by 4%. In addition, Moore and Negri (1992) estimate an economic model for crop supply and land allocation. Their results show that based on crops' water requirements, producers reallocate their land from crops with low water requirements to crops with high water requirements as water constraints are relaxed. However, a simulated 10% reduction in surface water by the U.S. Bureau of Reclamation will increase fallowed land and allocations to other crops having lower water requirements, reducing the amount of land allocated to crops with higher water requirements.

Khorshed (2015) surveyed 546 farming households in Bangladesh to investigate rice farmers' adaptation to water scarcity in a semi-arid climate. The study uses a multinomial logistic regression model to identify factors determining farmers' adaptation responses to water scarcity. The study shows that farmers with more experience in farming, better schooling, better access to electricity and institutional facilities, and an awareness of climatic effects are more likely to adopt alternative water scarcity adaptations. Farmers' with adaptations are examined in comparison to more traditional approaches of groundwater irrigation. The study finds that the use of groundwater for irrigation is the most commonly used adaptation strategy by farmers in response to water scarcity. This strategy raises issues about sustainability of agricultural adaptation practices with an increasing dependence on groundwater irrigation. The results provide an insight to sustainable irrigation practices and an understanding of the characteristics of farms and farming households to adopt better strategies to cope with drought-prone environments, which is similar to what farmers face in western Kansas.

Olen et. al. (2015) examine the impact of water scarcity and climate change on land use decisions of producers for major crops grown on the west coast (California, Oregon, and Washington). They estimate an irrigation management model for orchard/vineyard, vegetable, wheat, alfalfa, hay, and pasture. Using farm level data, the authors find that producers harvest fewer acres in response to declines in the depth to water. Changes in depth to water are driven by the amount of land devoted to pasture. In addition, producers who received surface water from a federal agency or that use surface water for irrigation have lower average water costs. These producers allocate more land to pasture than other crops. Moreover, the study finds that farmers harvest more land if irrigation is used to reduce frost damage to orchards and vineyards. Finally, producers respond to droughts by allocating more land to orchards and vineyards, while reducing land allocations to alfalfa and hay.

Gravelinand eMe´rel (2012) investigate extensive and intensive margin adjustments to water scarcity. Farmers may respond to water scarcity on the margin in three different ways: (1) shift to rain-fed agriculture (super-extensive margin); (2) shift towards less water-intensive crops (extensive margin); and/or (3) reduce water use for irrigated crops (intensive margin). Using a positive mathematical programming model, the study examines the effect of water availability reductions on these three adjustment margins in the Beauce cereal region of France's cereal belt, which relies on groundwater resources to meet irrigation needs. The results show that, for realistic water scarcity scenarios, 57% of producers respond to water scarcity by shifting to rain-fed agriculture. A shift towards less water-intensive crops (an extensive margin response) represents 28% of the total response to water scarcity, while reductions in water use for irrigated crops accounts for 15%.

Kettl et. al. (2007) study groundwater depletion and agricultural land use change in the High Plains. The study examines the relationship between groundwater depletion and agricultural land use change within Wichita County, Kansas where agro-economic systems and population are dependent on the groundwater supply. The study used remote sensing and GIS methods to examine the spatial relationship between groundwater and land use change. Results indicate that intensive groundwater withdrawals above areas of limited saturated thicknesses show a high percentage decrease in the groundwater table. In addition, improving irrigation efficiency from using center pivot in the 1990s instead of flood irrigation, which dominated the irrigation practices in the 1970s and 1980s, resulted in a decrease in groundwater depletion. The authors establish a significant relationship between groundwater depletion and land being switched from irrigated to non-irrigated production. Groundwater depletion results in a decrease in irrigated cropland and an increase in non-irrigated cropland.

Bhalla (2007) examines the impact of declines in groundwater levels on acreage allocation. This study attempts to examine the impact that a declining groundwater table has on farmer's crop decisions in Punjab and Haryana, India. Using a Nerlovian supply response approach, acreage response functions are estimated for two water-intensive crops (rice and sugar cane) and two less water-demanding crops (wheat and bajra). The results show that farmers respond to declines in depth to water tables by reducing acreage devoted to rice and sugar cane, the two most water-intensive crops, but not for the less water-intensive crops (wheat and bajra).

2.3 Water Scarcity and Kansas

The primary source of irrigation water in Kansas comes from the High Plains Aquifer (HPA). The HPA is a shallow water table aquifer located beneath the Great Plains in the central United States. The HPA is the largest aquifer in the United States and one of the largest aquifers in the world, underlying an area of approximately 174,000 square miles (450,000 km^2). The aquifer underlies portions of eight states including South Dakota, Wyoming, Nebraska, Colorado, Kansas, Oklahoma, New Mexico and Texas (Sophocleous, 2010). About 27% of irrigated land in the United States overlies this aquifer system, with aquifer providing about 30% of the total groundwater used for irrigation (USDA-NRCS,2011).

The HPA in Kansas includes the Ogallala, Great Bend Prairie, and Equus Bend Aquifers, supplying 70% to 80% of the total water used by the State of Kansas each day for cities, industry, and agriculture. The HPA in Kansas is the source of water for about 98% of all irrigated fields (Hendricks and Peterson, 2012). Extensive use of the HPA for agricultural irrigation in Kansas began in the 1930s and 1940s (Sampson and Perry, 2019). Prolonged pumping from this aquifer has led to declining water levels, especially in the southwestern part of the aquifer (Buchanan et. al., 2001). Water levels have decreased dramatically in the last two decades (KGS, 2019). Decreases in aquifer levels between 2000 and 2017 range from 5 feet to more than 80 feet. Moreover, in southwest Kansas, the decreased groundwater level is more than in any other part of the aquifer (Figure 1).

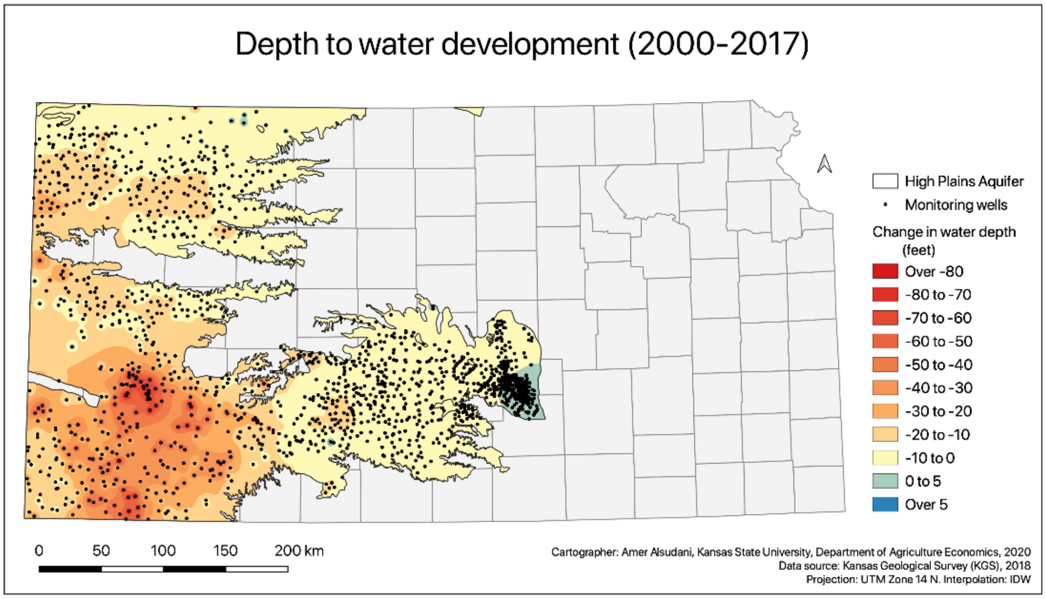

Fig.2.1: Depth to water development in the HPA Kansas (2000-2017). Source: Kansas Geological Survey (KGS, 2018).

Water availability in the aquifer has an impact on agriculture land use through allocation of land among different irrigated crops or switching agriculture land from irrigated to non-irrigated production. In Kansas, major irrigated crops include alfalfa, corn, sorghum, soybeans, and wheat, with corn being the most common. Estimated irrigated corn acreage has increased from approximately 1.29 million acres in 1992 to 1.65 million acres in 2016, accounting for 43% to 60% of yearly total irrigated acreage (USDA-FSA, 2017). Corn acreage accounts for 43% to 60% of total irrigated acreage on a county by county basis. In addition, corn is among the most water intensive crops in Kansas, with an average of 1.2 acre-feet of water used per acre (Kenny and Juracek, 2013).

2.4 The Model

In this study, we use a multinomial logit framework (MNL) to derive and estimate acreage share equations to examine the empirical relationship between irrigated crop production and water scarcity in western Kansas. The MNL functional form was formally derived by Carpentier and Letort (2014). The MNL is mainly used to model discrete choices or market shares (Gruca and Sudharshan 1991; Gensch and Recker 1979; Hongmin, and Huh 2011); and has been extensively used in the agricultural production economics and environmental economics literature (Wu and Segerson 1995; Wu and Adams 2002; Carpentier and Letort 2014). We adapt this framework by including water scarcity as a variable that can affect famers' land-use and cropping decisions.

2.4.1 Conceptual Framework

We develop a multinomial logit framework (MNL) to examine lands allocated to irrigated production in response to water scarcity. Following Carpentier and Letort (2014), in the short run, suppose a farmer grows i $(i =1,\ldots,I)$ crops, which are produced on heterogeneous land types j $(j=1,\ldots,J)$ that are differentiated by site specific characteristics, weather conditions, and other factors. The acreage share for crop i on land type j can be specified as s_{ij} , where $s_{ij} = \frac{A_{ij}}{A_j}$, where A_{ij} is the total acreage of crop i planted on land type j and A_j is the total acreage of land type j. For a given county, the total acreage share for crop i can be specified as $\mathrm{s}_i = \sum_{j=1}^{J} s_{ij}$. The acreage share dedicated to crop i should not exceed the total land in county j, implying $\sum_{i=1}^{I} s_i = 1$. Assume the expected gross margins per acre for crop i is given by: $\pi_i\big(\boldsymbol{p}, \boldsymbol{b}, \boldsymbol{d}, \theta(\boldsymbol{w})\big)$, where $\boldsymbol{p}$ is a vector of output prices, $\boldsymbol{b}$ is a vector of input prices not including water pumping costs, and $\boldsymbol{d}$ is a vector of weather and soil characteristics. Weather varies over time and space, while soil characteristics are fixed over time, varying over space only. $\theta(\boldsymbol{w})$ is defined as an irrigation cost function, where $\boldsymbol{w}$ is a vector of irrigation variables that include energy price, depth to water, and water deficit, which is evaporative demand not met by available water (Stephenson 1990).

Assuming the farmers are profit maximizers, a farmer's objective choosing a land allocation that maximizes their profit, which is given by:

$$\Pi\big(\boldsymbol{s};\boldsymbol{p},\boldsymbol{k},\boldsymbol{d},\theta(\boldsymbol{w})\big) = \Pi\Big(\boldsymbol{s};\boldsymbol{\pi}\big(\boldsymbol{p},\boldsymbol{k},\boldsymbol{d},\theta(\boldsymbol{w})\big)\Big) = \sum_{i=1}^{I} s_i \ \pi_i\big(\boldsymbol{p},\boldsymbol{k},\boldsymbol{d},\theta(\boldsymbol{w})\big) - C(\boldsymbol{s}) \tag{2.1}$$

where: $\Pi\big(\boldsymbol{s};\boldsymbol{p},\boldsymbol{k},\boldsymbol{d},\theta(\boldsymbol{w})\big)$ is the restricted indirect profit function and is subject to $\sum_{i=1}^{I} s_i \ = 1$; and $\boldsymbol{\pi}$ is a vector of crop gross margin functions. The restricted indirect profit function is assumed to be strictly increasing and convex in the vector of crop gross margins $\boldsymbol{\pi}$. $C(\boldsymbol{s})$ is defined as a management cost function. It reflects the non-linear effect of $\boldsymbol{s}$ in the restricted indirect profit function. It is a function of variables not included in the gross margin function such as general machinery, energy cost, maintenance cost, and other unobserved variable costs associated with crop acreage share devoted to crop i. As a result, $C(s)$ is determined by variables not considered in a crop's gross margins (Carpentier and Letort ,2014). The optimal land allocation is then given by $s_i\big(\boldsymbol{p},\boldsymbol{k},\boldsymbol{d},\theta(\boldsymbol{w})\big) \equiv \arg max_{s_{i\geq 0}}\{\Pi\Big(\boldsymbol{s};\pi_i\big(\boldsymbol{p},\boldsymbol{k},\boldsymbol{d},\theta(\boldsymbol{w})\big)\Big)\ s.t \sum_{i=1}^{I} s_i = 1\}\ for\ i\ = 1, \dots\dots, I$ (Carpentier and Letort ,2014).

2.4.2 MNL Acreage Share Empirical Model

The MNL acreage share model can be derived using the profit function given in equation (2.1). Following Carpentier and Letort (2014), the profit maximization problem is given by:

$$\underset{\boldsymbol{s}}{Max} \sum_{i=1}^{I} s_i \ \pi_i\big(\boldsymbol{p},\boldsymbol{k},\boldsymbol{d},\theta(\boldsymbol{w})\big) - C(\boldsymbol{s}) \quad s.t \sum_{i=1}^{I} s_i = 1 s_i \tag{2.2}$$

where $C(s)$ is assumed to take the following functional form:

$$C(s) = F + \sum_{i=1}^{I} s_i \ c_i + \ \alpha^{-1} \ \sum_{i=1}^{I} s_i\, ln s_i. \tag{2.3}$$

F is an unidentifiable total fixed cost and c_i is the variable cost (in the short-run) per acre for crop i. The term $\sum_{i=1}^{I} s_i \ln s_i$ can be interpreted as the opposite of the entropy function of the acreage share vector $\boldsymbol{s}$. In fact, "given that the acreage share lies between 0 and 1 and sum to 1, this term is negative. It is also strictly convex in $\boldsymbol{s}$. The term $\sum_{i=1}^{I} s_i \ln s_i$ is minimal at $s_i = I^{-1}$ for i = 1,….,I implying that F can be chosen to ensure that the cost function is positive" (Carpentier and Letort, 2014, p.543) . Alpha (α) is a scale parameter and is strictly positive to ensure $C(\boldsymbol{s})$ is strictly convex in $\boldsymbol{s}$ (Carpentier and Letort, 2014).

Thus, the farmer's profit maximization problem can be restated as:

$$\underset{\boldsymbol{s}}{Max} \sum_{i=1}^{I} s_i \ \pi_i - (F + \sum_{i=1}^{I} s_i \ c_i + \ \alpha^{-1} \sum_{i=1}^{I} s_i \ln s_i) \quad s.t \sum_{i=1}^{I} s_i = 1 \tag{2.4}$$

where $\pi_i = \pi_i\big(\boldsymbol{p}, \boldsymbol{k}, \boldsymbol{d}, \theta(\boldsymbol{w})\big)$. The restricted Lagrangian function for this optimization problem is defined as:

$$L(s, \lambda) = \sum_{i=1}^{I} s_i \ \pi_i - \ (F + \sum_{i=1}^{I} s_i \ c_i + \ \alpha^{-1} \ \sum_{i=1}^{I} s_i \ln s_i) - \ \lambda \, (\sum_{i=1}^{I} s_i - 1) \tag{2.5}$$

the first order conditions are:

$$\frac{\partial L}{\partial s_i} = \ \pi_i - c_i \ - \ \alpha^{-1}(\ \ln s_i + 1) - \ \lambda = 0 \text{ for } i = 1,\ldots,I \tag{2.6}$$

and

$$\frac{\partial L}{\partial \lambda} = \ \sum_{i=1}^{I} s_i - 1 = 0. \tag{2.7}$$

Solving for λ in equation (2.6), we get:

$$\lambda = \pi_i - c_i \ - \ \alpha^{-1}(\ ln\, s_i + 1) \text{ for } i \ = \ 1, \ldots, I, \tag{2.8}$$

implying that:

$$ln\, s_i = \alpha(\ \pi_i - c_i) - (\alpha\lambda + 1) \text{ for } i = 1,\ldots,I. \tag{2.9}$$

Applying the exponential function on both sides of this equation, gives:

$$s_i = exp[\alpha(\pi_i - c_i)]\, exp[-(\alpha\lambda + 1)] \text{ for } i = 1, \ldots, I \tag{2.10}$$

Given that $\sum_{n=1}^{I} s_n = 1$, substituting equation (2.10) into this leads to:

$$1 = \sum_{n=1}^{I} [exp[\alpha(\pi_n - c_n)]]\, exp[-(\alpha\lambda + 1)] \tag{2.11}$$

which implies:

$$exp[-(\alpha\lambda + 1)] = [\sum_{n=1}^{I} exp[\alpha(\pi_n - c_n)]\,]^{-1} \tag{2.12}$$

substituting equation (2.12) into equation (10), we get:

$$s_i = \frac{exp[\alpha(\pi_i - c_i)]}{\sum_{n=1}^{I} exp[\alpha(\pi_n - c_n)]}, \qquad \text{for } i = 1, \ldots, I. \tag{2.13}$$

Now consider a reference or base category crop *I* chosen at the discretion of the researcher given by:

$$s_I = \frac{exp[\alpha(\pi_I - c_I)]}{\sum_{n=1}^{I} exp[\alpha(\pi_n - c_n)]} \tag{2.14}$$

Taking the ratio of equations (2.13) and (2.14) gives:

$$\frac{s_i}{s_I} = \frac{exp[\alpha(\pi_i - c_i)]}{exp[\alpha(\pi_I - c_I)]}, \qquad \text{for } i = 1, \ldots, I-1. \tag{2.15}$$

Given that $\Pi_i = \pi_i - c_i$ and $\Pi_I = \pi_I - c_I$, where Π_i and Π_I are the sub indirect restricted profit functions for crop *i* and *I*, respectively, equation (2.15) can be interpreted as:

$$\frac{s_i}{s_I} = \frac{exp(\alpha\Pi_i)}{exp(\alpha\Pi_I)}, \qquad \text{for } i = 1, \ldots, I-1. \tag{2.16}$$

or,

$$ln\left(\frac{s_i}{s_I}\right) = \alpha\Pi_i - \alpha\Pi_I = \alpha(\Pi_i - \Pi_I), \qquad \text{for } i = 1, \ldots, I-1. \tag{2.17}$$

Now let $\Pi_i - \Pi_I = \delta(\mathbf{X})$, where $\mathbf{X} = \big(\boldsymbol{p}, \boldsymbol{b}, \boldsymbol{d}, \theta(\boldsymbol{w}), C(s)\big)$. Equation (2.17) can then be rewritten as:

$$\ln\left(\frac{s_i}{s_I}\right) = \alpha(\delta(\mathbf{X}), \qquad \text{for } i = 1, \dots, I-1. \tag{2.18}$$

Assuming $\delta(\mathbf{X}).\alpha = g(\mathbf{X}; \boldsymbol{\beta}_i)$, the equation (2.18) can be restated as:

$$\ln\left(\frac{s_i}{s_I}\right) = g(\mathbf{X}; \boldsymbol{\beta}_i), \qquad \text{for } i = 1, \dots, I-1. \tag{2.19}$$

where $\boldsymbol{\beta_i}$ is a vector of parameters associated with the. Note that the model may not be estimable or identified if s_i and/or $s_I = 0$. Equation (2.19) represents a system of estimable share equations that can be used to examine factors impacting land use (shares), which are used to examine irrigated land use decisions in this study.

2.4.3 Empirical Model Estimation

Because accurate farm-level data is not always available, especially for irrigated crop acreage, many studies have estimated acreage response models using aggregated data at the county-level (Wu and Brosen 1994; Wu and Segerson 1995; Miller and Plantinga 1999). Thus, given the limited availability and accuracy of irrigated crop acreage data below the county level, we conduct our analyses at the county level for this study. Based on this, after deriving the functional form of the acreage share equation in equation (2.19), we need to operationalize the conceptual model. Assuming linearity in the parameters and variables, equation (2.19) can be rewritten as:

$$\ln\left(\frac{s_{ijt}}{s_{Ijt}}\right) = \boldsymbol{\beta}_i' \boldsymbol{X}_{ijt} + \varepsilon_{ijt}, \qquad \text{for } i = 1, \dots, I-1 \tag{2.20}$$

where $s_{ijt}{}^{*}$ is the share of crop i in county j in time t; I is the reference crop in county j in time t ; $\boldsymbol{X}$ is a matrix of explanatory variables as defined earlier; $\boldsymbol{\beta_i}$ is a vector of parameters to be estimated; and ε_{ijt} is an iid mean zero error term.

Equation (2.20) results in a system of linear share equations, which can be estimated using seemingly unrelated regression methods (SUR) (Zellner,1962). This model has been used in previous studies to estimate systems of acreage share equations (Wu and Brosen, 1994 and Wu and Sergerson, 1995). However, the seemingly unrelated regression (SUR) model assumes strict exogeneity, homoscedasticity, and no autocorrelation (W. H. Greene, 2012). Given the same notations for crop, counties, and time in our study, SUR assumptions imply:

$$E[\varepsilon_i|\boldsymbol{X_i}] = 0, \qquad for\ i = 1, \dots, I-1. \tag{2.21}$$

homoscedasticity:

$$E[\varepsilon_i \varepsilon_i'|\boldsymbol{X_i}] = \sigma_{ii}\,, \qquad for\ i = 1, \dots, I-1. \tag{2.22}$$

where *ii* donates the observations for each crop-share equation; and that disturbances are uncorrelated across observations, but correlated across equations:

$$E\left[\varepsilon_{ijt}\varepsilon_{zsk}\middle|\boldsymbol{X_i}\right] = \sigma_{iz}, \qquad if\ t = k\ and\ 0\ otherwise \tag{2.23}$$

These assumptions imply that exogeneity, heteroscedasticity, and autocorrelation are not present in the model. However, these assumptions might not hold due to the probabilistic nature of the data included in our study.

The SUR-HEAR model proposed by Wu and Brorsen (1995) corrects for heteroscedasticity, autocorrelation, and contemporaneous correlation. To correct for autocorrelation, the SUR-HEAR correction approach starts by estimating each equation given in equation (2.20) by ordinary least square regression (OLS). Let $y_{ijt} = \ln(\frac{s_{ijt}}{s_{Ijt}})$. The regression residuals $\hat{\varepsilon}_{ijt}$ from the OLS regression are then used to estimate the autocorrelation coefficient, ρ_{ij}, for each crop in each county via the following equation:

$$\hat{\rho}_{ij} = \frac{\sum_{t=2}^{T} \hat{\varepsilon}_{ijt}\hat{\varepsilon}_{ijt-1}}{\sum_{t=1}^{T} \hat{\varepsilon}_{ijt}^{2}}. \tag{2.24}$$

The estimate $\hat{\rho}_{ij}$, is used to correct for autocorrelation by transforming the variables to correct for autocorrelation. That is:

$$y_{ijt}^{*} = y_{ijt} - \hat{\rho}_{ij} * y_{ijt-1}, \text{ and} \tag{2.25}$$

$$x_{ijt}^{*} = x_{ijt} - \hat{\rho}_{ij} * x_{ijt-1} \tag{2.26}$$

for all *i*, *j* and *t*.

The next step in the SUR-HEAR procedure is to correct for potential group-wise heteroscedasticity and contemporaneous correlation by estimating the share equations given in equation (2.20) via OLS using the transformed data, y_{ijt}^{*} and x_{ijt}^{*}, to obtain a new set of residuals, $\hat{\varepsilon}_{ijt}^{*}$. These new residuals are then used to estimate the error variance for crop *i* in county *j* as:

$$\hat{\sigma}_{ij}^{2} = \sum_{t=1}^{T} \frac{(\hat{\varepsilon}_{ijt}^{*})^{2}}{T} \tag{2.27}$$

Then, $\hat{\sigma}_{ij}$ is used to make another transformation of all the variables to correct for group-wise heteroscedasticity:

$$y_{ijt}^{**} = \frac{y_{ijt}^{*}}{\hat{\sigma}_{ij}} \tag{2.28}$$

and,

$$x_{ijt}^{**} = \frac{x_{ijt}^{*}}{\hat{\sigma}_{ij}} \tag{2.29}$$

for all *i*, *j* and *t*. Finally, this transformed data given by equations (2.28) and (2.29) are used to estimate the system of equations using SUR methods as:

$$y_{ijt}^{**} = \mathrm{X}_{ijt}^{\prime **}\beta_i + \varepsilon_{ijt}^{**} \qquad\qquad for\ i = 1, \dots, I-1. \tag{2.30}$$

The system of equations provided in equation (2.30) is a conditional system and does not take account of dryland irrigation or other land uses (e.g. CRP and pastureland). Thus, the model captures shifts in irrigated crop shares assuming a constant level of irrigated acreage over time. This also is a unique perspective that has not been examined often in the literature.

2.4.4 Acreage Share Elasticities

One of the main objectives of conducting acreage response models is identifying the acreage response elasticities with respect to the explanatory variables, specifically water scarcity elasticities, which are the primary interest in this study. The acreage elasticity for crop *i* in county *j* at year *t* with respect to explanatory variable, x_{jt}, is given by:

$$e_{ijt|x_{jt}} = \frac{\partial a_{ijt}}{\partial x}\frac{x_{jt}}{A_{ijt}} \tag{2.31}$$

where A_{ijt} is total acres for crop *i* in county *j* at year *t*. Using crop share formula, $s_{ijt} = \frac{A_{ijt}}{A_{jt}}$, equation (2.31) can *be* rewritten as:

$$e_{ijt|x_{jt}} = \frac{(\partial s_{ijt})A_{jt}}{\partial x_{jt}}\frac{x_{jt}}{(s_{ijt})A_{jt}}, \tag{2.32}$$

Implying:

$$e_{ijt|x} = \frac{\partial s_{ijt}}{\partial x_{jt}}\frac{x_{jt}}{s_{ijt}} \tag{2.33}$$

where $\frac{\partial s_{ijt}}{\partial x_{jt}} = ME_{ijt|x_{jt}}$ is the marginal effect of crop share to explanatory variable, x_{jt}. The marginal impact of the explanatory variable on crop share is calculated using the follow equation (Wu and Adams, 2002):

$$ME_{ijt|x} = s_{ijt}\left(\beta_{ix} - \sum_{h=1}^{I} s_{hj}\beta_{hx}\right), \quad \text{where } h = 1, \dots, I, \tag{2.34}$$

which implies that the acreage elasticity at time *t*, for crop i in county j with respect to explanatory variable x_{jt}, is:

$$e_{ijt|x_{jt}} = \frac{\partial s_{ijt}^{*}}{\partial x_{jt}} \frac{x_{jt}}{s_{ijt}^{*}} = \left(\beta_{ix} - \sum_{h=1}^{H} s_{hj}\beta_{hx}\right)x_{jt} \tag{2.35}$$

where β_{ix} is the coefficient of variable x_{jt} in the equation for crop *i*; β_{hx} is the coefficient of variable x_{jt} in the equation for crop *h*; and x_{jt} is the value of variable x_{jt} in county *j* at time *t*.

After calculating the elasticity by county level, one can estimate the elasticity at the state or regional-level as follows (Wu and Adams, 2002):

$$e_{it}^{R} = \overline{x}_{jt}[\beta_{ix} - \sum_{h=1}^{I}\left(\sum_{j=1}^{J} s_{ijt}\, a_{ijt}\right)\beta_{hx}] \tag{2.36}$$

where e_{it}^{R} is the acreage elasticity for crop i in region R in year t , $\overline{x}_{jt}$ is the average of x_{jt} across all *J* counties, $a_{ijt} = \frac{A_{ijt}}{A_{it}}$, A_{ijt} is the total acreage for crop i in county j in year t, and A_{it} is the total acreage for crop i in year t across all *J* counties. Regional-level elasticity estimates account for the weight of irrigated crop acreage of individual county relatively to total irrigated crop in the region in year *t*, which may be of more interest to policymakers that are interested in more aggregate effects. From equations (2.35) - (2.36), we aim to estimate elasticities of water scarcity variables (water deficit, depth to water, and water authorized for extraction) in addition to energy price and crop prices. Depth to water and natural gas price represent pumping cost, we assume that as depth to water and natural gas increase, farmers will decrease land share dedicated to irrigated crops.

2.5 Data Description

To estimate the empirical model, a county-level panel data subset of 50 counties in western Kansas from 2000-2018 is constructed. The reason for choosing these counties is to ensure all producers have access to groundwater from the HPA (figure 1). The primary irrigated crops grown in Kansas are corn, soybeans, alfalfa, wheat, and sorghum. Other crops include sunflowers, barley, oats, rye, and dry beans (Hendricks and Peterson, 2012). The dependent variables are represented by total irrigated acreages for major cash crops; alfalfa, corn, soybean, sorghum, wheat, and other crops at the county level. The explanatory variables in the study include output prices, input prices, soil and weather characteristics, and water scarcity variables. Descriptive statistics of the selected independent variables are provided in Table 2.1.

2.5.1 Acreage Shares

Acreage data is obtained from the Water Information Management & Analysis System (WIMAS). This data provides comprehensive data on irrigated acreages in Kansas. We aggregate farm level data to generate county level acreages for alfalfa, corn, sorghum, soybean, wheat, and all other irrigated crop acreages. From these acreages, the dependent acreage share variables are calculated as follows:

$$Y_{ijt} = ln(\frac{s_{ijt}}{s_{Ijt}}) \tag{2.37}$$

where s_{ijt} is the acreage share of irrigated crop *i* in county *j* at time *t* and s_{Ijt} is the share of acreage dedicated for the reference crop I in county *j* at time *t* . Reference crop *I* is the acreage for all other crops. In Kansas, farms growing the five major crops account for 95% of the total irrigated area. Corn is the primary irrigated crop, accounting for 45% of total irrigated acreage, while wheat and soybean account for 19% and 14%, respectively. Sorghum, alfalfa, and other crops represent 9%, 7%, and 5% or irrigated acreage across the counties, respectively (table 2.1).

2.5.2 Output and input Prices

The importance of expected future crop prices received at harvest time is an important factor in determining farmers' acreage decisions at planting time (Nerlove, 1956). However, the price received at harvest time is unknown to farmers at the time crop acreage decisions are made. For these reasons, expected harvest time output prices are calculated at the time of planting. Following the approach of Hendricks et al. (2014) and Ramsey (2017), expected prices are calculated using the following formula:

$$E(p_{ijt}) = F(p_{ijt}) + E(Bp_{ijt}) \tag{2.38}$$

The expected price for crop i in county j at time t is set equal to a futures price at the time of planting $F(p_{ijt})$, plus an expectation of the basis at harvest time, $E(Bp_{ijt})$. We calculate the future price $F(p_{ijt})$ by using cash prices across different elevator locations. Cash prices obtained for AgManager.info (AgManager.info, 2019). Each county has at least one spot cash price. Note that, some counties have missing observations for some years. Given that, we set the missing observation for each county equal to the average cash prices of the bordering counties. We calculate the future prices for each crop at planting time using the average price over the months of March and April for corn, sorghum, and soybean, and over the months of September and October for wheat. The expected basis price, $E(Bp_{ijt})$, was calculated using the average cash prices at time of harvest. We used the average cash price from September and October for corn, sorghum, and soybean, while for wheat we used the average cash prices in June. Expected basis price is then calculated using the following formula:

$$E(Bp_{ijt}) = cash\ price\ at\ harvest\ time_{ij,t-1} - contract\ price\ for\ harvest\ delivery_{ij,t-1} \tag{2.39}$$

Most empirical studies include input prices. It is clear that these prices are important in determining the net returns of different land uses. Fertilizer price indices have been included in previous studies (Wu and Segerson 1995; Wu and Brorsen 1995). These studies showed and exhibited a significant impact of the price of fertilizer on acreage crop decisions. National level fertilizer and labor price indices were obtained from the USDA, National Agricultural Statistics Service (USDA, NASS). Energy is also an important input used to extract groundwater for irrigation in western Kansas (Pfeiffer and Lin 2013). Since our study deals with irrigated crops, including energy prices is important to assess its impact on farmers' acreage decision, as it's the primary component in determining irrigation cost. In Kansas, the four major energy sources for pumping irrigation water are natural gas, electricity, diesel and propane (LP). Natural gas accounts for more than 50% of energy used in pumping irrigation water (Rogers, 2008; Pfeiffer and Lin, 2013). For this reason, we used only the natural gas price as an energy price. State level natural gas prices are obtained from the U.S Energy Information Administration (EIA). We expect farmers will respond negatively to an increase in natural gas prices (Pfeiffer and Lin, 2014).

2.5.3 Site Characteristics

Site characteristics included soil and climate variables. Soil characteristics were obtained from the USDA, National Resources Conversation Services (USDA, NRCS, 2015), Soil Survey Geographic database (SSURGO). From this database, we obtained data for average slope, as well as soil percentage for sand and silt in the soil (table 2.1). Soil data is assumed to be constant over time, but varies across space (county).

For climate data, we calculated county-level variables for growing degree-days (GDD), extreme degree-days (EDD), total precipitation, and evapotranspiration during the growing season for each crop (table 2.3). Weather variables were calculated using daily precipitation, and maximum and minimum temperature following Schlenker and Roberts (2009). They were created using data from the PRISM database. GDD measures the exposure to heat within a range of temperatures (8C^{o}-30 C^{o}). EDD measures the exposure to heat for temperatures exceeding a maximum GDD threshold (GDD>30). Both GDD and EDD are measured as accumulative degree days within the growing season for corn, sorghum, and soybeans (April 1- September 30), and for wheat (October 1- May 30). Precipitation and evapotranspiration are calculated as accumulative amounts within the growing season for each crop (Hendricks et. al., 2014).

2.5.4 Water Scarcity

We defined $\theta(\boldsymbol{w})$ as an irrigation cost function, where $\boldsymbol{w}$ is a vector of irrigation variables that includes energy price, depth to water, and water deficit. Irrigation water price is the cost of pumping an inch of water per acre to the land surface, which depends on the natural gas energy price and the pumping lift or depth to water (Hendricks and Peterson, 2012). Depth to water is the distance between the land surface and the groundwater table. Greater water depth reflects higher irrigation costs. We expect that farmers' will respond negatively as depth to water increases. Depth to water was obtained from the Kansas Geological Survey (KGS). KGS uses monitoring wells to calculate changes in the groundwater table. Each county has more than one monitoring well. We use measurements of the groundwater table for December and January prior to the planting season to ensure that groundwater table measurements are not affected by water extraction during the growing season. From this data, we obtained the county-level average depth to water. We expect that crop acreage share responds negatively as depth to water increases (Olen and Wu 2015; Pfeiffer and Lin, 2014; Bhalla 2007; Kettle et. al. 2007).

Water demand or water requirements for each crop are highly correlated with the amount of water lost via evapotranspiration (Ep), which includes evaporative water from both soil and crops, as well as transpiration of water from crops to the atmosphere (Gheewala et. al. 2017). Water deficit (WD), another indicator of water scarcity, is evaporative demand not met by available water or how much water transpired to the atmosphere from a site covered by a specific crop (Stephenson 1990). For simplicity, we estimate water deficit using the following formula:

$$WD_{jt} = Ep_{jt} - Precipitation_{jt} \qquad (2.40)$$

where WD_{jt} is the water deficit in county *j* at year *t* and $Ep_{jt}$is a potential evapotranspiration in county *j* at year *t* during the growing season. Potential evapotranspiration was obtained from the United States Geological Survey (USGS) for years 2000-2014 while the rest of time period were obtained from Kansas Mesonet.

Groundwater users in Kansas extract water under prior appropriation. Prior appropriation means “first in time, first in right.” That means the first individual to divert groundwater water from the aquifer has priority over later diverters. Under this regulation, users are allowed to extract the maximum amount of water each year. This annual amount is determined when the user applied for a permit (Pfeffer and Lin, 2012). The impact of amount of water authorized for irrigation on irrigated crop shares is coming from the new approved groundwater permits every year since the existing amount of water authorized for irrigation is fixed over time. This variable thus helps to capture local government policy related to water withdrawals over time on irrigated crop shares. County-level measures of total annual quantity of permitted water was calculated by summing all users’ quantities of permitted water for each year. Quantity of permitted water data is obtained from the Water Information Management & Analysis System (WIMAS).

2.6 Empirical Model Estimation

The available data set was used to estimate the SUR-HEAR regression. In addition, we estimated the elasticities of interested explanatory variables. However, before we run our estimation, we need to conduct misspecifications test to insure the validity of our estimations.

2.6.1 Model Specification Test

To motivate the SUR-HEAR estimation of the empirical model, misspecification tests were conducted for the five crop share equations being estimated. We first tested for correlation between the residuals of the five acreage share equations using a Breusch-Pagan test (Gatignon, 2003). Testing results indicate that correlations (covariances) between the five crop share equations are jointly significant ($\chi^2_{v=10} = 2191.067, Pr. = 0.0$) (table 3). The test suggests using a system of equations approach rather than estimating the system equation by equation independently. Table 2.2 shows the correlation coefficients between crop share equations residuals.

Given that counties may have geographical, cultural and policy factors that may affect variation in land use across space, group-wise heteroscedasticity may be a potential problem. In addition, using data for the same counties over time, serial autocorrelation may arise, as well (Wu and Brorsen, 1994). Thus, we tested for group-wise heteroscedasticity and serial autocorrelation for each individual equation. Following Wiggins and Poi (2003), likelihood ratio tests (LR-Test) reject the null hypothesis of no heteroscedasticity for all crop equations at a 1% level of significance when the SUR-HEAR procedures is not used. This indicates that group wise heteroscedasticity is likely an issue for the five crop share equations. In addition, we utilize the

Wooldridge-Test to test for serial autocorrelation prior to applying the SUR-HEAR procedure (Drukker, 2003). The null hypothesis for no autocorrelation was rejected for the soybean and wheat equations at a 5% level of significance, while we failed to reject the null hypothesis for the alfalfa, corn, and sorghum equations (table 2.3). Based on these results, we corrected for heteroscedasticity, autocorrelation, and contemporaneous correlation for all the variables in all crop acreage share equations using the SUR-HEAR procedure previously discussed.

2.6.2 SUR-HEAR Regression Results

SUR-HEAR regression estimation results for the crop acreage share equations are presented in Table 2.4. Given the limited interpretability of the regression coefficients, marginal effects were estimated following equation (2.34). Asymptotic bootstrapped standard errors for the marginal effects were obtained for the SUR-HEAR via a bootstrapping procedure with 100 replications. Discussion of the significance of individual variables factors here focuses on the marginal effects in Table 2.5.

Of primary interest is the impact of the water scarcity variables on the conditional irrigated crop share decisions. Irrigated crop acreage was not affected by water deficits from the previous irrigation season except sorghum and wheat, which were significantly affected at a 1% and 10% significance level, respectively. A water deficit, when precipitation does not offset evapotranspiration, irrigated land dedicated for corn and soybeans will shift to irrigated acreage shares for alfalfa, sorghum, and wheat. The two-years moving average of depth to water and natural gas price have a negative, but insignificant impact on all crop acreage decisions except for corn and sorghum. This result indicates that when the overall cost of pumping (which arises from an increase in natural gas prices and/or depth to water), farmers will respond to the increase in pumping costs by shift irrigated acreage to corn and/or sorghum. The quantity of groundwater authorized for extraction shows a positive and statistically significant impact on all crop acreage decisions, except for soybeans. This indicates that, when the amount of water authorized increases due to new permits, irrigated acreage shares will shift toward alfalfa, corn, sorghum, and/or wheat increase.

For output and input prices, the results showed that all crop acreage decisions are significantly and positively affected by their own prices. The fertilizer price index has a negative and significant impact on irrigated acreage decision for all crop acreage shares except for soybeans, which was a positive and significant impact.

For weather variables, total precipitation at planting time has a negative impact on all crops, except for alfalfa and corn, especially during March and April. This result indicates that farmers are willing to decrease irrigated acreage if they are expecting that crops can be rain fed. Growing degree-days (GDD) during the previous season has an impact on all cop acreages, except for corn and soybeans. Extreme degree-days (EDD), which represents times of heat stress during the growing season, has a significant impact on corn and sorghum crop acreage decisions. We find the slope percentage has a statistically significant impact on alfalfa. Percentage of sand has a statistically significant impact on acreage shares of alfalfa, corn, sorghum, and wheat.

For crop rotation, the results indicate that alfalfa, corn, soybeans have crop rotation with all other crops. Sorghum has crop rotation with all crops except with wheat. Sorghum and wheat have crop rotation with all crops except with each other.

2.6.3 Acreage Shares Elasticities

Another objective of the study is to estimate elasticities with respect to water scarcity and output price variables that can be utilized for modelling purposes at different scales. County-level acreage share elasticities for crop i across the J counties with respect to the explanatory variables were estimated using equation (2.35). The reported elasticities are the average across counties and time to find a mean crop acreage response at a county level (table 2.6). The regional-level acreage share elasticities were estimated using annual acreage-share elasticities across the *J* counties using equation (2.36) (Table 2.7). Generally, most of the elasticity's signs are consistent between the county- and regional-level. In addition, regional-level elasticities are slightly higher in magnitude than elasticities at the county level. This finding is expected as more specific elasticities are likely to show more responsiveness as you disaggregate and become more temporally or spatially explicit.

From tables (2.6) and (2.7), water deficit showed a significant impact on acreage share decision for corn, sorghum, and wheat. This indicates that, when the water deficit at time *t-1* increases by 10%, farmers will decrease land dedicated to irrigated corn and soybeans production by 1.2% and 2.7%, respectively. Given irrigated land is assumed constant, this corresponds to a 1%, 5.4%, and 3.5 increase in irrigated land dedicated for alfalfa, sorghum, and wheat, respectively. For the 2-year average depth to water, the result shows that it has a significant impact on irrigated crops' decision for alfalfa and wheat. The negative sign for this elasticity for crop acreage shares indicates that when the average depth to water increases, the land dedicated for irrigated alfalfa, soybean, and wheat will shift to corn and/or sorghum. This shift is likely due to higher pumping costs. We find that all natural gas price acreage elasticities are negative in sign for all crops, except for corn. When the natural gas price increases, acreage dedicated for irrigated alfalfa, sorghum, soybean, and wheat acreage will shift to corn because farmers expect an increase in pumping cost. The highest natural gas elasticity is for wheat since natural gas is higher during the wheat growing season in winter. The elasticity of the quantity of water authorized for extraction shows that if the amount of water permitted for extraction increases, farmers would increase irrigated land dedicated for all crops, especially for corn. This means 17 to 19 percent of new granted water permits will be dedicated to corn production.

For crop price elasticities, out of the 25-estimated price elasticities, 13 of the estimated elasticities are significant at a 10% level or lower. Own price elasticities for all crops are positive and inelastic. The cross-price acreage elasticities provide useful information too. As the price of alfalfa decreases, farmers prefer to switch from irrigated alfalfa to corn, soybean, and/or wheat. As corn price decreases, irrigated land dedicated for corn will shift to sorghum, soybean, and/or wheat. As sorghum price decreases, irrigated land will shift from sorghum to corn only. When price of soybean decreases, irrigated land dedicated for soybean will be redirected to alfalfa, corn, sorghum, and/or wheat. As price for wheat decreases, the land dedicated for wheat will shift to alfalfa, and/or soybean production.

2.7 Conclusion and discussion

Decisions for agricultural land-use are made at the farm level. However, such decisions may have impacts at the county or regional scale, especially with regard to water conservation in areas where irrigation is primarily obtained from ground water sources. In addition, policy is usually decided based impacts at these more aggregate scales. Land-use change is influenced by a variety of economic and non-economics factors. Economic factors, such as output and input prices are important in determining farm profitability. In addition, non-economic or biophysical factors such as local climate and soil type, as well as groundwater can affect crop yield. This study utilized a multinomial logit framework to analyze land use decision for major irrigated crops in Kansas. We used a county level dataset across 50 counties and 19 years in western Kansas. This area overlaps the High Plain Aquifer in Kansas, which provides the primary source for these irrigated crops. The heteroskedastic and time-wise autoregressive seemingly unrelated regression model (SUR-HEAR) was used to estimate a system of crop share equations based on the multinomial framework. From model estimation, we derive and estimate elasticities at two scales: county- and regional-levels. Generally, regional-level elasticity estimates are more inelastic than county-level elasticities.

The results indicate that water scarcity and market factors are important in determining producer's crop acreage decisions. Elasticities estimates show that producers respond significantly to crop prices, natural gas prices, depth to water, water deficit, and the total amount of water permitted for extraction, more than other factors included in this study. Growing degree-days and extreme degree-days that represent heat stress in previous growing season show a significant impact in some crop acreage decisions, as well. This indicates that producer consider changes in temperature in pervious growing seasons, thus past experiences, in making their cropping decisions for the current season.

Since many acreage response studies combine irrigated and non-irrigated acreage as one dependent variable, results may not provide correct magnitude shifts in water usage or land use decisions for policymaking, in particular when the irrigation water factors have a significant influence on irrigated land-use decisions. This study helps to delve into how irrigated acreages would be used if water was to become less available through policy or other means. Knowing the magnitude of the shifts in acreage decisions to water scarcity factors on irrigated acreage alone can help policymakers and producers' design policies that promote water conservation in new ways.

The study focuses only on irrigated crop acreage, which assume land shifts within irrigated crops in response to change in water scarcity factors and crop prices. The study did not account other land uses, such as dryland and non-cropland uses. For future study, we suggest considering irrigated and non-irrigated crops in acreage response studies together without aggregating them to find the impact of shifting from one group (i.e. irrigated or non-irrigated) on other, as well as shifts from one crop to another in each group. This will give more holistic insight for policies related to land-use change and water conservation. We suggest using the Nested Multinomial Logit framework, which can integrate land budgeting techniques that help to better capture land use decision by producers.

Tables

Table 2.1: Descriptive Statistics of dependent and independent variables

Variable	Definition (Unit)	Obs.	Mean	Std.
Dependent Variables				
Alfalfa	Average crop share (0-1)	878	0.102	0.083
Corn	Average crop share (0-1)	878	0.475	0.122
Sorghum	Average crop share (0-1)	878	0.080	0.050
Soybean	Average crop share (0-1)	878	0.177	0.115
Wheat	Average crop share (0-1)	878	0.136	0.079
Other crops	Average crop share (0-1)	878	0.030	0.031
Independent Variables				
Water Scarcity Variables				
WD	Water deficit. The difference between the potential evapotranspiration and precipitation during the growing season (mm)	878	854.384	96.377
QWA	Quantity of water authorized for extraction by county (1000-acre ft.)	878	140.528	139.613
DTW	Average depth to water by county (ft.)	878	99.614	70.983
NG_P	Natural gas price ($/ 1000 cubic ft.)	19	11.663	2.826
Output and input prices				
Alfalfa_P	Alfalfa price ($/ton)	878	124.016	43.999
Cron_P	Corn price ($/ton)	878	140.197	71.083
Sorghum_P	Sorghum price ($/ton)	878	153.380	59.371
Soybeans_P	Soybeans price ($/ton)	878	343.947	138.742
Wheat_P	Wheat price ($/ton)	878	188.626	61.368
Fertilizer_P	Fertilizer price index	19	69.675	25.145
Weather variables				
PrecMarch	Total precipitation during March (mm)	878	37.814	32.805
PrecAprl	Total precipitation during April (mm)	878	58.789	36.086
GDD	Accumulative growing degree days (8C^0-30C^0)	878	2236.673	1719.782

EDD	Accumulative growing degree days (GDD>30C^0)	878	435.864	907.941
Soil Characteristics				
Sand	Sand in the soil texture (%)	50	23.56	11.32
Silt	Silt in the soil texture (%)	50	50.77	11.04
Slop	The value for the range of slope of a soil component within a map unit (%)	50	1.97	1.03

Table 2.2: Correlation of Crop Share Residuals for Crop Acreage SUR Model					
Equation	Alfalfa	Corn	Sorghum	Soybean	Wheat
Alfalfa	1				
Corn	0.489	1			
Sorghum	0.6059	0.691	1		
Soybean	0.4611	0.6071	0.5704	1	
Wheat	0.426	0.7176	0.7141	0.4172	1
Breusch-Pagan test of independence: $\chi^2_{v=10} = 2191.067$, Pr. = 0.0					

Table 2.3: Heteroscedasticity and autocorrelation misspecification tests			
LR-test for Group Wise Heteroscedasticity			
Equation	Chi2	P-value	Decision
Alfalfa	103.61	0.01	Rejected
Corn	103.88	0.01	Rejected
Sorghum	130.14	0.01	Rejected
Soybean	132.95	0.01	Rejected
Wheat	149.9	0.01	Rejected
Wooldridge test for Autocorrelation			
Equation	F-statistics	P-value	Decision
Alfalfa	5.079	0.03	Rejected
Corn	3.147	0.04	Rejected
Sorghum	3.192	0.04	Rejected
Soybean	4.124	0.04	Rejected
Wheat	3.948	0.05	Rejected

Table 2.4: SUR-HEAR estimations of irrigated crop acreage share

Variable	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Water scarcity					
WD(t-1)	-0.0001 (0.0002)	-0.0004 (0.0002)	0.0004 (0.0003)	-0.0006* (0.0003)	0.0002 (0.0002)
DTW(2 year)	-0.0008*** (0.0003)	-0.0006** (0.0003)	-0.0006* (0.0003)	-0.0008*** (0.0003)	-0.0011*** (0.0003)
AWQ	0.0003 (0.0003)	0.0010*** (0.0003)	0.0006 (0.0004)	-0.0002 (0.0004)	0.0014*** (0.0003)
NG_P	-0.0184*** (0.0053)	-0.0141*** (0.0052)	-0.0265*** (0.0069)	-0.0141** (0.0069)	-0.0142** (0.0056)
Output & input prices					
Alfalfa_P	0.0021*** (0.0007)	-0.0037*** (0.0007)	-0.0012 (0.0009)	-0.0043*** (0.0009)	-0.0040*** (0.0007)
Corn_P	0.0003 (0.0004)	0.0005 (0.0004)	-0.0005 (0.0005)	0.0015*** (0.0005)	0.0001 (0.0004)
Sorghum_P	0.0025 (0.0020)	0.0032* (0.0019)	-0.0050** (0.0025)	-0.0009 (0.0024)	-0.0006 (0.0020)
Soybeans_P	-0.0039 (0.0024)	-0.0055** (0.0024)	0.0066** (0.0030)	-0.0019 (0.0029)	0.0013 (0.0025)
Wheat_P	0.0016* (0.0009)	0.0036*** (0.0009)	0.0026** (0.0011)	0.0011 (0.0011)	0.0034*** (0.0009)
Fertilizer_p	0.0010 (0.0019)	0.0005 (0.0019)	-0.0004 (0.0023)	0.0071*** (0.0023)	-0.0014 (0.0019)
Weather variables					
Prec_Mar	0.0009* (0.0006)	0.0010* (0.0006)	0.0005 (0.0007)	0.0012* (0.0007)	0.0002 (0.0006)
Prec_Apr	0.0010** (0.0004)	0.0009* (0.0004)	0.0004 (0.0006)	0.0007 (0.0005)	0.0005 (0.0005)
Prec_May	-0.0008** (0.0003)	-0.0006* (0.0003)	-0.0000 (0.0004)	-0.0007** (0.0003)	-0.0010*** (0.0003)
GDD(t-1)	0.0002* (0.0001)	-0.0000 (0.0001)	-0.0001 (0.0002)	0.0004** (0.0001)	0.0002 (0.0001)
EDD(t-1)	-0.0005** (0.0002)	0.0001 (0.0002)	0.0001 (0.0003)	-0.0006** (0.0003)	-0.0004* (0.0002)
Crop rotation					
ln_alfalfa (t-1)	0.8712*** (0.0293)	-0.0841*** (0.0283)	0.0257 (0.0326)	-0.0845*** (0.0322)	-0.0274 (0.0292)
ln_corn(t-1)	0.0051 (0.0386)	0.8104*** (0.0391)	-0.0983** (0.0460)	0.1929*** (0.0457)	0.0371 (0.0392)
ln_sorghum(t-1)	0.0543 (0.0338)	0.0474 (0.0331)	0.6997*** (0.0362)	0.0726* (0.0374)	0.1447*** (0.0351)
ln_soybeans (t-1)	-0.0899*** (0.0292)	0.0421 (0.0297)	0.0205 (0.0353)	0.7908*** (0.0346)	-0.0702** (0.0303)
ln_wheat(t-1)	-0.1870***	-0.1587***	0.0476	-0.2930***	0.5191***

	(0.0385)	(0.0390)	(0.0404)	(0.0429)	(0.0424)
Soil characteristics					
slope	-0.0199 (0.0155)	-0.0264* (0.0160)	-0.0441** (0.0179)	-0.0499** (0.0204)	-0.0558*** (0.0155)
sand	0.0054 (0.0033)	0.0121*** (0.0034)	0.0012 (0.0041)	0.0020 (0.0037)	0.0019 (0.0034)
silt	0.0056* (0.0033)	0.0142*** (0.0034)	0.0060 (0.0042)	0.0029 (0.0037)	0.0063* (0.0034)
Time trend dummy					
Time_trend	-0.0142 (0.0859)	0.0648 (0.0895)	-0.0772 (0.0867)	-0.1910** (0.0854)	-0.0661 (0.0871)
Time_trend (sq)	-0.0001 (0.0041)	-0.0034 (0.0042)	0.0034 (0.0041)	0.0077* (0.0041)	0.0027 (0.0041)
Constant	0.2065 (0.4012)	-0.1586 (0.4175)	0.5764 (0.4097)	0.9176** (0.4001)	0.4079 (0.4055)
Observations	775	775	775	775	775
R-squared	0.89	0.95	0.73	0.91	0.89

Bootstrap standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 2.5: Marginal effect estimations of irrigated crop acreage share

Variable	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Water scarcity					
WD(t-1)	0.0001 (0.0005)	-0.0001 (-1.00E-05)	0.0001*** (-6.00E-05)	-0.0001* (-1.00E-05)	0.0001* (-2.00E-5)
DTW(2 year)	-6E-06 (-2.9E-05)	5.60E-05 (-7.7E-05)	9E-06 (-5E-05)	-2.4E-05 (-6.6E-05)	-6E-05 (-5E-05)
AWQ	4.20E-05* (-2.40E-05)	1.37E-04** (-6.50E-05)	7.00E-06*** (-2.05E-05)	-1.61E-04*** (-5.60E-05)	9.40E-05 (-3.50E-05)
NG_P	-0.0003 (0.0003)	0.0005 (0.0010)	-0.0009** (0.0004)	0.0002 (0.0006)	-0.0001 (0.0004)
Output & input prices					
Alfalfa_P	0.0005** (0.0002)	-0.0004* (0.0002)	0.0001 (0.0001)	-0.0002 (0.0002)	-0.0001* (0.0001)
Corn_P	0.0001 (0.0001)	0.0010*** (0.0003)	-0.0005** (0.0002)	-0.0004 (0.0003)	-0.0002 (0.0002)
Sorghum_P	-0.0001 (0.0002)	-0.0013** (0.0006)	0.0007*** (0.0002)	0.0001 (0.0003)	0.0005* (0.0003)
Soybeans_P	-0.0001 (0.0000)	0.0001 (0.0001)	-0.0001*** (-1.01E-05)	0.0002*** (0.0001)	-0.0001 (0.0001)
Wheat_P	-0.0001** (0.0001)	0.0004 (0.0003)	-0.0000 (0.0001)	-0.0003 (0.0002)	0.0001 (0.0001)
Fertilizer_p	-0.0001 (0.0001)	-0.0004* (0.0002)	-0.0001 (0.0001)	0.0010*** (0.0002)	-0.0004*** (0.0001)
Weather variables					
Prec_Mar	9.00E-06 -2.90E-05	7.70E-05 -1.55E-04	-3.00E-05 -4.50E-05	5.80E-05 -1.26E-04	-8.90E-05* -4.80E-05
Prec_Apr	2.50E-05 -2.30E-05	5.80E-05 -9.50E-05	-2.80E-05 -5.80E-05	-1.80E-06 -4.30E-06	-3.20E-05 -8.00E-05
Prec_May	-1.20E-05 -2.60E-05	1.30E-05 -9.80E-05	4.70E-05** -1.60E-05	-1.70E-05 -5.60E-05	-5.00E-05 -5.40E-05
GDD(t-1)	1.3E-05** (-6E-06)	-5.2E-05* (-3.1E-05)	-2E-05 (-1E-05)	4.6E-05** (-2.2E-05)	1.2E-05 (-8E-06)
EDD(t-1)	-3.03E-05** (-1.47E-05)	1.22E-04 (-6.00E-05)	1.6E-05 (-2E-05)	-9.4E-05** (-3.8E-05)	-4E-05 (-3E-05)
Crop rotation					
ln_alfalfa (t-1)	0.0855*** (0.0017)	-0.0553*** (0.0079)	-0.0005 (0.0031)	-0.0206*** (0.0051)	-0.0081** (0.0041)
ln_corn(t-1)	-0.0420*** (0.0034)	0.1870*** (0.0121)	-0.0412*** (0.0043)	-0.0396*** (0.0071)	-0.0516*** (0.0044)
ln_sorghum(t-1)	-0.0063*** (0.0020)	-0.0328*** (0.0056)	0.0466*** (0.0044)	-0.0077 (0.0074)	0.0038 (0.0046)
ln_soybeans (t-1)	-0.0237***	-0.0479***	-0.0098***	0.1146***	-0.0289***

	(0.0015)	(0.0035)	(0.0035)	(0.0057)	(0.0047)
ln_wheat(t-1)	-0.0117*** (0.0039)	-0.0412*** (0.0059)	0.0096 (0.0065)	-0.0391*** (0.0059)	0.0803*** (0.0035)
Soil characteristics					
slope	0.0015* (0.0008)	0.0039 (0.0024)	-0.0008 (0.0008)	-0.0027 (0.0038)	-0.0029 (0.0020)
sand	-0.0002* (0.0001)	0.0024*** (0.0007)	-0.0005 (0.0003)	-0.0009 (0.0007)	-0.0007* (0.0004)
silt	-0.0004** (0.0002)	0.0024*** (0.0004)	-0.0003 (0.0002)	-0.0011*** (0.0003)	-0.0004 (0.0004)

Bootstrap standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 2.6: County-level elasticities of irrigated acreage shares

Variable	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Water scarcity					
WD(t-1)	0.100 (0.101)	-0.122* (0.0642)	0.546*** (0.165)	-0.279 (0.285)	0.351** (0.137)
DTW(2 year)	-0.0839* (0.0462)	0.0481 (0.0776)	0.0503 (0.110)	-0.1000 (0.0678)	-0.156** (0.0755)
AWQ	0.0557 (0.174)	0.177* (0.101)	0.0705 (0.148)	-0.128*** (0.0361)	0.0970** (0.0397)
NG_P	-0.191*** (0.0634)	0.0336 (0.0264)	-0.239*** (0.0422)	-0.239** (0.121)	-0.463** (0.210)
Crop's price					
Alfalfa_P	0.650* (0.347)	-0.0959* (0.0542)	0.220** (0.0965)	-0.172 (0.167)	-0.141** (0.0603)
Corn_P	0.189 (0.215)	0.737 (0.513)	-0.853** (0.360)	-0.289 (0.209)	-0.243 (0.364)
Sorghum_P	-0.198 (0.306)	-0.433* (0.228)	0.809* (0.420)	0.110 (0.340)	0.601 (0.555)
Soybeans_P	-0.0601 (0.0675)	0.00466 (0.0644)	-0.343*** (0.122)	0.579* (0.312)	-0.159 (0.109)
Wheat_P	-0.216* (0.130)	0.164** (0.0663)	-0.0287 (0.0768)	-0.303 (0.207)	0.434** (0.221)

Bootstrap standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 2.7: Region-level elasticities of irrigated acreage shares

Variable	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Water scarcity					
WD(t-1)	0.128 (0.1000)	-0.0944 (0.0592)	0.573*** (0.161)	-0.252 (0.279)	0.378*** (0.146)
DTW(2 year)	-0.0874* (0.0453)	0.0516 (0.0786)	0.0538 (0.111)	-0.103 (0.0679)	-0.160** (0.0793)
AWQ	0.0692 (0.173)	0.191* (0.103)	0.0840 (0.150)	-0.114*** (0.0348)	0.111** (0.0447)
NG_P	-0.179*** (0.0600)	0.0218 (0.0237)	-0.228*** (0.0395)	-0.222** (0.109)	-0.475** (0.218)
Crop' price					
Alfalfa_P	0.607* (0.323)	-0.138** (0.0647)	0.178* (0.107)	-0.215 (0.156)	-0.183*** (0.0679)
Corn_P	0.156 (0.224)	0.704 (0.522)	-0.885** (0.366)	-0.322 (0.210)	-0.275 (0.377)
Sorghum_P	-0.135 (0.320)	-0.371* (0.226)	0.871** (0.409)	0.172 (0.349)	0.663 (0.525)
Soybeans_P	-0.0763 (0.0700)	-0.0115 (0.0671)	-0.359*** (0.131)	0.563* (0.307)	-0.176 (0.119)
Wheat_P	-0.177 (0.122)	0.203*** (0.0701)	0.0104 (0.0855)	-0.264 (0.196)	0.473** (0.230)

Bootstrap standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Chapter 3 - Land-use budgeting and land-use responsiveness to water scarcity, climate, and policy: A nested logit framework

3.1 Introduction

Land use change is a phenomenon by which human activities transform the natural landscape from one activity to another. It is referring to how a particular type of land is being used, usually emphasizing the use of land for economic activities (Paul and Rashid, 2016). The word 'use' in the term 'land use' refers to the purposes for which the land is being occupied or managed for human needs (e.g., cropland, pastureland, or settlements, etc.). The land that is not being used by humans for any purpose is usually designated as being 'wild', 'native' or 'natural' land. The word 'change' in the term 'land use change' refers to the conversion of land used by humans, from one purpose to another. For instance, land may be converted from agriculture to settlement or from grassland to cropland. The conversion can be within the same category such that converting land from one crop to another in dryland crop production or production intensity (Lee-Gammage, 2018). Furthermore, the conversion can be from a dryland crop to an irrigated crop or from non-cropland to cropland uses and vice versa. Consideration of all of these scenarios requires one to categorize land uses, which may require the recognition of different groups of land uses and being able to capture land use change between different categories and land use transitions between different groups (e.g. Fig. 3.1).

Many factors can influence land use. In agriculture, land quality is an essential factor. For instance, land used for crop production tends to be of higher quality than land used for pastureland or dedicated to land retirement programs, such as the Conservation Reserve Program (CRP)

(Lubowski 2002; Luboweski et. al. 2005; Lubowski et. al. 2008). Climate change and weather can also play an important role in determining land-uses (Olesen and Bindi 2002; Mao et. al. 2011). Another significant environmental factor in agricultural land use is water availability and scarcity. These factors can affect land-use transitions from non-irrigated to irrigated crop production. In addition, it can play an important role as farmers decide how to allocate land among different irrigated crops. Overall, land use and land cover plays an important role in global environmental change (Wu 2000; Kline 2005).

There are many external economic and policy factors that influence land use. Significant growth in the population, urban land development, and industrial expansion have generated a decrease in lands available for agriculture. In the United States, from 1992-2012 there was a dramatic change in major agricultural land uses. Total cropland decreased from 460 to 392 million acres (14.7%), grassland increased from 591 to 655 million acres (10.8%), forest decreased from 648 to 632 million acres (0.2%), and urban areas increased from 59 to 70 million acres (18.6%) (Bigelow and Borchers, 2017). In addition, CRP, the largest land conservation program in the United States, has affected land use, as well. CRP acreage has changed over time from 13.7 to 32.4 to 24.2 million acres from 1987 to 2007 to 2012, respectively (NRS 2016).

Change in land-use patterns can generate significant economic and environmental changes. (Lubowski et al. 2005; Lubowski et al. 2008; Majumdar et. al. 2009; Yan et. al. 2013). Thus, land-use assessment is an important consideration for policy makers, providing knowledge about potential impacts from water scarcity, climate change, soil degradation, biodiversity, environmental quality, soil health, agricultural productivity, economic growth, amongst others. The consideration of these issues requires understanding about and interactions between alternative land-use categories, which may require a more flexible land-use framework in order to better understand these processes and achieve policy goals.

The purpose of this paper is to extend the use of the nested logit model proposed by developed by Carpentier and Letort (2014). The paper extends this framework to develop a flexible land-use analytical framework through use of land budgeting. We categorize agricultural land-use into different groups and subgroups to account for factors that impact land-use change within groups and amongst different groups. For example, water scarcity and irrigations decision have a direct impact on irrigated cropland uses, but can indirectly affect land use decisions for dryland crops and other agricultural land uses. Furthermore, by using a land budgeting approach we can better take account of land uses that incur a higher fixed cost (e.g. irrigation infrastructure) and/or have higher transactions costs of transitioning out of different uses (e.g. land under CRP contracts).

In this study, we consider changes among four major land use groups: irrigated crops, non-irrigated crops, non-cropland, and all other crops. Many other studies have only considered relatively aggregate land use groupings for a particular land-use (Wu and Brorsen 1995; Lubowski et. al. 2006; Luboweski et. al. 2008; Wang et. al. 2012). For example, some studies have aggregated irrigated and non-irrigated cropland into one category. This study tries to capture the nuances among different land use categories and groups. We specifically consider irrigated and non-irrigated cropland as two different land use groupings. Then within the dryland and irrigated grouping, there are five sub-categories of crops (alfalfa, corn, sorghum, soybean, and wheat) that capture the irrigation versus dryland cropping decisions. In addition, we consider pastureland and CRP as non-cropland sub-categories, while all other agricultural land uses and fallow are captured in other crops category.

The study adds to the literature by providing a more flexible framework for examining land-use change and transitions among different categories and sub-categories using land budgeting. In addition, the study aims to demonstrate the usefulness of this approach by examining how water scarcity, weather, and other factor have an impact within land-use categories and across land-use categories, capturing direct and indirect effects. For example, the study helps to address the question of how water scarcity influences cropping patterns within an irrigated cropland category and transitions from irrigated cropland to other uses, such as dryland crop production, and vice versa.

3.2 Literature Review of Past Nested Approaches

In the literature, acreage response and land-use change studies do not usually take into account land budgeting or multiple nested land use categories. There are a number of studies though that have used nested approaches. A number of these studies are summarized here.

Majumdar et. al. (2009) examined the impacts of urbanization on changes in forestland use and land cover in Alabama for the period between 1972 and 2000. Land use change and changes in land cover due to the increase in human needs for land are commonly associated with population growth, market development, technical and institutional innovation, and policy action. To satisfy growth for human needs, land-use change affects ecosystems and its functions, such as watershed protection, biogeochemical cycling, soil degradation, and as a habitat for different species. In their analysis, Majumdar et al. (2009) used a nested logit framework with a three-level nested representation of landowner decisions (non-harvest versus harvest, non-forest versus forest, and forest type) to examine the impacts of urbanization on changes in forest land-use and land-use cover. The results show that initial forest type and a population gravity index significantly explain the variation in forest type transition. Moreover, the results indicate that anthropogenic factors influence the decisions about forestland conversion to non-forest land uses.

Land-use changes generate numerous impacts on the economy, environment, international trade, climate change, and ecosystems. Lubowski et al. (2008) help to identify the factors driving land-use change in the United States (1982-1997). Their study specified a nested logit-modeling framework based on land quality requirements using three nests (groups): (1) crops, CRP, and pastureland; (2) forest and rangeland; and (3) urban land. The study quantified the effects of net returns to different land-uses on private landowners' decisions to allocate land among the six major uses. The study estimated the elasticity for the probability of choosing each land-use alternative with respect to the net returns to that alternative (own return elasticities). The results indicate that land-use decisions are significantly affected by land quality, net returns to alternative uses, and in some cases affected significantly by public policy.

Increasing concern about the impact of global climate change has led to examinations of the importance of the growth of forests to help mitigate carbon dioxide (CO2) from the atmosphere (Lubowski et. al 2006). A study by Lubowski et al. (2006) investigated the cost of forest-based carbon sequestration on revealed landowner preferences. The study specified a nested logit modeling framework based on land quality requirements into three nests: (1) crop land, CRP, and pasture; (2) forest and rangeland; (3) urban land. The econometric model estimated was used to simulate landowner responses to sequestration policies. Six major land uses were modeled, and commodity prices were assumed endogenous in the simulations of the carbon sequestration supply function. The results show that when timber harvesting is prohibited on lands enrolled in the carbon sequestration program, lower marginal costs of carbon sequestration are realized. In addition, the restrictions on timber harvesting on enrolled lands raise timber prices and create incentives for landowners to retain existing lands in forest.

Changes in land-use patterns are a result of transitioning between the different categories and number of relevant land-use alternatives (Lubowski 2002). A study by Lubowski (2002) examined the determinants of land-use transitions in the United States among different land-use categories. The study specified a nested logit model with three separated nests based on land quality: 1) the farm nest containing crops, CRP, and pastureland; 2) the non-farm nest containing forests and range; and 3) the urban nest containing only urban land. The study estimated parameters, transition probabilities, and elasticities to identify the impact on economic profits from land-use transitions and the effects of land quality on transition probabilities among different uses. Estimated elasticities indicate that conversions from cropland and from pasture are responsive to profits of alternative land uses more than conversions from forests and rangeland. Forestlands exhibit responsiveness to both crop and urban development profits, while rangelands appear responsive to urban land values only. In addition, historical simulations provide a better understanding of the effects of historical changes in land-use profits on different land-use transitions. Historical simulations for the period from 1987 to 1997 showed increases in timber profits as the major factor encouraging the increase in forest areas, while an increase in urban profits was an important factor restraining forest area expansion.

This study advances this literature by (i) providing a deeper framework for examining land use that is based on theoretical economic foundations and provides for a richer discussion of factors impacting agricultural land use; (ii) examining the implications of applying land use budgeting for land use studies within that framework; and (iii) building on the efforts of Lubowski (2008) to provide a more flexible way to examine factors that can indirectly influence land-use transitions.

In addition, the approach examined here examines more detailed land use categories than other nested approaches in the literature.

3.3 The Model

In this study, we use a nested multinomial logit framework (NMNL) to derive a system of acreage share equations for different land-use categories (groups) based on land budgeting, building on the approach proposed by Carpentier and Letort (2014).

3.3.1 Land Budgeting

For the approach developed here, we adopt a land budgeting framework. Land use budgeting is an allocation decision process by agricultural producers in which produces allocate a given pieces of land into different uses. Farmers have to make decisions on how to allocate their land amongst competing uses, such as dryland crop production, irrigated crop production, CRP, pasture, and others groups, as well as within each of these groups (e.g. types of crops to grow). Factors such as significant financial investments (e.g. irrigation equipment) and/or contracts (e.g. CRP) may influence land uses over time that directly influence how certain land is treated. The approach described here tries to capture the decision-making process related to this. Land use budgeting is similar to the approach of consumer budgeting in demand analysis, in which consumers allocate a given amount of income amongst different goods and services. Consumer budgeting is widely used in estimating demand share functions when consumers face more than one category of goods, such as that food and non-food categories, and different goods within each category. Goods can be partitioned into groups and each group has more than one good. The change in price of a good in one group affects the demand for all goods in another group (Klonaris and Hallam 2003).

For this study, Figure 1 shows the assumed land use budgeting process used by a potential agricultural producer. In the first stage, the producer allocates his total acreage into four categories (or nests); irrigated crops, non-irrigated crops, non-cropland uses (CRP and pastureland), and all other uses including fallow. Then, in the second stage, the producer allocates land-use within irrigated and non-irrigated crops (alfalfa, corn, sorghum, soybean, and wheat) and non-cropland use (CRP and pastureland). Water availability and irrigation investment costs play a significant role when produces chose to dedicate land to irrigated cropland or dryland. Farmers may have an incentive on land that can be irrigated due to the potential high fixed cost of irrigation infrastructure. In addition, land quality is an important characteristic when producers decide to use the land in cropland activity or switch the land to another uses, such as when considering to participate in conservation programs managed by the government. For example, CRP contracts last 10 to 15 years, limiting the ability to switch this type of land to another use without breaking the contract under penalty. Without land use budgeting, land is assumed to be perfectly substitutable between uses, which may not be the case (Coyle, 1993).

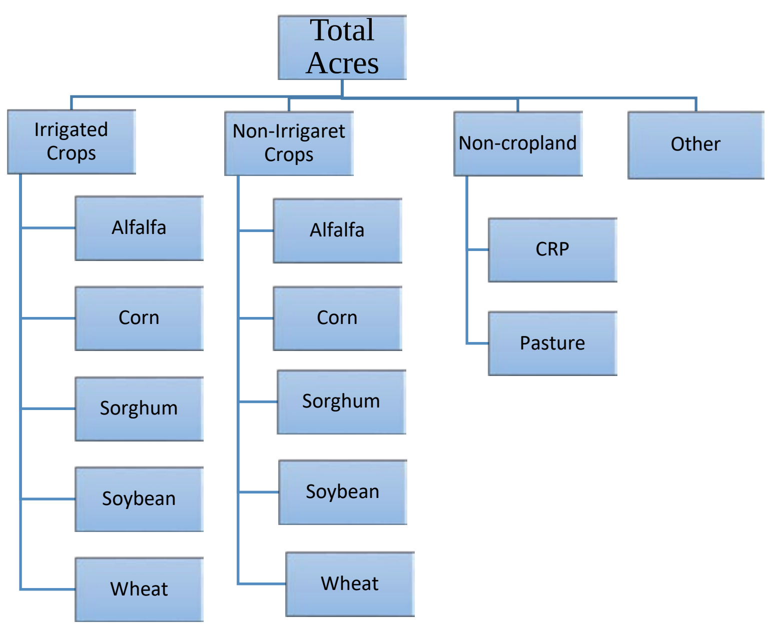

Fig. 3.1: Land budgeting. Nested crop partition

3.3.2 Conceptual Framework

Following the work of Carpentier and Letort (2014), in the short run, suppose a farmer grows $i = 1,\ldots,I$ crops, which are produced on heterogeneous land types $j = 1,\ldots,J$ that are differentiated by site specific characteristics, weather conditions, and other factors. The acreage share for crop i and land type j can be specified as $s_{ij} = \frac{A_{ij}}{A_j}$, where A_{ij} is the total acres for crop i on field j and A_j is the total acres planted on field j . For a given region, the total acreage share for crop i can be specified as $s_i = \sum_{j=1}^{J} s_i^j$. Farmers allocate the amount of land for each crop i to plant on land type j to maximize their expected profit such that the land allocated to crop i does not exceed the total acreage of land. Thus, $\sum_{i=1}^{I} s_i = 1$. Assume that for each type of land, the expected gross margins per acre for crop i is given by: $\pi_i(\boldsymbol{p}, \boldsymbol{b}, \boldsymbol{d}, \theta(\boldsymbol{w}))$, where $\boldsymbol{p}$ is a vector output prices, $\boldsymbol{b}$ is a vector of input prices not including irrigation pumping costs, $\boldsymbol{d}$ is a vector of weather and soil characteristics (which vary across regions), $\theta(\boldsymbol{w})$ is defined as a pumping cost or irrigation cost function, and $\boldsymbol{w}$ is a vector of irrigation variables that include energy price and depth to water. The producers' restricted indirect profit function can then be represented as:

$$\Pi(\boldsymbol{s}; \boldsymbol{p}, \boldsymbol{k}, \boldsymbol{d}, \theta(\boldsymbol{w})) = \sum_{i=1}^{I} s_i \ \pi_i(\boldsymbol{p}, \boldsymbol{k}, \boldsymbol{d}, \theta(\boldsymbol{w})) - C(\boldsymbol{s}) \qquad (3.1)$$

where π_i is gross margins per acre for crop i and $C(\boldsymbol{s})$ is defined as a management cost function that captures the non-linear effect of $\boldsymbol{s}$ in the restricted indirect profit function. It is a function of variables not included in the gross margin function such as general machinery cost, energy costs (not including irrigation cost), maintenance costs, and other unobserved variable costs associated with crop acreage shares. As a result, $C(s)$ is determined by variables not considered in the crop's gross margins (Carpentier and Letort 2014). Assume the cost function takes the following functional form based on that proposed by Carpentier and Letort (2014):

$$C(s) = F + \sum_{q=1}^{Q} \{ \sum_{i \in B(q)} s_i c_i + \alpha^{-1} \ln \overline{s}_q + \rho_q{}^{-1} \sum_{i \in B(q)} (s_{i/q}) \, ln(s_{i/q}) \} \quad (3.2)$$

where F is an unobserved total fixed cost and c_i is the cost (in the short-run) per acre for crop *i*. Assume $\alpha > 0$ and $\rho_q \geq \alpha > 0$ for $q = 1, \ldots, Q$. The α and ρ_q parameters are strictly positive to ensure $C(\boldsymbol{s})$ is strictly convex in $\boldsymbol{s}$. The terms $\sum_{q=1}^{Q} \overline{s}_q \ln \overline{s}_q$ and $\sum_{i \in B(q)} (s_{i/q}) \, ln(s_{i/q})$ can be interpreted as the opposite of the entropy function of the acreage share vector $\boldsymbol{s}$. In fact, "given that the acreage share lies between 0 and 1 and sum to 1, this term is negative implying that F can be chosen to ensure that the cost function is positive" (Carpentier and Letort 2014, p.543). The optimal land allocation is:

$$\boldsymbol{s}^*\big(\boldsymbol{p}, \boldsymbol{k}, \boldsymbol{d}, \theta(\boldsymbol{w})\big) \equiv \arg max_{\boldsymbol{s} \geq 0} \left\{ \Pi\left(\boldsymbol{s}; \pi_i\big(\boldsymbol{p}, \boldsymbol{k}, \boldsymbol{d}, \theta(\boldsymbol{w})\big)\right) \; s.t \sum_{i=1}^{I} s_i = 1 \right\} \text{ for } i = 1, \ldots \ldots, I \, .$$

Assume further that crops are allocated to exclusive nests (or categories) denoted by *B(q)*, for *q= 1,……, Q*, following a land budgeting approach. The share of land allocated to crops in nest *q* is donated by $\overline{s}_q \equiv \sum_{i \in B(q)} s_i$ and the share of crop *i* within nest *q* is donated by $s_{i/q} = s_i / \overline{s}_q$.

Putting this information all together, the profit maximization problem can now be represented as:

$$\underset{\boldsymbol{s} \geq \boldsymbol{0}}{Max} \sum_{q=1}^{Q} \{ \sum_{i \in B(q)} s_i \pi_i - \sum_{i \in B(q)} s_i c_i - \alpha^{-1} \ln \overline{s}_q - \rho_q{}^{-1} \sum_{i \in B(q} (\mathrm{s_{i/q}}) ln(\mathrm{s_{i/q}}) \} - F \;\; s.t \;\; \sum_{i=1}^{I} s_i = 1 \quad (3.3)$$

The associated Lagrangian function for the optimization problem given by (3.3) is defined as:

$$L(s, \lambda) = \sum_{\mathrm{q=1}}^{\mathrm{Q}} \{ \sum_{\mathrm{i \in B(q)}} \mathrm{s_i} \pi_i - \sum_{\mathrm{i \in B(q)}} \mathrm{s_i c_i} - \alpha^{-1} \ln \overline{\mathrm{s}}_{\mathrm{q}} - \rho_{\mathrm{q}}{}^{-1} \sum_{\mathrm{i \in B(q}} (\mathrm{s_{i/q}}) \ln(\mathrm{s_{i/q}}) \} - \mathrm{F} - \lambda \left(\sum_{i=1}^{I} s_i - 1 \right) (3.4)$$

The first order conditions for determining the optimal crop share *i* in nest *q* is given by:

$$\frac{\partial L}{\partial s_i} = \pi_i - c_i - \alpha^{-1}\big(\ln \overline{s}_q + 1 \big) - \rho_q{}^{-1} (ln s_{i/q} + 1) - \lambda = 0 \quad (3.5)$$

$$\frac{\partial L}{\partial \lambda} = \sum_{i=1}^{I} s_i - 1 = 0 \quad (3.6)$$

Equation (3.5) can be written as a follow:

$$ln(s_{i/q}) \rho_q{}^{-1} + \alpha^{-1} \ln \overline{s}_q = \pi_i - c_i - \alpha^{-1} - \rho_q{}^{-1} - \lambda \quad (3.7)$$

Given that $s_{i/q} = \frac{s_i}{\bar{s}_q}$,equation (3.7) can be rearranged to give:

$$\rho_q{}^{-1} ln s_i - \rho_q{}^{-1} \ln \bar{s}_q = \pi_i - c_i - \alpha^{-1} - \alpha^{-1} \ln \bar{s}_q - \rho_q{}^{-1} - \lambda \tag{3.8}$$

From equation (3.8), solving for s_i gives:

$$s_i = \exp[\{ \pi_i - c_i - \alpha^{-1} - \alpha^{-1} \ln \bar{s}_q - \rho_q{}^{-1} - \lambda - \rho_q{}^{-1} \ln \bar{s}_q \ \ \} \rho_q] \tag{3.9}$$

Rearranging equation (3.9), gives:

$$s_i = \exp(\rho_q(\pi_i - c_i))\exp(-\rho_q(\alpha^{-1} + \lambda) + 1)\exp\left(\left(1 - \rho_q \alpha^{-1}\right) ln \bar{s}_q\right) \tag{3.10}$$

Using the definition, $\bar{s}_q = \sum_{m \in B(q)} s_m$:

$$\bar{s}_q = \sum_{m \in B(q)} \exp(\rho_q(\pi_m - c_m) \exp(-\rho_q(\alpha^{-1} + \lambda) + 1)\exp((1 - \rho_q \alpha^{-1}) \ ln \bar{s}_q) \tag{3.11}$$

Now dividing equation (3.10) by equation (3.11), we obtain the conditional share:

$$\frac{s_i}{\bar{s}_q} = s_{i/q} = \frac{\exp(\rho_q(\pi_i - c_i)}{\sum_{m \in B(q)} \exp(\rho_q(\pi_m - c_m)} \tag{3.12}$$

Rearranging equation (3.12), we get:

$$s_i = \frac{\exp(\rho_q(\pi_i - c_i)}{\sum_{m \in B(q)} \exp(\rho_q(\pi_m - c_m)} \ \bar{s}_q \tag{3.13}$$

Equation (3.11) can be represented as:

$$\bar{s}_q = \sum_{m \in B(q)} \exp(\rho_q(\pi_m - c_m) \exp(-\rho_q(\alpha^{-1} + \lambda) + 1) \ \times \bar{s}_q{}^{1 - \rho_q \alpha^{-1}}, \tag{3.14}$$

which implies:

$$\bar{s}_q{}^{\rho_q \alpha^{-1}} = \sum_{m \in B(q)} \exp(\rho_q(\pi_m - c_m) \exp(-\rho_q(\alpha^{-1} + \lambda) + 1) \tag{3.15}$$

and:

$$\bar{s}_q = [\sum_{m \in B(q)} \exp(\rho_q(\pi_m - c_m)]^{\alpha \rho_q{}^{-1}} \exp[((-\rho_q(\alpha^{-1} + \lambda) + 1)] \ {}^{\alpha \rho_q{}^{-1}} \tag{3.16}$$

Summing on both sides and takings account of the fact that, $\sum_{r=1}^{Q} \bar{s}_r = 1$, provides:

$$1 = [\sum_{m \in B(r)} \exp(\rho_r(\pi_m - c_m)]^{\alpha \rho_r{}^{-1}} \exp[((-\rho_q(\alpha^{-1} + \lambda) + 1)] \ {}^{\alpha \rho_q{}^{-1}} \tag{3.17}$$

Dividing equation (3.16) by equation (3.17), then gives:

$$\bar{s}_q = \frac{[\sum_{m \in B(q)} \exp(\rho_q(\pi_m - c_m)] \ {}^{\alpha \rho_q{}^{-1}}}{\sum_{r=1}^{Q} [\sum_{m \in B(r)} \exp(\rho_r(\pi_m - c_m)] \ {}^{\alpha \rho_r{}^{-1}}} \tag{3.18}$$

Finally, substituting equation (3.18) into equation (3.13), we get the unconditional share equation:

$$s_i \;= \frac{\exp(\rho_q(\pi_i - c_i)}{\sum_{m\in B(q)}\exp(\rho_q(\pi_m - c_m)} \; \frac{[\sum_{m\in B(q)}\exp(\rho_q(\pi_m - c_m)]^{\alpha\rho_q{}^{-1}}}{\sum_{r=1}^{Q}[\sum_{m\in B(r)}\exp(\rho_r(\pi_m - c_m)]^{\alpha\rho_r{}^{-1}}} \tag{3.19}$$

where $i \in B(q)$. Let nest g be composed of a single crop, which can be designated as land use category *I*. In this asymmetric nest, $\rho_g = \alpha$, implying:

$$\overline{s}_g \;= \frac{exp(\alpha(\pi_I - c_I))}{\sum_{r=1}^{Q}[\sum_{m\in B(r)} exp(\rho_r(\pi_m - c_m)]^{\alpha\rho_r{}^{-1}}} = \; s_I \tag{3.20}$$

Then for any crop $i \neq I$ belonging to nest q, we have

$$\frac{s_i}{s_I} = \frac{exp\big(\rho_q(\pi_i - c_i)\big)\times[\sum_{m\in B(q)} exp(\rho_q(\pi_m - c_m)]^{\alpha\rho_q{}^{-1}-1}}{exp(\alpha(\pi_I - c_I))} \tag{3.21}$$

Applying the natural log to both sides of equation (3.21), gives:

$$\ln\left(\frac{s_i}{s_I}\right) = \rho_q(\pi_i - c_i) + \left(\alpha\rho_q{}^{-1} - 1\right)ln\,[\textstyle\sum_{m\in B(q)}\exp(\rho_q(\pi_m - c_m)] - \alpha(\pi_I - c_I) \tag{3.22}$$

Applying the natural log to both sides of equation (3.12), gives:

$$ln\big(s_{i/q}\big) = \; \rho_q(\pi_i - c_i) - ln\big[\textstyle\sum_{m\in B(q)} exp(\rho_q(\pi_m - c_m)\big], \tag{3.23}$$

which can be rewritten as:

$$\ln\big[\textstyle\sum_{m\in B(q)} exp(\rho_q(\pi_m - c_m)\big] = \rho_q(\pi_i - c_i) - \ln\big(s_{i/q}\big). \tag{3.24}$$

Substituting equation (3.24) into equation (3.22), gives:

$$\ln\left(\frac{s_i}{s_I}\right) = \rho_q(\pi_i - c_i) - \alpha(\pi_I - c_I) + \left(\alpha\rho_q{}^{-1} - 1\right)[\rho_q(\pi_i - c_i) - \ln\big(s_{i/q}\big)] \tag{3.25}$$

Equation (25) can be rewritten to provide:

$$\ln\left(\frac{s_i}{s_I}\right) = \; \alpha(\pi_i - c_i) - \alpha(\pi_I - c_I) \; + \left(1 - \alpha\rho_q{}^{-1}\right)\ln(s_{i/q}) \tag{3.26}$$

Letting $\Pi_i = \pi_i - c_i$ and $\left(1 - \alpha\rho_q{}^{-1}\right) = \delta_q$, where π_i is gross margins per acre for crop *I* and c_i is the variable cost (in the short-run) per acre for crop *i* . The optimal land share allocation can be represented as:

$$\ln\left(\frac{s_i^*}{s_I^*}\right) = \; \alpha(\Pi_i - \Pi_I) \; + \delta_q\ln(s_{i/q}) \tag{3.27}$$

where Π_i and Π_I are the restricted indirect profit function for crop *i and I*, respectively.

Now, let $\mathbf{\Pi} = \Pi_i - \Pi_I = g(\mathbf{X})$, where $\mathbf{X} \equiv \big(\boldsymbol{p}, \boldsymbol{b}, \boldsymbol{d}, \theta(\boldsymbol{w}), C(\boldsymbol{s})\big)$. Note that $\theta(\boldsymbol{w}) = 0$ for non-irrigated land uses. Equation (3.27) can be rewritten as:

$$\ln\left(\frac{s_i^*}{s_I^*}\right) = \alpha[g(\mathbf{X})] + \delta_q \ln(s_{i/q}) \tag{3.28}$$

Assuming $g(\mathbf{X}) = g(\mathrm{X_i}; \beta_i)$, then equation (3.28) becomes:

$$\ln\left(\frac{s_i^*}{s_I^*}\right) = \alpha g(\mathrm{X_i}; \beta_i) + \delta_q \ln(s_{i/q}) \tag{3.29}$$

If $\alpha g(\mathrm{X_i}; \beta_i) = \mathrm{X}_i' \frac{\beta_i}{\alpha} = \mathrm{X}' \tilde{\beta}_i$, this implies:

$$\ln\left(\frac{s_i^*}{s_I^*}\right) = \mathrm{X}_i' \tilde{\beta}_i + \delta_q \ln\left(s_{i/q}\right), \text{such that } \frac{\beta_i}{\alpha} = \tilde{\beta}_i \tag{3.30}$$

Equation (3.32) is empirically tractable if the endogeneity of $\ln(s_{i/q})$ is accounted for during estimation (Carpentier and Letort, 2014).

3.3.3 Empirical Model and Estimation

Since farm-level data is not always available, many studies have estimated acreage response and land use models using aggregate data at the county-level (Wau and Brosen 1994; Wau and Sergerson 1995; Miller and Plantinga 1999). We adopt this approach here. Based on the linear functional form of the acreage share equation in equation (3.30), let:

$$\ln\left(\frac{s_i^{j*}}{s_I^{j*}}\right) = \mathbf{X}_i'^j \tilde{\beta}_i + \delta_q \ln\left(s_{i/q}^j\right) + \gamma_j + \varepsilon_i, \qquad i = 1, \ldots, I \tag{3.31}$$

where $s_{ij}{}^*$ is the share of land use i in county j ; I is share of the I^{th} asymmetric reference crop in county j (often a all other category); $s_{i/qj}$ is the share of land use i in county j within nest q; **X** is a matrix of explanatory variables; $\tilde{\boldsymbol{\beta}}$ and $\boldsymbol{\delta}$ are vectors of parameters being estimated; and $\boldsymbol{\varepsilon}$ is a vector of unobserved error terms. The model is assumed to include fixed effects, γ_j, to capture unobserved time invariant characteristics such as soil characteristics and depth to water across the different spatial regions of the model (e.g. farms, counties, states).

There exists contemporaneous correlation between the error terms across the land use equations. Given this, the system of equations given by (3.31) can be estimated using Seemingly Unrelated Regression (SUR) estimation methods (Zellner 1962). This model has been used in previous studies to estimate systems of acreage share equations (Wu and Brosen 1994; Wu and Sergerson 1995). However, seemingly unrelated regressions (SUR) models assume strict exogeneity, homoscedasticity, and autocorrelation (W. H. Greene 2012). That is, given that the vector of error terms across equations is:

$$\boldsymbol{\varepsilon} = [\varepsilon_1', \varepsilon_2', \ldots., \varepsilon_I']', \tag{3.32}$$

the SUR approach assumes strict exogeneity of the explanatory variables such that:

$$E[\varepsilon | X_1, X_2, \ldots. X_I] = 0, \tag{3.33}$$

as well as homoscedasticity:

$$E[\varepsilon_i \varepsilon_i' | X_1, X_2, \ldots. X_I] = \sigma_{ii} \mathbf{I}_{IT} \tag{3.34}$$

where *IT* donates the total number of observations for each crop-share equation (Ramsey, 2017). In addition, this approach assumes that disturbances are uncorrelated across observations but correlated across equations such that:

$$E\left[\varepsilon_{i,j,t} \varepsilon_{zsk} \middle| X_1, X_2, \ldots. X_I\right] = \begin{cases} \sigma_{i,z} & for\ i = z\ and\ t = k \\ 0 & otherwise \end{cases} \tag{3.35}$$

where i and $z=1,\ldots.,I$ refer to land use types, and time t and $k=1,\ldots.,T$ are time indices (Ramsey 2017). These assumptions might not hold due to the probabilistic nature of the data included in a study and should be tested and/or corrected for if needed. Therefore, we need to test for exogeneity, heteroscedasticity, and autocorrelation in the data before estimating any SUR models. Breusch-Pagan tests can be used to check for independence between crop share equations' residuals (Gatignon 2003), likelihood ratio tests (LR-Test) can be used to check for heteroscedasticity

(Wiggins and Poi, 2003), and Wooldridge-Tests can use to test for serial autocorrelation (Drukker 2003).

The SUR-HEAR model proposed by Wu and Brorsen (1995) is one proposed method that can be used to correct for heteroscedasticity, autocorrelation, and contemporaneous correlation dependence. To correct for autocorrelation, the SUR-HEAR correction approach starts by estimating each equation given in equation (3.31) by ordinary least square regression (OLS), where $y_{i,t}^{j} = \ln(\frac{s_{i,t}^{j*}}{s_{I,t}^{j**}})$. The fitted regression residuals, $\hat{\varepsilon}_{i,t}^{j}$, are then used to find the autocorrelation coefficient, ρ_{ij}, for each land use in each region via following equation:

$$\hat{\rho}_{i}^{j} = \frac{\sum_{t=2}^{T} \hat{\varepsilon}_{i,t}^{j} \hat{\varepsilon}_{i,t-1}^{j}}{\sum_{t=1}^{T} (\hat{\varepsilon}_{i,t}^{j})^2} \tag{3.36}$$

Then one uses $\hat{\rho}_{ij}$, to make the following transformation to correct for autocorrelation in the dependent variable:

$$y_{i,t}^{j*} = y_{i,t}^{j} - \hat{\rho}_{i}^{j} * y_{i,t-1}^{j} \tag{3.37}$$

The same transformation is also applied to each of the explanatory variables:

$$x_{i,t}^{j*} = x_{i,t}^{j} - \hat{\rho}_{i}^{j} * x_{i,t-1}^{j} \tag{3.38}$$

The next step in the SUR-HEAR procedure is to correct for heteroscedasticity by estimating the share equations given in equations (3.37)-(3.38) via OLS using the transformed data, y_{ijt}^{*} and x_{ijt}^{*}, to obtain a new set of fitted residuals, $\hat{\varepsilon}_{it}^{j*}$. These new residuals are then used to estimate the error variance for each crop in each region as:

$$(\hat{\sigma}_{i}^{j})^2 = \sum_{t=1}^{T} \frac{(\hat{\varepsilon}_{i,t}^{j*})^2}{T} \tag{3.39}$$

The estimate $\hat{\sigma}_{ij}$ is used to transform all the variables again to correct for group-wise heteroscedasticity:

$$y_{i,t}^{j**} = \frac{y_{i,t}^{j*}}{\hat{\sigma}_i^j} \tag{3.40}$$

and,

$$x_{i,t}^{j**} = \frac{x_{i,t}^{j*}}{\hat{\sigma}_i^j} \tag{3.41}$$

Finally, the last transformed data used to estimate the linear system of equations given by:

$$y_{i,t}^{j**} = \quad X_{i,t}^{j**}\widetilde{\boldsymbol{\beta}}_i \ + \delta_{i/q,t}\ln\left(s_{i/q}^{**}\right) + \gamma_j + \varepsilon_{i,t}^{j}\ I = 1,\ldots,I \tag{3.42}$$

3.3.4 Endogeneity of Conditional Shares

Since $\ln(s_{i/q})$ is an endogenous variable, we need take account of this during estimation. To deal with this problem, instrumental variables are used to instrument for $\ln(s_{i/q})$ to control for endogeneity. To estimate the system of now simultaneous equations, three stage least squares (3SLS) can be used, which combines two stages least square (2SLS) and SUR methods (Zellner and Theil, 1962). The other approach is using 2SLS. In the first stage, we estimate $\ln(s_{i/q})$ with instrumental variables. In the second stage, we estimate SUR with the predicted results of the endogenous variables from the first stage. This estimation method is accomplished as follow.

Let $Z_i = [X_i^{**}\ \ \ln\left(s_{i/q}^{**}\right)]$ and $\gamma_i = [\begin{smallmatrix}\beta_i \\ \delta_{i/q}\end{smallmatrix}]$. The SUR matrix specification used to correct for endogeneity can be represented as follows:

$$\begin{bmatrix} \mathrm{y}_1 \\ \mathrm{y}_2 \\ \mathrm{y}_i \end{bmatrix} = \begin{bmatrix} \mathrm{Z}_1 & 0 & 0 \\ 0 & Z_2 & 0 \\ 0 & 0 & Z_i \end{bmatrix} \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_i \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_i \end{bmatrix} \equiv \boldsymbol{Y} = \ \boldsymbol{Z\delta} + \boldsymbol{\varepsilon} \tag{3.67}$$

The variance-covariance matrix for each $t=1,\ldots,T$ is:

$$E(\varepsilon\boldsymbol{\varepsilon}') = \Omega = \sum \otimes I_T = \begin{bmatrix} \sigma_{11I_T} & \sigma_{12}I_T & \ldots & \sigma_{1M}I_T \\ \sigma_{21}I_T & \sigma_{22}I_T & \ldots & \sigma_{2M}I_T \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{M1}I_T & \sigma_{M2}I_T & \ldots & \sigma_{MM}I_T \end{bmatrix}_{MT\times MT}, \tag{3.68}$$

where:

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1M} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{M1} & \sigma_{M2} & \cdots & \sigma_{MM} \end{bmatrix}_{M\times M} . \tag{3.69}$$

Applying the principle of SUR-HEAR estimation:

$$\gamma = (W'(\hat{\Sigma}^{-1} \otimes I)Z)^{-1} W'(\hat{\Sigma}^{-1} \otimes I)Y) \tag{3.70}$$

where W is an instrumental variable matrix. Producers make their decision about the share of land dedicated for a certain type of agriculture activity based on the prior period's decision (Nerlove 1956). In addition, farmers often adopt and use crop rotations for different reasons, especially to improve land quality to mitigate environmental impacts (Havlin 1990; Bullock 1992; Liebman and Dyck 1993). We adopt crop rotation variables, as the lags of the conditional share $\ln(s_{i/q\,(t-1)})$ variables within each nest as instrumental variables to control for endogeniety in each equation.

3.3.5 Nested Acreage Share Elasticities

One of the main objectives of conducting acreage response models is identifying the acreage response elasticities with respect to the explanatory variables. These elasticities provide a way to examine the direct and indirect (marginal) effects on land-use decisions and transitions, as the coefficient estimates in the model, may not be as interpretable. The acreage share elasticity for crop i in county j at year t with respect to explanatory variable k, $x^j_{i,k,t}$, in county j at year t is given by:

$$e^j_{i,t}|x^j_{i,k,t} = \frac{\partial s^j_{i,t}}{\partial x^j_t}\frac{x^j_{i,k,t}}{s^j_{i,t}} \tag{3.71}$$

Given that $s^j_{it} = (s^j_{i/q,t}) * \bar{s}^j_{qt}$, the marginal effect can be decomposed using the product rule as:

$$\frac{\partial s_{it}^{j}}{\partial x_{i,k,t}^{j}} = \frac{\partial s_{i/q,t}^{j}}{\partial x_{i,k,t}^{j}} \bar{s}_{q,t}^{j} + \frac{\partial \bar{s}_{q,t}^{j}}{\partial x_{i,k,t}^{j}} s_{i/q,t}^{j} \tag{3.72}$$

Then, the acreage share elasticity for crop *i* in county *j* at time *t* with respect to explanatory variable *x* can rewritten as a follow:

$$e_{i,t}^{j}|x_{i,k,t}^{j} = \left[\frac{\partial s_{i/q,t}^{j}}{\partial x_{i,k,t}^{j}} \bar{s}_{qt}^{j} + \frac{\partial \bar{s}_{q,t}^{j}}{\partial x_{i,k,t}^{j}} s_{i/q,t}^{j}\right] \frac{x_{i,k,t}^{j}}{s_{t}^{j}} \tag{3.73}$$

This implies:

$$e_{it}^{j}|x_{i,k,t}^{j} = \frac{\partial s_{i/q,t}^{j}}{\partial x_{i,k,t}^{j}} \frac{\bar{s}_{qt}^{j} x_{i,k,t}^{j}}{s_{i,t}^{j}} + \frac{\partial \bar{s}_{q,t}^{j}}{\partial x_{i,k,t}^{j}} \frac{(s_{i/q,t}^{j}) x_{i,k,t}^{j}}{s_{i,t}^{j}} \tag{3.74}$$

For simplicity, we drop the subscribe *t* from both sides, so that:

$$e_{i}^{j}|x_{i,k}^{j} = \frac{\partial s_{i/q}^{j}}{\partial x_{i,k}^{j}} \frac{x^{j}}{s_{i/q}^{j}} + \frac{\partial \bar{s}_{q}^{j}}{\partial x^{j}} \frac{x_{i,k}^{j}}{\bar{s}_{\bar{s}_{q}^{j}}} \tag{3.75}$$

This implies:

$$e_{i}^{j}|x_{i,k}^{j} = e_{i/q}^{j}|x_{i,k}^{j} + e_{q}^{j}|x_{i,k}^{j} \tag{3.76}$$

where $e_{i}^{j}|x_{i,k}^{j}$ is the unconditional acreage share elasticity for crop *i* in county *j* with respect to explanatory variable $x_{i,k}^{j}$; $e_{i/q}^{j}|x_{i,k}^{j}$, is the conditional acreage share elasticity for crop *i* in county *j* within nest *q* with respect to explanatory variable $x_{i,k}^{j}$; and $e_{q}^{j}|x_{i,k}^{j}$ is the acreage share elasticity for nest *q* in county *j* with respect to explanatory variable $x_{i,k}^{j}$. The unconditional acreage share elasticity is a sum of two effects. The first component of the unconditional elasticity captures the change in acreage share within nest *q*. We interpret this elasticity as the conditional relative substitutability between categories in that nest. That is, it would tell us that within a group or nest, how much a crop share would change relative to changes in the other crop shares, assuming the group share remains constant. The second component is the change in the share of nest *q* with respect to the change in explanatory variable of interest. It is group level acre share elasticity here that provides how land would shift between groups for a particular producer, for a fixed quantity of land.

From equation (2.19) and other equations, the unconditional acreage share is:

$$s_i = s_{i/q} \times \bar{s}_q = \frac{\exp(\mathbf{X}_i'\boldsymbol{\beta}_i)}{\sum_{m\in B(q)} \exp(\mathbf{X}_m'\boldsymbol{\beta}_m)} \times \frac{\left[\sum_{m\in B(q)} \exp(\mathbf{X}_m'\boldsymbol{\beta}_m)\right]^{\alpha\rho_q{}^{-1}}}{\sum_{r=1}^{Q} \left[\sum_{m\in B(r)} \exp(\mathbf{X}_m'\boldsymbol{\beta}_m)\right]^{\alpha\rho_r{}^{-1}}} \tag{3.77}$$

The conditional marginal effect for $s_{i/q}$ with respect to explanatory variable x is:

$$\frac{\partial s_{i/q}}{\partial x_{i,k}^j} = \frac{\{[\sum_{m\in B(q)} \exp(\mathbf{X}_m'\boldsymbol{\beta}_m)] \times \exp(\mathbf{X}_i'\boldsymbol{\beta}_i) \times \beta_{i,k}\} - \{\exp(\mathbf{X}_i'\boldsymbol{\beta}_i) \times [\sum_{m\in B(q)} \exp(\mathbf{X}_m'\boldsymbol{\beta}_m)\beta_{m,k}]\}}{\left[\sum_{m\in B(q)} \exp(\mathbf{X}_m'\boldsymbol{\beta}_m)\right]^2} \tag{3.78}$$

or,

$$\frac{\partial s_{i/q}}{\partial x_{i,k}^j} = \frac{[\exp(\mathbf{X}_i'\boldsymbol{\beta}_i)] \times [\beta_{i,k} - (s_{i/q})] \times [\sum_{m\in B(q)} \exp(\mathbf{X}_m'\boldsymbol{\beta}_m)\beta_{m,k}]}{\sum_{m\in B(q)} \exp(\mathbf{X}_m'\boldsymbol{\beta}_m)} \tag{3.79}$$

This implies:

$$\frac{\partial s_{i/q}}{\partial x_{i,k}^j} = \left[(s_{i/q}) \times \beta_{i,k}\right] - \left[(s_{i/q}) \times \sum_{m\in B(q)} (s_{m/q,j})\beta_{m,k}\right] \tag{3.80}$$

or,

$$\frac{\partial (s_{i/q})}{\partial x_{i,k}^j} = (s_{i/q})\left[\beta_{i,k} - \sum_{m\in B(q)} \left(s_{m/q,j}\right)\beta_{m,k}\right] \tag{3.81}$$

The conditional acreage share elasticity for land use *i* in county *j* within nest *q* with respect to explanatory variable x_k can then be derived as:

$$e_{i/q}^j | x_{i,k}^j = \left[\beta_{i,k} - \sum_{m\in B(q)} (s_{m/q})\beta_{m,k}\right] x_{i,k}^j \tag{3.82}$$

Letting $\alpha\rho_q{}^{-1} = \delta_q$, $\bar{s}_q$ can then be written as:

$$\bar{s}_q = \frac{\left[\sum_{m\in B(q)} \exp(\mathbf{X}_m'\boldsymbol{\beta}_m)\right]^{\delta_q}}{\sum_{r=1}^{Q} \left[\sum_{m\in B(r)} \exp(\mathbf{X}_m'\boldsymbol{\beta}_m)\right]^{\delta_r}} \tag{3.83}$$

then,

$$\frac{\partial \bar{s}_q}{\partial x_{i,k}^j} = \frac{\left[\sum_{r=1}^{Q} \left[\sum_{m\in B(r)} \exp(\mathbf{X}_m'\boldsymbol{\beta}_m)\right]^{\delta_r}\right] \times \delta_q \left[\sum_{m\in B(q)} \exp(\mathbf{X}_m'\boldsymbol{\beta}_m)\right]^{\delta_q - 1} \times \left[\sum_{m\in B(q)} \exp(\mathbf{X}_m'\boldsymbol{\beta}_m)\beta_{m,k}\right]}{\left[\sum_{r=1}^{Q} \left[\sum_{m\in B(r)} \exp(\mathbf{X}_m'\boldsymbol{\beta}_m)\right]^{\delta_r}\right]^2} -$$

$$\frac{\left[\sum_{m\in B(q)} \exp(\mathbf{X}_m'\boldsymbol{\beta}_m)\right]^{\delta_q} \times \left\{\sum_{r=1}^{Q} \left(\delta_r \left[\sum_{m\in B(q)} \exp(\mathbf{X}_m'\boldsymbol{\beta}_m)\right]^{\delta_r - 1} \times \left[\sum_{m\in B(r)} \exp(\mathbf{X}_m'\boldsymbol{\beta}_m)\beta_{m,k}\right]\right)\right\}}{\left[\sum_{r=1}^{Q} \left[\sum_{m\in B(r)} \exp(\mathbf{X}_m'\boldsymbol{\beta}_m)\right]^{\delta_r}\right]^2} \tag{3.84}$$

or,

$$\frac{\partial \bar{s}_q}{\partial x_{i,k}^j} = \delta_q \bar{s}_q \left[\sum_{m\in B(q)} \exp(\mathbf{X}'_{\boldsymbol{m}}\boldsymbol{\beta}_{\boldsymbol{m}})\right]^{-1} \times \left[\sum_{m\in B(q)} \exp(\mathbf{X}'_{\boldsymbol{m}}\boldsymbol{\beta}_{\boldsymbol{m}})\, \beta_{m,k}\right] -$$

$$\bar{s}_q \sum_{r=1}^{Q} \left(\bar{s}_r \delta_r \left[\sum_{m\in B(r)} \exp(\mathbf{X}'_{\boldsymbol{m}}\boldsymbol{\beta}_{\boldsymbol{m}})\right]^{-1} \times \left[\sum_{m\in B(r)} \exp(\mathbf{X}'_{\boldsymbol{m}}\boldsymbol{\beta}_{\boldsymbol{m}})\beta_{m,k}\right]\right) \quad (3.85)$$

or,

$$\frac{\partial \bar{s}_q}{\partial x_{i,k}^j} = \bar{s}_q \left\{\delta_q \, \frac{\sum_{m\in B(q)} \exp(\mathbf{X}'_{\boldsymbol{m}}\boldsymbol{\beta}_{\boldsymbol{m}})\beta_{m,k}}{\sum_{m\in B(q)} \exp(\mathbf{X}'_{\boldsymbol{m}}\boldsymbol{\beta}_{\boldsymbol{m}})} - \sum_{r=1}^{Q} \frac{\delta_r \bar{s}_r \sum_{m\in B(r)} \exp(\mathbf{X}'_{\boldsymbol{m}}\boldsymbol{\beta}_{\boldsymbol{m}})\beta_{m,k}}{\sum_{m\in B(r)} \exp(\mathbf{X}'_{\boldsymbol{m}}\boldsymbol{\beta}_{\boldsymbol{m}})}\right\} \quad (3.86)$$

or:

$$\frac{\partial \bar{s}_q}{\partial x_{i,k}^j} = \bar{s}_q \left\{ \delta_q \left[\sum_{m\in B(q)} (\mathrm{s}_{m/q})\beta_m, k\right] - \left[\sum_{r=1}^{Q} \left(\delta_r \bar{s}_r \sum_{m\in B(r)} (\mathrm{s}_{m/r})\beta_{m,k}\right)\right]\right\} \quad (3.87)$$

This implies, the acreage share elasticity for nest q in county j with respect to explanatory variable, x^j is:

$$e_q^j | x_{i,k}^j = \left\{ \delta_q \left[\sum_{m\in B(q)} (\mathrm{s}_{m/q})\beta_{m,k}\right] - \left[\sum_{r=1}^{Q} \left(\delta_r \bar{s}_{rq} \sum_{m\in B(q)} (\mathrm{s}_{m/r})\beta_{m,k}\right)\right]\right\} x_{i,k}^j \quad (3.88)$$

Substituting equation (3.82) and equation (3.88) into equation (3.76), give:

$$e_i^j | x_{i,k}^j = \left\{\left[\beta_{i,k} - \sum_{m\in B(q)} (s_{m/q})\beta_{m,k}\right] x_{i,k}^j\right\} + \left\{ \delta_q \left[\sum_{m\in B(q)} (\mathrm{s}_{m/q})\beta_{m,k}\right] - \left[\sum_{r=1}^{Q} \left(\delta_r \bar{s}_r \sum_{m\in B(r)} (\mathrm{s}_{m/r})\beta_{m,k}\right)\right]\right\} x_{i,k}^j \quad (3.89)$$

Rearranging equation (3.89), we get:

$$e_i^j | x_{i,k}^j = \left\{\left[\beta_{i,k} - \sum_{m\in B(q)} (s_{m/q})\beta_{m,k}\right] + \delta_q \left[\sum_{m\in B(q)} (\mathrm{s}_{m/q})\beta_{m,k}\right] - \left[\sum_{r=1}^{Q} \left(\delta_r \bar{s}_r \sum_{m\in B(r)} (\mathrm{s}_{m/r})\beta_{m,k}\right)\right]\right\} x_{i,k}^j \quad (3.90)$$

Equation (3.90) provides a useful approach in calculating acreage share elasticities, since it considers the share of land use elasticity $e_q^j | x_{i,k}^j$ of choosing any of the alternatives within nests q; and the conditional share of land use elasticity $e_{i/q}^j | x_{i,k}^j$ of choosing i given the choice of nest q.

3.4 Empirical Application

Freshwater is an essential source of water for most of human needs, including drinking, agriculture, industry, and other uses. Globally, food and other agricultural products account for 70% of freshwater withdrawals from rivers and groundwater, and in the United States, irrigated farms account for 80%–90% of the consumptive use of water (Molden 2007; Winter et. al 2017). Water scarcity plays an important role in allocating land among different irrigated crops (Olen et. al. 2015; Khorshed Alam 2015; Kettle et al. 2007; Bhalla 2007). In the United States, the High Plains aquifer (HPA) underlies about 174,000 square miles of the central United States. The aquifer underlies portions of eight states including South Dakota, Wyoming, Nebraska, Colorado, Kansas, Oklahoma, New Mexico and Texas (USGS). This aquifer is the largest freshwater aquifer in the US. It is the main source of irrigation for agricultural in the US. About 27% of the irrigated land in the US overlies this aquifer system and about 30% of the total groundwater used for irrigation (USDA-NRCS 2011).

In Kansas, groundwater is the main water source for the region's cities, industry, and agriculture. The Kansas portion of the HPA, which includes the Ogallala aquifer, Great Bend Prairie, and Equus Bend is the most important groundwater source in Kansas, supplying 70% to 80% of statewide total water use and the source for about 98% of irrigated fields in Kansas (Hendricks and Peterson 2012). Increasing groundwater pumping from the aquifer for different uses, especially for irrigation has led to declining groundwater levels in most parts of the aquifer (Buchanan et. al. 2001). The consequences of this reduction in groundwater table generates higher pumping costs due to less groundwater availability and increases in depth to water. Minimizing the effects of the shortage in groundwater supply requires an optimal use from farmers, as well as sustainable groundwater management (Roumasset and Wada 2014). Farmers attempt to reduce this impact of water scarcity by choosing less intensive water use crops, decrease water applied per acre, or convert land from irrigated to non-irrigated crop production.

3.4.1 Study Region

To implement our empirical model, a county-level panel data subset of 48 counties in western Kansas over the HPA Kansas from 2003-2018 is used as the study region. The reason for choosing this region is that producers in this region have direct access to groundwater from the HPA, providing them the opportunity to choose between irrigated and dryland crop production. The primary irrigated crops grown in this region of Kansas are corn, soybeans, alfalfa, wheat, and sorghum. Other crops include sunflowers, barley, oats, rye, and dry beans (Hendricks and Peterson 2012). Primary land use categories include irrigated and dryland production for major cash crops (alfalfa, corn, soybean, sorghum, and wheat), grassland, CRP, and other. We assume producers use land budgeting and follow the nesting structure provided in Figure 3.1. We assume agricultural land use decisions are influenced by output prices, input prices, soil and weather characteristics, and water scarcity factors as evidenced in the literature (Christopher and Shideed 1989; Duffy and Shalishali 1994; Bailey and Womack 1985; Kettle et al. 2007; Bhalla 2007; Huang and Khanna 2010; Haile et al. 2014; Hodjo et al. 2016; Saddiq 2014; Olen et. al., 2015; Khorshed Alam, 2015).

3.4.2 Data

This subsection describes the data used for the empirical application presented here. Descriptive statistics of the variables are provided in Table 3.1. We obtain our data from different sources.

3.4.2.1 Acreage Shares

Acreage data was obtained from Farm Services Agency (USDA-FSA). From these acreages, the dependent acreage share variables are calculated as follows:

$$y_{i,t}^{j} = \ln\left(\frac{s_{i,t}^{j}}{s_{I,t}^{j}}\right) \tag{3.91}$$

where $s_{i,t}^{J}$ is the acreage share of crop *i* in county *j* at time *t* and $s_{I,t}^{j}$ is the share of acreage dedicated for the reference crop I in county *j* at time *t* (which is the total acreage share for other crops). Total irrigated and non-irrigated area accounts for 12% and 47% of the total agriculture land, respectively. In addition, grassland, CRP, and other crops including fallow account for 18%, 9%, and 14%, respectively. Corn is the primary crop, with irrigated corn accounting for 6% and non-irrigated corn accounting for 27% of the total acreage. Irrigated wheat accounts for 3%, while non-irrigated wheat accounts for 7% of total cultivated land. Irrigated sorghum accounts for 1%, while non-irrigated sorghum accounts 10% of the total crop acreage. Irrigated soybean accounts for 1% and non-irrigated soybean accounts for 2% of total crop acreage. Both irrigated and non-irrigated alfalfa account for 1% of total cultivated area in the study region (Table 3.1).

3.4.2.2 Water Scarcity

Irrigation water price is the cost of pumping an inch of water per acre to the land surface, which is dependent on natural gas, which has a marginal energy cost, and the pumping lift or depth to water (Hendricks and Peterson, 2012). We defined, $\theta(\boldsymbol{w})$ as a pumping cost or irrigation cost function, where $\boldsymbol{w}$ is defined as water scarcity, which is a vector of irrigation variables that include energy price and depth to water. Depth to water is the distance between the land surface and the groundwater. Depth to water was obtained from the Kansas Geological Services (KGS). From this data, we obtained county-level average depth to water. We expect that farmers will respond negatively, reducing irrigated acreage, with greater depth to water levels. Since our study deals with irrigated crops, including energy prices is important to assess its impact on farmers' acreage decision since it's the primary component in determining irrigation cost. Energy is an important input used to extract groundwater for irrigation in western Kansas (Pfeiffer and Lin 2013). In

Kansas, the four major energy sources for pumping irrigation water are natural gas, electricity, diesel and propane (LP). Natural gas accounts for more than 50% of energy used in pumping irrigation water (Rogers 2008; Pfeiffer and Lin 2013). Therefore, we used the natural gas price as an energy price. State level natural gas prices were obtained from the U.S Energy Information (EIA).

Water demand or water requirement for each crop refers to the amount of water lost via evapotranspiration (Ep) which includes evaporative water from soil and crops as well as transpiration water from crops to the atmosphere (Gheewala et. al. 2017). Water deficit (WD) is evaporative demand not met by available water or how much water transpired to the atmosphere from a site covered by a specific crop (Stephenson 1990). For simplicity, water deficit is calculated using the following formula:

$$WD_{j,t} = Ep_{j,t} - Precipitation_{j,t} \tag{3.92}$$

where $WD_{j,t}$ is the water deficit in county *j* at year *t* and $Ep_{j,t}$is a potential evapotranspiration in county *j* at year *t* during the growing season. Potential evapotranspiration was obtained using data from the United States Geological Survey (USGS) for years 2003-2014 while the rest of time was obtained from Kansas Mesonet.

Groundwater users in Kansas extract water under prior appropriation. Prior appropriation means “first in time, first in right.” That means the first individual to divert groundwater water from the aquifer has priority over later diverters. Under this regulation, users are allowed to extract the maximum amount of water each year. This annual amount is determined when the user applied for a permit (Pfeffer and Lin, 2012). The impact of amount of water authorized for irrigation on irrigated crop shares is coming from the new approved groundwater permits every year since the existing amount of water authorized for irrigation is fixed overtime. This variable exhibit the local geverment policy impact on irrigated crop shares. County-level measures of total annual quantity of permitted water was calculated by summing all users' quantities of permitted water for each year. Quantity of permitted water data is obtained from the Water Information Management & Analysis System (WIMAS). This variable captures the potential water authorized to be pumped from the aquifer, providing another aspect of potential water demand. This variable will provide a direct impact on irrigated crop acreage shares and indirect impact on other land-uses.

3.4.2.3 Output and Input Prices

Output prices for the five crops represented in the model are the expected prices at the time of planting. Following the approach of Hendricks et al. (2014) and Ramsey (2017), expected prices are calculated using the following formula:

$$E\left(p_{i,t}^{j}\right) = F\left(p_{i,t}^{j}\right) + E\left(Bp_{i,t}^{j}\right) \tag{3.93}$$

The expected price for crop i in county j at time t is set equal to a futures price at the time of planting plus an expectation of the basis at harvest time. We calculate the future $F\left(p_{i,t}^{j}\right)$ by using cash prices at the elevator location. Each county has at least one spot cash price. If multiple elevators are included in a county, then an average across the different elevators is used for the output and input prices. Note that some counties have missing observations for some years. Given that, we set the missing observation for each county equal to the average cash price of the surrounding counties. Cash prices at elevator locations were obtained from AgManager.info (AgManager.info, 2019) except for alfalfa, which was obtained from USDA, National Agricultural Statistics Service for the county level. We calculate the future prices for each crop at planting using the average price across March and April for corn, sorghum, and soybean and the average across September and October for wheat. The expected basis price $E\left(Bp_{i,t}^{j}\right)$ calculated using the average cash prices at time of harvest. We used the average cash price across September and October for corn, sorghum, and soybean, and the average cash prices in June for wheat. Expected basis price was then calculated using the following formula:

$$E\left(Bp_{i,t}^{j}\right) = cash\ price\ at\ harvest\ time_{i,t-1}^{j} - contract\ price\ for\ harvest\ delivery_{i,t-1}^{j} \qquad (3.94)$$

CRP rental rates were obtained from the Farm Service Agency (FSA). FSA uses county-level cash rent estimates of cropland and non-cropland to determine market-based payment rates of Conservation Reserve Program (CRP). Pastureland rental rates were obtained from from agmanger.info.

Most empirical studies include input prices. It is clear that these prices are important in determining the net returns of different land uses. Fertilizer price indices have been included in previous studies (Wu and Sergeson 1995; Wu and Brorsen 1995). These studies showed that these price indices can exhibit a significant impact on acreage crop decisions. Fertilizer price indices were obtained from the USDA, National Agricultural Statistics Service Information (USDA, NASS, 2019).

3.4.2.3 Climate data

For climate data, we calculated county-level variables for growing degree-days (GDD), extreme degree-days (EDD), and total precipitation within the growing season for each crop (table 4). Whether variables were calculated using daily data provided by Schlenker and Roberts (2009). They were created using data from the PRISM database (available at http://www.wolfram-schlenker.com/dailyData.html). Weather variables were calculated using daily precipitation as maximum and minimum temperature. GDD measures the exposure to heat within a range of temperatures ($8C^{o}$-30 C^{o}). EDD measures the exposure to heat for temperatures exceeding the maximum in GDD (GDD>30). Both GDD and EDD are measured as accumulative degree days within the growing season (April 1- September 30) for corn, sorghum, and soybean, and (October 1- May 30) for wheat. Precipitation is calculated as the accumulative amount of precipitation within the growing season for each crop (Hendricks et. al. 2014).

3.5 Results

In this section will present the regression estimations for the transformed system of equations (SUR-HEAR) with IV estimations. The flexibility of the framework we develop in this chapter allows us to estimate conditional and unconditional (land use) acreage share elasticities in addition to group acreage share elasticities. However, before we run our estimation, we need to conduct the misspecification test to insure the validity of our estimations.

3.5.1 Model Specification Testing

To empirical model consists of 12 equations; five irrigated crops, five non-irrigated crop, grassland, and CRP share equations. The residuals from each estimated equation were used to test for independence between land use categories using a Breusch-Pagan test (Gatignon 2003). The results indicate that the 12 land use share equations correlation coefficients are jointly significant ($\chi^2_{v=66} = 15806.373, \mathrm{Pr} = 0.0000$(Table 3.3). The test suggests using a system of equation rather than estimating equations individually. Table 3.3 shows the correlation coefficients between crop share equations residuals.

Given that conditions in counties vary across space in terms of land use, weather and soil characteristics, we expect heteroscedasticity to be a potential problem, especially when some conditions cannot be modeled directly. In addition, using same data for the counties overtime, we expect potential serial autocorrelation to be present (Wu and Brorsen 1994). Thus, we test for heteroscedasticity and autocorrelation. Following Wiggins and Poi (2003), the likelihood ratio test (LR-Test) rejects the null hypothesis of no heteroscedasticity for all crop share equations except for the irrigated corn share equations. This indicates that heteroscedasticity is present in the crop share equations except for irrigated corn. In addition, we use the Wooldridge-Test to test for serial autocorrelation (Drukker 2003). The null hypothesis for no autocorrelation was rejected for all crop share equations at a 1% level of significance, except for the irrigated alfalfa, soybean, and wheat share equations. This indicates that autocorrelation is present in most of the regression equations and should be corrected for (Table 3.4).

Based on these results, we adopt the SUR-HEAR procedure to correct for heteroscedasticity and autocorrelation only for the crop share equations that exhibit heteroscedasticity and autocorrelation using the methods described in section 3.3.3. We then use the 2SLS estimator to estimate the transformed system after correcting for heteroskedasticity and autocorrelation to estimate the system and to control for endogeneity of the conditional shares.

3.5.2 Nested Multinomial Logit (NMNL) Estimations

The available data set was used to estimate the nested multinomial logit estimations (NMNL) using 2SLS regressions. In addition, we estimated the elasticities of interested explanatory variables. Second stage estimation results are presented in Table 3.4 while the first stage estimations are presented in Table 3.8. Given the limited interpretability of the regression coefficients, we will not discuss the results from the regression in detail. Instead, we focus the discussion on the elasticity estimates. Asymptotic bootstrapped standard errors for the elasticities were obtained via a bootstrapping procedure with 20 replications.

A significant purpose of the approach presented is the estimation of elasticities with respect to explanatory variables of interest. County-level acreage share elasticities for crop i across the J counties with respect to the explanatory variables were estimated using the elasticity equations given by equations (3.82), (3.88), and (3.90). We estimated conditional, share, and unconditional elasticities for the different model factors of interest, which include the water scarcity factors (energy price, depth to water, water rights, etc.) and crop prices.

3.5.3 Conditional Land Use Shares Elasticities

We estimated the conditional acreage share elasticities using equation (3.82). The results can be found in Table 3.5. Most of the own price elasticities are significant at the 1%, 5%, and 10% significance level. However, all of the own price elasticities are inelastic. Natural gas price shows a negative impact on all conditional irrigated acreage shares except for irrigated soybeans. Depth to water has a negative impact on irrigate alfalfa, corn, and wheat acreage share. Note that, conditional land use elasticities examine the shift in land use within each group in response to change in explanatory variable.

For the water scarcity explanatory variables, we find that all natural gas price conditional acreage elasticities in the irrigated group are negative in sign for all irrigated crops except for irrigated soybean. When the natural gas price increases, acreage dedicated for irrigated alfalfa, corn, sorghum, and wheat acreage will switch to soybeans, because farmers expect an increase in pumping cost. For depth to water, the result shows that it has a significant impact on irrigated crops' decision for alfalfa, corn, and wheat. The negative sign for these crops indicates that when the average depth to water increases, the land dedicated for irrigated alfalfa, corn, and wheat will switch to irrigated sorghum and/or soybeans. In addition, when depth to water increases, farmers are less willing to increase land dedicated for irrigated crops because they expect an increase in pumping costs. Combining the results from the conditional elasticities of the natural gas price and depth to water provides evidence that as pumping costs increase, farmers respond by shifting the amount of land dedicated to irrigated land use share for alfalfa, corn, and wheat to sorghum and soybeans. The elasticity of quantity of water authorized for extraction shows that if the amount of water permitted for extraction increase, farmers would increase irrigated land dedicated for all irrigated crops, especially for irrigated corn wheat acreage share. This increase is resulting from switch land dedicated to other crops to irrigated crops.

For crop prices, the results suggest that, as alfalfa price decreases, land dedicated to irrigated alfalfa will shift to any of irrigated corn, soybeans, and/or wheat, while land dedicated to non-irrigated alfalfa will shift to soybeans, sorghum, and/or wheat. As corn price decreases, land dedicated to non-irrigated corn will shift to non-irrigated soybeans. We find that, as sorghum price decreases, land will shift from to non-irrigated soybeans. When price of soybean decreases, land dedicated for irrigated soybean will shift to for irrigated alfalfa and/or sorghum, while land dedicated to non-irrigated soybeans will shift to non-irrigated alfalfa, sorghum, and/or wheat. As price for wheat decreases, the land dedicated for no-irrigated wheat will shift to non-irrigated corn. When the rental rate of grassland decrease, land dedicated for grazing will shift to CRP.

3.5.4 Group Share Elasticities

The NMNL elasticities estimation provide the indirect impact of natural gas prices and water scarcity variables on non-irrigated crops, CRP, and grassland since $\theta(\boldsymbol{w}) = 0$ for these land types. The indirect impact of changes in these variables is captured by the group share elasticities given by equation (3.88). These elasticity estimates capture changes in land allocation between land use groups, such as irrigated cropland to non-irrigated cropland or non-cropland in response to changes in an explanatory variable. We focus specifically here on price and water scarcity variables:

natural gas (energy) price, depth to water, and water rights. Group share elasticities are presents in Table 3.7.

Elasticity estimates show that as the price of alfalfa increases, land dedicated for irrigated and non-irrigated cropland decreases while land dedicated to non-cropland increases . As the price of corn increases by 10%, land dedicated to irrigated and non-irrigated cropland increases by 1.4% and 1.6%, while land dedicated for non-cropland decreases by 4.6%. This indicates that as the price of corn increases, non-cropland shifts to either irrigated or non-irrigated cropland. As price of sorghum, soybeans, and wheat increase, land dedicated for non-cropland shifts to either irrigated or non-irrigated cropland. The results indicate that, as CRP rental payments increase, land dedicated to non-irrigated cropland shifts to non-cropland. As rent for grassland increases, land dedicated to irrigated and non-irrigated cropland shifts to non-cropland due to the fact that landowners may now want to rent this land instead of using it for cropland cultivation .

For the natural gas price, as natural gas prices increase by 10%, about 0.03% of land dedicated to irrigated cropland will shift to either non-irrigated cropland or non-cropland. As depth to water increases by 10%, about 0.05% land dedicated to irrigated cropland will shift toward non-irrigated cropland or non-cropland. The reason why land dedicated for irrigated cropland will shift to either non-irrigated cropland or non-cropland is due to farmers reacting to an expected increase in pumping costs. When the amount of water permitted for irrigation increases, land dedicated for non-irrigated cropland and non-cropland will shift to irrigated cropland.

3.5.5 Unconditional Land Use Share Elasticities

When we combine conditional and group share elasticities, we can generate unconditional land-use elasticity as given by equation (3.90). Unconditional land-use elasticities are reported in Table 8. These show the actual changes on the group between the bottom level categories in the land budget framework. That is, the unconditional acreage elasticities capture the shifts between categories in a nest and between nests (or groups). For instance, as the price of alfalfa decreases, land dedicated to irrigated and non-irrigated alfalfa will shift to irrigated (corn and wheat), non-irrigated (sorghum, soybeans, and wheat), and/or CRP. Similar interpretations will apply for other crop prices.

3.6 Conclusion and Discussion

A framework of land use compatible with regional water scarcity, climate change, and government program model that more directly takes account of land use planning (through land budgeting) was introduced in this paper to provide a better understanding for land-use management and policy makers. The main purpose of this article is to demonstrate that NMNL acreage share framework can provide a flexible model to address a multi crop and multi land use response model for assessment of the impacts on land use from economic and non-economic factors. First, we show that NMNL acreage share models can be derived from well-defined profit maximizing behavior under specific assumptions. Second, we show that the NMNL acreage share model can provide a multi crop and multi land use econometric model that can be used to estimate unconditional, conditional and group acreage share elasticities that allow for the assessment of direct and indirect effects of explanatory factors on land use decisions and allocation. The model is illustrated using an empirical example of farmer land use allocation between irrigated cropland, non-irrigated cropland, and noncropland categories.

We determine the impact of water scarcity and market factors on land use decisions in the on the allocation different agricultural land uses in western Kansas over time. Land-use change is influenced by a variety of economic and non-economics factors. In this study, we used the NMNL framework to analyze land use decision for major irrigated crops, non-irrigated crops, CRP, and grassland above the High Plains Aquifer in Kansas. We used a county level dataset for 50 counties across 16 years. The results show that water scarcity variables, such as energy prices, depth to water, water rights, amongst others have a significant and direct influence on irrigated land-use decisions, as well as significant and indirect effect on non-irrigated and non-cropland use decisions. The NMNL model provides elasticities estimates that can show the direct impact of irrigation water factors on irrigated crops and indirect impacts on non-irrigated crops, CRP, and grassland. Other elasticity estimates show that producers respond significantly to crop prices and other noneconomic factors. These findings are important to policy makers to understand how water scarcity factors can affect other non-irrigated crops and non-cropland land-use.

For future study, we suggest considering NMNL framework to analyze the land-use change among different uses such that irrigated crops, forest, and residential use to provide a better understanding of deforestation as response to climate change and population growth.

Tables

Table 3.1: Descriptive Statistics for the Explanatory Variables

Variable	Definition (Unit)	Obs.	Mean	Std.
Crop Share				
Irrigated Alfalfa	Share of irrigated alfalfa (Percent)	714	0.01	0.02
Irr-Corn	Share of irrigated corn (Percent)	714	0.06	0.06
Irr-Sorghum	Share of irrigated sorghum (Percent)	714	0.01	0.01
Irr-Soybean	Share of irrigated soybeans (Percent)	714	0.01	0.02
Irr-Wheat	Share of irrigated wheat (Percent)	714	0.03	0.03
Nirr-Alfalfa	Share of non-irrigated alfalfa (Percent)	714	0.01	0.02
Nirr-Corn	Share of non-irrigated corn (Percent)	714	0.27	0.14
Nirr-Sorghum	Share of non-irrigated sorghum (Percent)	714	0.10	0.06
Nirr-Soybean	Share of non-irrigated soybeans (Percent)	714	0.02	0.04
Nirr-Wheat	Share of non-irrigated wheat (Percent)	714	0.07	0.09
Grassland	Share of grassland (Percent)	714	0.18	0.15
CRP	Share of CRP (Percent)	714	0.09	0.07
Other Crops	Share of other crops (Percent)	714	0.14	0.09
Crop's Prices				
Alfalfa_P	Alfalfa expected price($/ton)	714	116.54	39.69
Corn_P	Corn expected price($/ton)	714	373.99	104.64
Sorghum_P	Sorghum expected price($/ton)	714	173.63	50.36
Soybeans_P	Soybean expected price($/ton)	714	184.77	54.01
Wheat_P	Wheat expected price($/ton)	714	197.33	62.44
Pasture_Rent	Pastureland rent($/acre)	714	11.30	3.08
CRP_Rent	CRP payment($/acre)	714	36.36	3.59
Input Price				
NG_P	Natural gas price (dollars per thousand cubic Feet)	714	11.66	2.82
Fertilizer_P	Fertilizer Price index	714	77.62	24.64
Water Scarcity Variables				
WD(t-1)	Water deficit(mm)	714	686.15	242.94
WD(2-3)	2-3 years moving average water deficit (mm)	714	1358.30	428.32

WD(4-5)	4-5 years moving average water deficit (mm)	714	1299.03	411.56
DTW	Depth to water(ft.)	714	48.25	44.06
DTW(2-3)	2-3 years moving average depth to water (ft.)	714	20.75	12.98
DTW(4-5)	4-5 years moving average depth tow water (ft.)	714	21.44	13.25
Authorized_Q	Amount of water permitted (1000 acre/feet)	714	70.86	74.21
Weather Variables				
GDD(t-1)	Accumulative growing degree days (8C<GDD<30C)	714	1255.05	2531.58
EDD(t-1)	Accumulative growing degree days (GDD>30C)	714	54.54	124.6
GDD(2-3)	2-3 years moving average for accumulative growing degree days (8C<GDD<30C)	714	511.42	1045.05
EDD(2-3)	2-3 years moving average for accumulative growing degree days (GDD>=30C)	714	1.09	3.3
GDD(4-5)	4-5 years moving average for accumulative growing degree days (8C<GDD<30C)	714	2304.05	141.21
EDD(4-5)	4-55 years moving average for accumulative growing degree days (GDD>=30C)	714	96.33	19.04

Table 3.2: SUR-test for independence

	Irrigated					Non-irrigated					Non-cropland	
	Alfalfa	Corn	Sorghum	Soybean	Wheat	Alfalfa	Corn	Sorghum	Soybean	Wheat	CRP	Grassland
Irr-Alfalfa	1.00											
Irr-Corn	0.92	1.00										
Irr-Sorghum	0.92	0.91	1.00									
Irr-Soybean	0.98	0.91	0.93	1.00								
Irr-Wheat	0.96	0.88	0.90	0.98	1.00							
Nirr-Alfalfa	0.35	0.37	0.38	0.34	0.33	1.00						
Nirr-Corn	0.23	0.25	0.23	0.24	0.19	0.47	1.00					
Nirr-Sorghum	0.35	0.37	0.38	0.35	0.33	1.00	0.47	1.00				
Nirr-Soybean	0.35	0.37	0.38	0.35	0.33	1.00	0.46	1.00	1.00			
Nirr-Wheat	0.31	0.34	0.35	0.31	0.37	0.87	0.41	0.87	0.87	1.00		
CRP	0.35	0.37	0.37	0.35	0.37	0.72	0.33	0.72	0.72	0.72	1.00	
Grassland	0.40	0.42	0.42	0.39	0.41	0.74	0.32	0.74	0.74	0.74	0.95	1.00
Breusch-Pagan test of independence: $\chi^2_{v=66} = 15806.373$, Pr. = 0.0000												

Table 3.3: Heteroscedasticity and Autocorrelation Tests

Equation	LR-Test for Heteroscedasticity			Wooldridge Test for Autocorrelation		
	Chi-seq.	P-Value	Decision	F-Test	P-Value	Decision
Irr-Alfalfa	70.37	0.03	Rejected	15.275	0.00	Rejected
Irr-Corn	59.96	0.05	Rejected	16.629	0.00	Rejected
Irr-Sorghum	78.69	0.00	Rejected	4.920	0.03	Rejected
Irr-Soybean	64.37	0.08	Rejected	8.335	0.06	Rejected
Irr-Wheat	70.56	0.02	Rejected	13.175	0.07	Rejected
Nonirr-Alfalfa	197.56	0.00	Rejected	36.969	0.00	Rejected
Nonirr-Corn	184.08	0.00	Rejected	238.271	0.00	Rejected
Nonirr-Sorghum	207.05	0.00	Rejected	40.925	0.00	Rejected
Nonirr-Soybean	192.32	0.00	Rejected	36.023	0.00	Rejected
Nonirr-Wheat	159.96	0.00	Rejected	58.588	0.00	Rejected
CRP	180.00	0.00	Rejected	17.582	0.00	Rejected
Grassland	144.76	0.00	Rejected	34.517	0.00	Rejected

Table 3.4: SUR-HEAR estimations for land-use share

Variable	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Ln_share	0.4087*** (0.0180)	0.4087*** (0.0180)	0.4087*** (0.0180)	0.4087*** (0.0180)	0.4087*** (0.0180)
WD(t-1)	0.0003 (0.0003)	-0.0006*** (0.0002)	0.0072** (0.0034)	-0.0001 (0.0003)	0.0006* (0.0003)
WD(2-3 years)	0.0009*** (0.0002)	0.0005*** (0.0002)	0.0000 (0.0006)	0.0022*** (0.0003)	0.0021*** (0.0003)
WD(4-5 years)	0.0115*** (0.0039)	0.0184*** (0.0055)	-0.0060* (0.0033)	-0.0011 (0.0036)	-0.0092** (0.0042)
GDD(t-1)	0.0001* (0.0001)	-0.0002** (0.0001)	-0.0001 (0.0003)	-0.0004*** (0.0001)	-0.0004** (0.0001)
GDD(2-3 years)	0.0001 (0.0001)	-0.0003*** (0.0001)	0.0005 (0.0005)	0.0004* (0.0002)	-0.0002 (0.0002)
GDD(4-5 years)	0.0008*** (0.0003)	0.0012*** (0.0002)	0.0000 (0.0009)	0.0027*** (0.0004)	0.0004 (0.0003)
EDD(t-1)	-0.0003** (0.0001)	0.0003** (0.0002)	0.0000 (0.0006)	0.0008*** (0.0003)	0.0006** (0.0003)
EDD(2-3 years)	-0.0005 (0.0003)	0.0007*** (0.0002)	-0.0012 (0.0011)	-0.0006 (0.0005)	0.0006 (0.0004)
EDD(4-5 years)	-0.0096*** (0.0018)	-0.0074*** (0.0015)	-0.0008 (0.0056)	-0.0238*** (0.0024)	-0.0022 (0.0025)
Alfalfa_P	0.0021*** (0.0004)	-0.0012*** (0.0003)	0.0007 (0.0017)	-0.0039*** (0.0006)	0.0003 (0.0006)
Corn_P	0.0110*** (0.0015)	0.0037*** (0.0011)	0.0090** (0.0046)	0.0119*** (0.0022)	0.0105*** (0.0019)
Sorghum_P	0.0117*** (0.0016)	0.0059*** (0.0011)	0.0115** (0.0050)	0.0142*** (0.0022)	0.0098*** (0.0019)
Soybeans_P	-0.0004 (0.0003)	0.0002 (0.0002)	-0.0015 (0.0010)	0.0008* (0.0004)	0.0006 (0.0004)
Wheat_P	0.0037*** (0.0004)	0.0004 (0.0003)	0.0017 (0.0013)	0.0021*** (0.0006)	0.0028*** (0.0006)
CRP_Rent	0.0028 (0.0036)	0.0039 (0.0026)	0.0100 (0.0096)	-0.0009 (0.0045)	0.0074* (0.0039)
Grassland_Rent	-0.0171*** (0.0028)	0.0038* (0.0022)	0.0001 (0.0076)	-0.0124*** (0.0040)	0.0165*** (0.0035)
NG_P	-0.0105*** (0.0033)	-0.0027 (0.0024)	-0.0138 (0.0097)	0.0074 (0.0049)	-0.0072 (0.0054)
DTW	-0.0002** (0.0001)	-0.0005*** (0.0001)	0.0002 (0.0010)	0.0020*** (0.0003)	-0.0022*** (0.0005)
DTW(2-3 years)	-0.0001 (0.0006)	0.0005 (0.0004)	0.0006 (0.0014)	-0.0012*** (0.0004)	0.0003 (0.0007)
DTW(4-5 years)	-0.0002 (0.0006)	-0.0007* (0.0004)	-0.0020 (0.0014)	-0.0082 (0.0070)	0.0004 (0.0007)
Authorized_Q	0.0007	0.0006**	0.0005	0.0019***	0.0050***

	(0.0005)	(0.0003)	(0.0018)	(0.0006)	(0.0006)
Fertilizer_P	-0.0072*** (0.0008)	-0.0027*** (0.0006)	-0.0030 (0.0035)	-0.0072*** (0.0011)	-0.0039*** (0.0010)
Time_trend	0.3451 (0.4009)	1.2730** (0.5685)	-0.0387 (0.0904)	0.7818** (0.3636)	-0.2936 (0.4489)
Time_trend_sq	-0.0315* (0.0184)	-0.0682*** (0.0263)	0.0014 (0.0040)	-0.0415** (0.0167)	-0.0028 (0.0206)
Constant	-31.499*** (4.7299)	-66.9250*** (7.8185)	-5.8695*** (1.8133)	-46.7456*** (5.5490)	7.5961 (4.7956)
Observations	627	627	627	627	627
R-squared	0.98	0.99	0.92	0.99	0.99

Bootstrap standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.4: SUR-HEAR estimations for land-use share (continued)

Variable	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Ln_share	0.7174*** (0.0169)	0.7174*** (0.0169)	0.7174*** (0.0169)	0.7174*** (0.0169)	0.7174*** (0.0169)
WD(t-1)	0.0002 (0.0002)	-0.0052 (0.0040)	0.0010*** (0.0003)	0.0008 (0.0005)	0.0109 (0.0067)
WD(2-3 years)	0.0001 (0.0002)	-0.0011* (0.0007)	-0.0006** (0.0003)	0.0004 (0.0005)	0.0009 (0.0011)
WD(4-5 years)	0.0007 (0.0028)	0.0046 (0.0039)	-0.0022 (0.0059)	-0.0020* (0.0011)	-0.0106 (0.0067)
GDD(t-1)	-0.0001 (0.0001)	0.0003 (0.0003)	-0.0001 (0.0002)	-0.0008*** (0.0003)	0.0010* (0.0005)
GDD(2-3 years)	-0.0004* (0.0002)	-0.0008* (0.0005)	0.0007*** (0.0002)	-0.0008* (0.0005)	0.0049*** (0.0008)
GDD(4-5 years)	-0.0001 (0.0003)	0.0032*** (0.0008)	0.0022*** (0.0003)	0.0031*** (0.0007)	-0.0002 (0.0014)
EDD(t-1)	0.0001 (0.0002)	-0.0008 (0.0006)	0.0002 (0.0003)	0.0015*** (0.0005)	-0.0013 (0.0010)
EDD(2-3 years)	0.0007* (0.0004)	0.0017 (0.0010)	-0.0014*** (0.0004)	0.0016* (0.0009)	-0.0093*** (0.0017)
EDD(4-5 years)	-0.0010 (0.0020)	-0.0156*** (0.0057)	-0.0155*** (0.0026)	-0.0233*** (0.0044)	0.0116 (0.0093)
Alfalfa_P	0.0017*** (0.0005)	0.0064*** (0.0018)	-0.0008 (0.0007)	-0.0007 (0.0011)	-0.0060** (0.0030)
Corn_P	0.0019 (0.0016)	0.0004 (0.0036)	0.0059*** (0.0021)	-0.0003 (0.0040)	0.0103 (0.0074)
Sorghum_P	0.0029* (0.0017)	0.0001 (0.0041)	0.0078*** (0.0022)	-0.0017 (0.0040)	0.0207** (0.0081)
Soybeans_P	-0.0001 (0.0003)	-0.0002 (0.0010)	-0.0005 (0.0004)	0.0020*** (0.0008)	-0.0031* (0.0016)
Wheat_P	0.0008* (0.0005)	-0.0026** (0.0013)	0.0011** (0.0005)	0.0021** (0.0010)	-0.0004 (0.0022)
CRP_Rent	0.0002 (0.0035)	0.0044 (0.0096)	-0.0042 (0.0039)	0.0002 (0.0081)	-0.0430*** (0.0155)
Grassland_Rent	-0.0010 (0.0027)	-0.0024 (0.0076)	0.0006 (0.0036)	-0.0019 (0.0050)	-0.0132 (0.0125)
Fertilizer_P	-0.0030*** (0.0010)	0.0151*** (0.0036)	-0.0020 (0.0012)	-0.0019 (0.0021)	-0.0142** (0.0060)
Time_trend	-0.0584 (0.2887)	-0.5366*** (0.0933)	-0.2501 (0.5830)	-0.3792*** (0.1185)	0.9933*** (0.1552)
Time_trend_sq	-0.0009 (0.0135)	0.0219*** (0.0041)	0.0141 (0.0264)	0.0155*** (0.0055)	-0.0443*** (0.0068)
Constant	-4.7142 (7.8815)	-1.5358 (1.6707)	-95.928*** (13.2686)	-12.836** (5.7808)	-13.003*** (2.7147)
Observations	627	627	627	627	627
R-squared	0.99	0.78	0.98	0.99	0.81

Bootstrap standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.4: SUR-HEAR estimations for land-use share (continued)

Variables	CRP	Grassland
Ln_share	0.5262*** (0.0271)	0.5262*** (0.0271)
WD(t-1)	-0.0013*** (0.0003)	-0.0025*** (0.0007)
WD(2-3 years)	-0.0006*** (0.0002)	-0.0035*** (0.0006)
WD(4-5 years)	0.0013 (0.0014)	-0.0009 (0.0010)
GDD(t-1)	0.0006*** (0.0002)	0.0024*** (0.0004)
GDD(2-3 years)	0.0005* (0.0002)	0.0026*** (0.0005)
GDD(4-5 years)	-0.0023*** (0.0004)	-0.0056*** (0.0009)
EDD(t-1)	-0.0011*** (0.0003)	-0.0041*** (0.0008)
EDD(2-3 years)	-0.0011** (0.0005)	-0.0056*** (0.0010)
EDD(4-5 years)	0.0147*** (0.0028)	0.0420*** (0.0065)
Alfalfa_P	0.0007 (0.0007)	0.0054*** (0.0016)
Corn_P	-0.0004 (0.0019)	-0.0348*** (0.0045)
Sorghum_P	0.0005 (0.0020)	-0.0337*** (0.0045)
Soybeans_P	-0.0033*** (0.0005)	-0.0036*** (0.0009)
Wheat_P	-0.0006 (0.0006)	-0.0106*** (0.0014)
CRP_Rent	0.0161*** (0.0046)	0.0122 (0.0101)
Grassland_Rent	0.0003 (0.0039)	0.0107* (0.0061)
Fertilizer_P	0.0072*** (0.0012)	0.0228*** (0.0029)
Time_trend	-0.1384 (0.1388)	-0.0094 (0.0954)
Time_trend_sq	0.0041 (0.0065)	0.0036 (0.0044)
Constant	2.899 (2.2539)	23.099*** (3.6956)
Observations	627	627
R-squared	0.99	0.98

Bootstrap standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.5 : Conditional land-use share elasticity estimations

	Irrigated cropland					Non-irrigated cropland					Non-cropland	
Variable	Alfalfa	Corn	Sorghum	Soybeans	Wheat	Alfalfa	Corn	Sorghum	Soybeans	Wheat	CRP	Pastureland
Alfalfa_P	0.553** (0.240)	-0.133*** (0.0415)	0.0404 (0.430)	-0.497*** (0.122)	-0.0417 (0.110)	0.504** (0.203)	0.749*** (0.252)	-0.165*** (0.0351)	-0.142 (0.262)	-0.874** (0.439)	-0.0661 (0.148)	0.609* (0.342)
Cron_P	1.389*** (0.508)	0.417* (0.239)	1.505*** (0.533)	1.599*** (0.578)	0.997*** (0.358)	0.196 (0.339)	0.429* (0.256)	0.684** (0.299)	-0.155 (0.999)	0.922*** (0.295)	1.023 (0.931)	-0.444*** (0.115)
Sorghum_P	1.584** (0.637)	0.759** (0.339)	0.618*** (0.239)	2.053** (0.846)	0.909** (0.424)	0.353 (0.482)	0.822 (0.833)	0.665* (0.378)	-0.419 (1.323)	2.375*** (0.336)	1.230 (0.965)	-0.484*** (0.177)
Soybeans_P	-0.129 (0.261)	0.0539 (0.181)	-0.310 (0.404)	0.553 (0.897)	0.294 (0.195)	-0.0388 (0.0676)	0.0462 (0.108)	-0.127 (0.0980)	0.708 (0.434)	-0.776** (0.369)	-0.821* (0.425)	-0.885** (0.450)
Wheat_P	0.681*** (0.127)	0.0302 (0.0772)	0.513** (0.257)	0.393*** (0.136)	0.555*** (0.0863)	0.143 (0.0939)	-0.199 (0.215)	0.245** (0.108)	0.414** (0.202)	0.465 (1.736)	0.329** (0.152)	-1.701*** (0.397)
CRP_Rent	0.0714 (0.241)	0.129 (0.131)	0.475 (0.665)	-0.0591 (0.616)	0.237 (0.199)	0.0184 (0.178)	0.332 (0.344)	-0.151* (0.0833)	0.0193 (0.753)	-1.460*** (0.545)	0.447** (0.228)	0.307 (0.418)
Pasture_Rent	-0.191*** (0.0591)	0.0438 (0.0483)	0.0293 (0.174)	-0.141*** (0.0267)	0.0350 (0.0497)	-0.00710 (0.0305)	-0.00481 (0.0368)	0.0184 (0.0301)	-0.0200 (0.0509)	-0.143 (0.115)	-0.0332 (0.0607)	0.447*** (0.00419)
NG_P	-0.173 (0.180)	-0.0413 (0.0786)	-0.196 (0.128)	0.139 (0.194)	-0.153 (0.209)							
DTW	-0.196 (0.604)	-0.242 (0.200)	0.0236 (0.0435)	0.214*** (0.0683)	-0.109*** (0.0317)							
Authorized_Q	0.103 (0.105)	0.337 (0.299)	0.0608 (0.357)	0.263 (0.171)	0.216** (0.103)							

Bootstrap standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.6 : Unconditional land-use share elasticity estimations

	Irrigated cropland					Non-irrigated cropland					Non-cropland	
Variables	Alfalfa	Corn	Sorghum	Soybeans	Wheat	Alfalfa	Corn	Sorghum	Soybeans	Wheat	CRP	Pastureland
Alfalfa_P	0.486*** (0.109)	-0.200*** (0.0690)	-0.0264 (0.186)	-0.563*** (0.136)	-0.109 (0.104)	0.468*** (0.00954)	0.713*** (0.0986)	-0.201*** (0.0686)	-0.178 (0.268)	-0.910 (0.683)	-0.0366 (0.197)	0.639** (0.255)
Corn_P	1.531*** (0.0702)	0.558* (0.328)	1.646*** (0.0407)	1.740*** (0.472)	1.139*** (0.0708)	0.357 (0.580)	0.590** (0.279)	0.846** (0.335)	0.00650 (0.635)	1.083 (1.656)	0.564 (1.175)	-0.903*** (0.367)
Sorghu_P	1.706*** (0.237)	0.881*** (0.246)	0.740*** (0.140)	2.176*** (0.491)	1.031** (0.516)	0.496*** (0.170)	0.966 (0.784)	0.808 (0.703)	-0.275 (0.490)	2.518*** (0.0819)	0.706* (0.418)	-1.008*** (0.164)
Soybeans_P	-0.0302 (0.286)	0.152 (0.156)	-0.211 (0.395)	0.659*** (0.246)	0.393* (0.208)	0.393* (0.208)	0.393* (0.208)	-0.0347 (0.0722)	0.800** (0.406)	-0.684 (0.735)	-0.912** (0.374)	-0.976* (0.566)
Wheat_P	0.794*** (0.140)	0.143* (0.0789)	0.626** (0.277)	0.506*** (0.190)	0.668*** (0.0934)	0.240 (0.175)	-0.102 (0.183)	0.342*** (0.0105)	0.510** (0.209)	0.561 (2.152)	0.184 (0.201)	-1.846*** (0.300)
CRP_Rent	0.0752 (0.235)	0.133 (0.148)	0.479 (0.661)	-0.0553 (0.619)	0.241 (0.218)	0.00433 (0.0657)	0.318 (0.376)	-0.166 (0.167)	0.00520 (0.677)	-1.474*** (0.0354)	0.516*** (0.0872)	0.376 (0.622)
Pasture_Rent	-0.194*** (0.0581)	0.0408 (0.0516)	0.0263 (0.178)	-0.144*** (0.0174)	0.0321 (0.0487)	-0.0123 (0.0342)	-0.0101 (0.0417)	0.0132** (0.00602)	-0.0252 (0.0968)	-0.148 (0.128)	-0.0181 (0.0550)	0.461*** (0.008)
NG_P	-0.176 (0.179)	-0.0445 (0.0793)	-0.199 (0.132)	0.136 (0.193)	-0.156 (0.213)							
DTW	-0.197 (0.604)	-0.242 (0.201)	0.0231 (0.0423)	0.213*** (0.0693)	-0.109*** (0.0317)							
Authorized_Q	0.109 (0.106)	0.344 (0.300)	0.0673 (0.358)	0.270 (0.170)	0.222** (0.105)							

Bootstrap standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.7 : Group share elasticities

Variables	Irrigated cropland	Non-irrigated cropland	Non-cropland
Alfalfa_P	-0.0668*** (0.0247)	-0.0359*** (0.0118)	0.0294 (0.0267)
Corn_P	0.142** (0.0651)	0.161** (0.0747)	-0.460*** (0.104)
Sorghum_P	0.122 (0.157)	0.144** (0.0699)	-0.524** (0.226)
Soybeans_P	0.0986** (0.0389)	0.0921*** (0.0214)	-0.0904 (0.0719)
Wheat_P	0.113*** (0.0311)	0.0965*** (0.0182)	-0.145** (0.0641)
CRP_Rent	0.00377 (0.0363)	-0.0141 (0.0240)	0.0684*** (0.00848)
Pasture_Rent	-0.00293 (0.0143)	-0.00525 (0.0106)	0.0151* (0.00782)
NG_P	-0.00322* (0.00179)	0.000716 (0.000694)	0.000716 (0.000675)
DTW	-0.000560*** (0.000174)	0.000125 (0.000294)	0.000125 (0.000624)
Authorized_Q	0.00649*** (0.00100)	-0.00144*** (0.000246)	-0.00144* (0.000767)

Bootstrap Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix: Additional tables

Table 3.8: First stage estimations for SUR-HEAR land-use share equations

Variables	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Ln_sAlflfa(t-1)	0.9561***	0.0249*	0.1005***	0.0084	0.0163
	(0.0184)	(0.0133)	(0.0311)	(0.0192)	(0.0181)
Ln_sCorn(t-1)	-0.0820***	0.8711***	-0.0655	0.0452	-0.0298
	(0.0237)	(0.0205)	(0.0488)	(0.0380)	(0.0288)
Ln_sSorghum(t-1)	0.0180	0.0022	0.5791***	-0.0300	-0.1268
	(0.0184)	(0.0150)	(0.0379)	(0.0236)	(0.0934)
Ln_sSoybeans(t-1)	0.0279*	0.0833***	0.1192***	0.9765***	0.0105
	(0.0156)	(0.0150)	(0.0397)	(0.0255)	(0.0211)
Ln_sWheat(t-1)	-0.0317	0.0269	0.1620***	-0.0910***	0.9070***
	(0.0237)	(0.0179)	(0.0411)	(0.0254)	(0.0263)
WD(t-1)	0.0125*** (0.0026)	0.0052 (0.0039)	0.0040*** (0.0008)	0.0104*** (0.0026)	0.0472*** (0.0054)
WD(2-3 years)	0.0014*** (0.0002)	0.0004*** (0.0001)	0.0017*** (0.0005)	0.0001 (0.0003)	-0.0027*** (0.0003)
WD(4-5 years)	-0.0010*** (0.0002)	-0.0003* (0.0002)	-0.0039*** (0.0008)	-0.0005* (0.0003)	-0.0042*** (0.0006)
GDD(t-1)	-0.0001 (0.0001)	-0.0008*** (0.0001)	-0.0002 (0.0003)	0.0001 (0.0002)	-0.0000 (0.0000)
GDD(2-3 years)	-0.0007*** (0.0001)	-0.0006*** (0.0001)	-0.0002 (0.0003)	0.0008*** (0.0002)	-0.0005*** (0.0000)
GDD(4-5 years)	0.0007*** (0.0001)	0.0015*** (0.0002)	0.0011* (0.0005)	0.0001 (0.0003)	-0.0002 (0.0002)
EDD(t-1)	0.0001 (0.0002)	0.0015*** (0.0002)	0.0002 (0.0006)	0.0000 (0.0004)	-.0003 (0.0009)
EDD(2-3 years)	0.0014*** (0.0002)	0.0014*** (0.0002)	0.0006 (0.0006)	-0.0021*** (0.0003)	0.0066 (.00176)
EDD(4-5 years)	-0.0067*** (0.0012)	-0.0074*** (0.0012)	-0.0107** (0.0044)	-0.0181*** (0.0020)	-0.0040 (0.0032)
Alfalfa_P	0.0049*** (0.0005)	-0.0061*** (0.0004)	-0.0033** (0.0014)	-0.0108*** (0.0008)	-0.0041*** (0.0012)
Corn_P	-0.0044*** (0.0014)	-0.0064*** (0.0011)	0.0113*** (0.0038)	-0.0191*** (0.0022)	-0.0051*** (0.0011)
Sorghum_P	-0.0013 (0.0015)	-0.0034*** (0.0012)	0.0168*** (0.0037)	-0.0130*** (0.0022)	0.0349 0(.01228)
Soybeans_P	0.0008** (0.0003)	0.0015*** (0.0003)	-0.0017* (0.0010)	0.0002 (0.0005)	-0.0015** (0.0007)
Wheat_P	0.0005 (0.0004)	0.0019*** (0.0004)	0.0026* (0.0014)	0.0001 (0.0007)	0.0018 (0.0012)
CRP_Rent	0.0007 (0.0025)	0.0039*** (0.0005)	-0.0095* (0.0053)	0.0014* (0.0008)	-0.0172*** (0.0015)
Grassland_Rent	0.0131***	-0.0006	0.0159**	-0.0091**	-0.0328***

	(0.0020)	(0.0020)	(0.0069)	(0.0044)	(0.0069)
NG_P	-0.0109*** (0.0024)	-0.0068*** (0.0020)	0.0003 (0.0058)	-0.0050 (0.0040)	-0.0511*** (0.0078)
DTW	0.0009*** (0.0001)	-0.0004*** (0.0001)	0.0013 (0.0011)	0.0023*** (0.0003)	0.0003 (0.0013)
DTW(2-3 years)	-0.0001 (0.0008)	0.0014** (0.0006)	0.0004 (0.0017)	-0.0029** (0.0014)	-0.0003 (0.0019)
DTW(4-5 years)	-0.0006 (0.0008)	-0.0011** (0.0006)	-0.0024 (0.0017)	0.0009 (0.0013)	-0.0008 (0.0018)
Authorized_Q	-0.0004** (0.0002)	0.0002 (0.0002)	0.0025*** (0.0006)	0.0009*** (0.0003)	0.0095*** (0.0004)
Fertilizer_P	-0.0054*** (0.0009)	-0.0078*** (0.0007)	-0.0060** (0.0026)	-0.0038*** (0.0014)	-0.0071*** (0.0022)
Constant	-10.614*** (2.3797)	-4.2831 (3.5475)	-3.3830*** (0.6286)	-8.9780*** (2.3661)	-3.9292 (5.4668)
Observations	662	663	659	663	663
R-squared	0.98	0.99	0.89	0.99	0.98

Bootstrap standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.8: First stage estimations for SUR-HEAR land-use share equations (continued)

Variable	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Ln_sAlflfa(t-1)	0.8434*** (0.0263)	0.0042 (0.0111)	0.0151*** (0.0052)	0.0704*** (0.0176)	-0.0091 (0.0171)
Ln_sCorn(t-1)	-0.0466*** (0.0179)	0.2903*** (0.0258)	-0.0192 (0.0123)	-0.0575*** (0.0206)	0.6179*** (0.0396)
Ln_sSorghum(t-1)	-0.1195*** (0.0239)	0.0591 (0.0413)	0.7458*** (0.0229)	-0.0607 (0.0400)	-0.0280 (0.0633)
Ln_sSoybeans(t-1)	0.0146* (0.0079)	0.0160* (0.0095)	-0.0157*** (0.0041)	0.9275*** (0.0122)	0.0183 (0.0146)
Ln_sWheat(t-1)	-0.0534*** (0.0154)	0.0501** (0.0195)	-0.0320*** (0.0104)	0.0519*** (0.0177)	0.6055*** (0.0299)
WD(t-1)	-0.0077 (0.0062)	0.0023*** (0.0009)	0.0063* (0.0037)	0.0010 (0.0007)	0.0025 (0.0016)
WD(2-3 years)	0.0003 (0.0002)	-0.0003 (0.0005)	-0.0004** (0.0002)	-0.0005 (0.0004)	0.0003 (0.0009)
WD(4-5 years)	0.0004 (0.0003)	-0.0011 (0.0010)	0.0001 (0.0002)	0.0004 (0.0004)	-0.0018 (0.0017)
GDD(t-1)	-0.0005*** (0.0001)	-0.0026*** (0.0003)	0.0002 (0.0002)	-0.0008*** (0.0003)	0.0008 (0.0006)
GDD(2-3 years)	-0.0000 (0.0002)	0.0004 (0.0003)	-0.0007*** (0.0001)	-0.0002 (0.0002)	-0.0060*** (0.0005)
GDD(4-5 years)	0.0012*** (0.0004)	0.0031*** (0.0005)	-0.0002 (0.0002)	0.0014*** (0.0004)	0.0022** (0.0010)
EDD(t-1)	0.0009*** (0.0003)	0.0043*** (0.0006)	-0.0004 (0.0003)	0.0016*** (0.0005)	-0.0011 (0.0011)
EDD(2-3 years)	0.0002 (0.0004)	-0.0010 (0.0006)	0.0015*** (0.0003)	0.0003 (0.0004)	0.0113*** (0.0011)
EDD(4-5 years)	-0.0099*** (0.0023)	-0.0361*** (0.0044)	0.0087*** (0.0018)	-0.0150*** (0.0026)	0.0018 (0.0081)
Alfalfa_P	0.0064*** (0.0007)	-0.0107*** (0.0017)	-0.0011 (0.0007)	-0.0146*** (0.0012)	0.0060** (0.0027)
Corn_P	-0.0058*** (0.0018)	-0.0199*** (0.0033)	-0.0052*** (0.0013)	-0.0159*** (0.0032)	0.0011 (0.0059)
Sorghum_P	-0.0021 (0.0019)	-0.0103*** (0.0031)	-0.0023* (0.0013)	-0.0162*** (0.0032)	-0.0134** (0.0057)
Soybeans_P	0.0006 (0.0004)	0.0022** (0.0010)	-0.0014*** (0.0005)	0.0052*** (0.0007)	0.0031* (0.0019)
Wheat_P	0.0032*** (0.0006)	0.0032** (0.0014)	0.0011* (0.0006)	0.0041*** (0.0009)	0.0015 (0.0025)
CRP_Rent	0.0064* (0.0035)	0.0254*** (0.0054)	0.0049*** (0.0011)	-0.0021** (0.0010)	0.0159* (0.0096)
Grassland_Rent	-0.0078*** (0.0026)	0.0176*** (0.0068)	0.0099*** (0.0030)	-0.0029 (0.0043)	-0.0032 (0.0121)
Fertilizer_P	-0.0114***	-0.0297***	0.0034**	-0.0114***	0.0240***

	(0.0012)	(0.0030)	(0.0013)	(0.0021)	(0.0052)
Constant	-18.2611** (8.7595)	-2.2972*** (0.5978)	-7.0757** (3.3171)	-0.9890 (0.6157)	-1.0707 (1.0646)
Observations	651	663	663	635	663
R-squared	0.9998	0.7488	0.9857	0.9959	0.6822

Bootstrap standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 3.8: First stage estimations for SUR-HEAR land-use share equations (continued)

Variable	CRP	Pasture
Ln_CRP(t-1)	0.9010*** (0.0118)	0.0371 (0.0265)
Ln_Grassland(t-1)	-0.0144 (0.0098)	0.6485*** (0.0278)
WD(t-1)	-0.0019** (0.0008)	-0.0038*** (0.0006)
WD(2-3 years)	0.0001 (0.0002)	-0.0018*** (0.0005)
WD(4-5 years)	0.0002 (0.0002)	0.0032*** (0.0006)
GDD(t-1)	0.0003** (0.0002)	-0.0004 (0.0003)
GDD(2-3 years)	0.0011*** (0.0001)	0.0018*** (0.0003)
GDD(4-5 years)	-0.0020*** (0.0002)	-0.0010*** (0.0004)
EDD(t-1)	-0.0007** (0.0003)	0.0007 (0.0006)
EDD(2-3 years)	-0.0024*** (0.0003)	-0.0043*** (0.0006)
EDD(4-5 years)	0.0157*** (0.0019)	0.0147*** (0.0039)
Alfalfa_P	0.0057*** (0.0007)	0.0233*** (0.0020)
Corn_P	0.0162*** (0.0016)	0.0224*** (0.0038)
Sorghum_P	0.0148*** (0.0017)	0.0010 (0.0038)
Soybeans_P	-0.0027*** (0.0005)	0.0016 (0.0011)
Wheat_P	0.0008 (0.0006)	-0.0036** (0.0016)
CRP_Rent	-0.0017*** (0.0005)	0.0025 (0.0023)
Grassland_Rent	0.0028 (0.0029)	-0.0078 (0.0051)
Fertilizer_P	0.0001 (0.0013)	0.0212*** (0.0034)
Constant	1.5698** (0.7361)	3.4411*** (0.5383)
Observations	663	663
R-squared	0.98	0.99

Bootstrap standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Chapter 4 - Local irrigation decisions and irrigated crop acreage response to ethanol market expansion in the High Plains Aquifer Kansas

4.1 Introduction

The 2005 Energy Policy Act (EPA) created the renewable fuel standard (RFS) and mandated the amount of biofuel mixed with gasoline sold in the United States to 7.5 billion gallons by 2012. Two years later, Congress passed the Energy Independence and Security Act of 2007, which extended the target amount of biofuel that must be mixed with gasoline sold in the United States to 36 billion gallons by 2022 (NRC, 2012). From 2001 to 2016, global ethanol production grew from about 5 billion gallons to over 25 billion gallons. Currently, about half of global ethanol production is met by the U.S. Moreover, more than 98% of gasoline sold in the United States contains 10% ethanol (Beckman and Nigatu 2017; RFA 2018).

The increase in biofuel production led to concerns over food availability and environmental impacts (Hausman et al., 2012). The biofuel industry primarily relies on corn as feedstock to ethanol production. Nearly 5.5 billion bushels of corn were used for ethanol production in 2018 (ERS, 2019). Corn acreage has increased substantially in Kansas since passage of the RFS mandate. From 2006 to 2007 total corn acreage increased by 550,000 acres (i.e., a 16.5% increase). Approximately half the increase in corn acreage was met by increases in irrigated production (USDA-NASS). Many U.S ethanol plants are located in the Corn Belt region, which is the nation's largest corn producing region (Motamed et al. 2016; Wright et al. 2017). In Kansas, out of 12 ethanol plants, 9 ethanol plants are located over the High Plains Aquifer (HPA) region of the state, which also largest corn producing region in Kansas (Fig. 4.1).

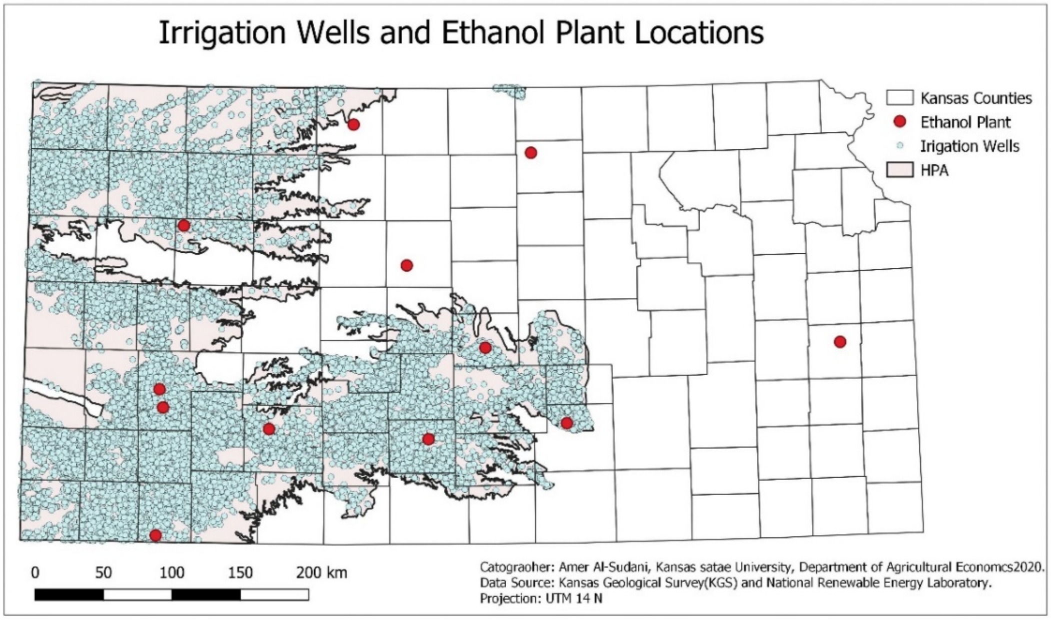

Fig. 4.1: Irrigation fields and ethanol plant locations over HPA Kansas. Source: KGS, 2018

The HPA is the primary water source in western and central Kansas. However, intensive pumping from the aquifer has led to declining water levels, especially in the western part of the aquifer (Buchanan et. al., 2001). Water level declines from 2000 to 2017 ranged from 5 feet to more than 80 feet in southwest Kansas (Fig. 4.2).

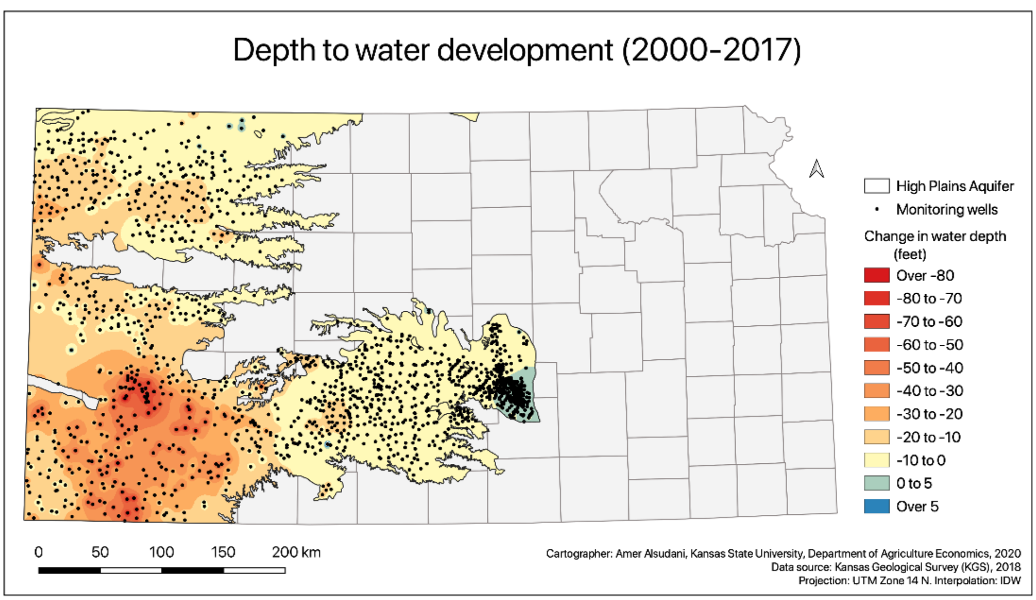

Fig. 4.2: Depth to water development in the HPA Kansas (2000-2017). Source: KGS, 2018.

Despite goals of government policies (e.g., RFS mandate) to improve environmental standards and decrease U.S reliance on oil, the RFS may affect groundwater depletion due to changes in farmer's crop choices and irrigation decisions. Expansions in ethanol production necessary to meet RFS mandates have caused an increase in the demand for feedstock grains (e.g., corn), resulting in crop price increases and crop grains production (Rosegrant 2008; Babcock 2011; McPhail and Babcock 2012; Gorter et. al. 2013; Serra and Zilberman 2013; Motamed et al. 2016; Wright et al. 2017).

Much of the existing literature on the impact of biofuel policy has focused on commodity prices and land use change, and crop selection (Miao 2016; Motamed et al. 2016; Wright et al. 2017). However, the resultant local environmental (e.g., groundwater depletion) impacts are less studied. The purpose of this chapter is to examine the impact of ethanol market expansion on local irrigation decisions in the Kansas portion of the HPA. In addition, we aim to quantify the impact of RFS policy on irrigated cropping patterns. We aim to estimate the effect of an ethanol plant's location and production capacity on irrigation water demand using the following three margins of adjustment: (i) extensive margin (changes in irrigated acreage per field), (ii) intensive margin (changes in water applied per acre), and (iii) total margin (changes in total water use per field). Furthermore, we aim to estimate the effect of an ethanol plant's location and production capacity on irrigated cash crop acreage (alfalfa, corn, sorghum, soybeans, and wheat).

Results of this study are expected to provide policymakers with important information concerning the potential impacts of RFS policy on changing in irrigation decisions and the consequences on groundwater availability. Moreover, much of the existing research on land use change and water resources is aggregated up to the county, national, or global scale (Delucchi, 2010; Fingerman, 2010; Piroli and Ciaian 20102; Pimental et. al. 2008). Aggregated analyses can mask important spatial heterogeneities and suffer from omitted variable bias. By comparison, this analysis uses a comprehensive field-level data on groundwater use and irrigated crops acreages, which allows for a more fine scale control of factors influencing irrigation decisions (e.g., hydrologic and climate conditions).

4.2 Background

The ethanol industry is the largest biofuel sector in the United States, with production increasing from 2 billion gallons in 2000 to about 15 billion gallons in 2015 (Fig. 4.3). However, the largest shift in ethanol production occurred in 2009 when the production increased from 7 billion gallons in 2008 to 12 billion gallons in 2009. This increase in ethanol production is tied to increased corn acreage in Iowa, Illinois, Nebraska, and Minnesota. The largest increases were in South and North Dakota. Kansas also had substantial increase in corn production in responses to ethanol market expansion (Duffield et. al., 2015).

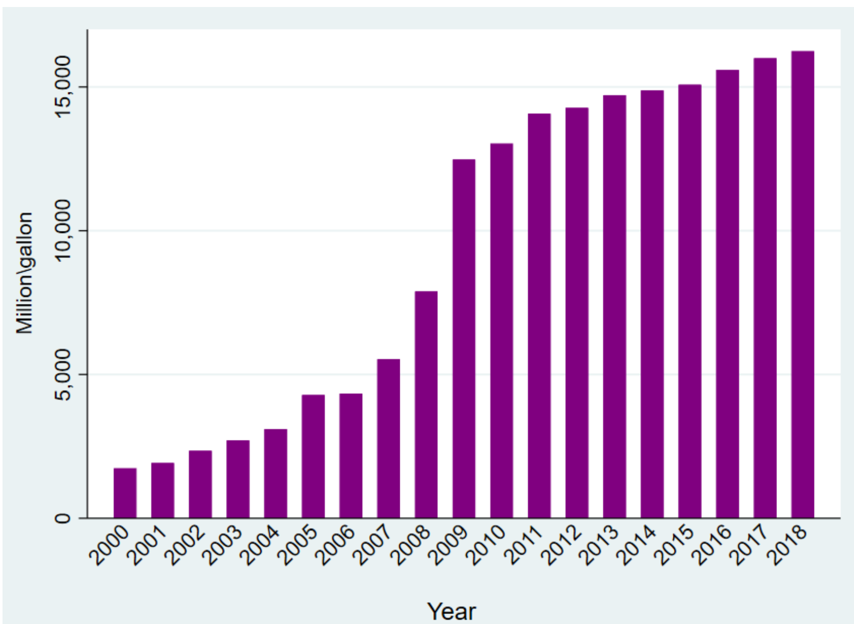

Fig. 4.3: Total USA ethanol production Capacity. Source: RFA, 2018.

In Kansas, from 2004 to 2009, statewide ethanol capacity grew from about 103 million gallons to 490 million gallons (Fig. 4). After 2009, statewide capacity remained relatively constant until 2015 where the capacity again increased slightly.

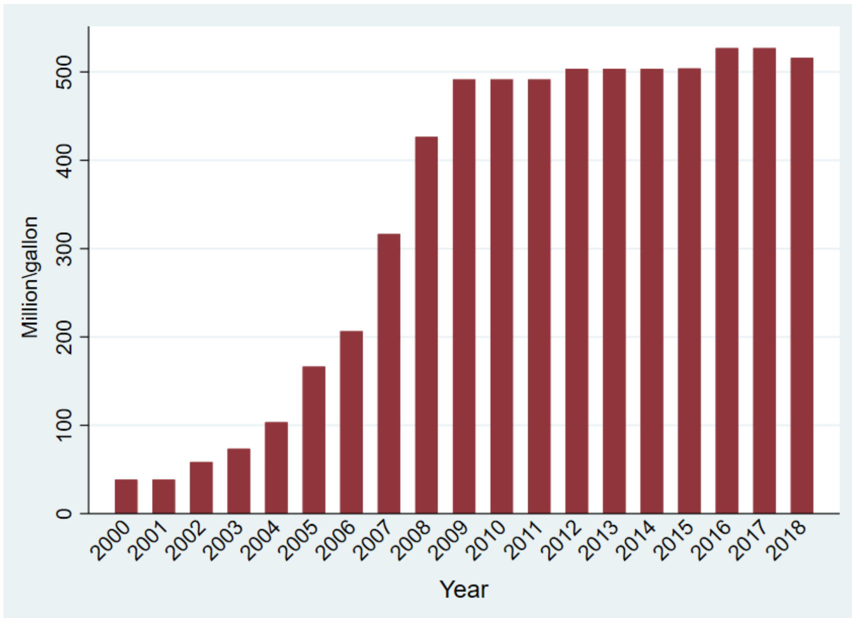

Fig. 4.4: Total Kansas ethanol production capacity. Source: RFA, 2018.

Fig. 4.5 shows the share of Kansas ethanol industry relates the US ethanol industry. In 2000, the share was 2%. The highest level of shares occurred in 2007 at about 5% of the total domestic production. After 2007, the share of Kansas ethanol production declined due to higher rates of increase in nationwide ethanol production relative to the rate of increase in Kansas (Figs. 4.3 and 4.4).

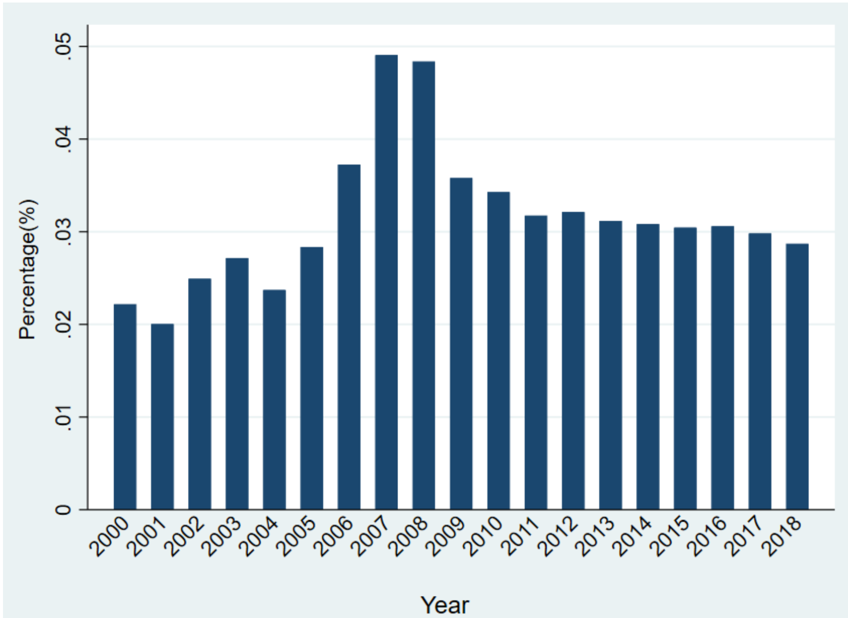

Fig. 4.5: Kansas share of ethanol production capacity. Source: RFA, 2018.

The ethanol industry mainly relies on corn as a feedstock for ethanol production. In addition, net price received by farmers depends on the location of the ethanol plant location as a market terminal. Wright et al. (2017) finds that corn production increased within 50 miles, with significant increases occurring within 25 miles from an ethanol plant location. In addition, Brown et al. (2014) estimate a significant relationship between county-level corn acreage and distance to the nearest ethanol plant. In this essay, we examine the relationship between ethanol plant location and irrigation decisions within 25KM and 50KM neighborhoods[1] to capture the impact of local ethanol markets on irrigation decision and irrigated crop acreage.

The most common irrigated crop in Kansas is corn. Irrigated corn acreage has increased over the last 20-year period, representing between 43% and 60% of the total irrigated area. In addition, corn considered the most water intensive crop in Kansas, with an average of 1.2 acre-feet applied per acre. Therefore, an increase in corn production increases concern over depletion of the

[1] The area located within radius of 25KM and 50KM around ethanol plant location

Kansas HPA (Kenny and Juracek 2013). Corn acreage has increased substantially in Kansas since passage of the RFS mandate. From 2006 to 2008 irrigated corn acreage per field increased within 50KM neighborhood distance around ethanol plants, while for the distance >50KM there is a decrease in the irrigated area dedicated to corn production per field (Fig. 4.6).

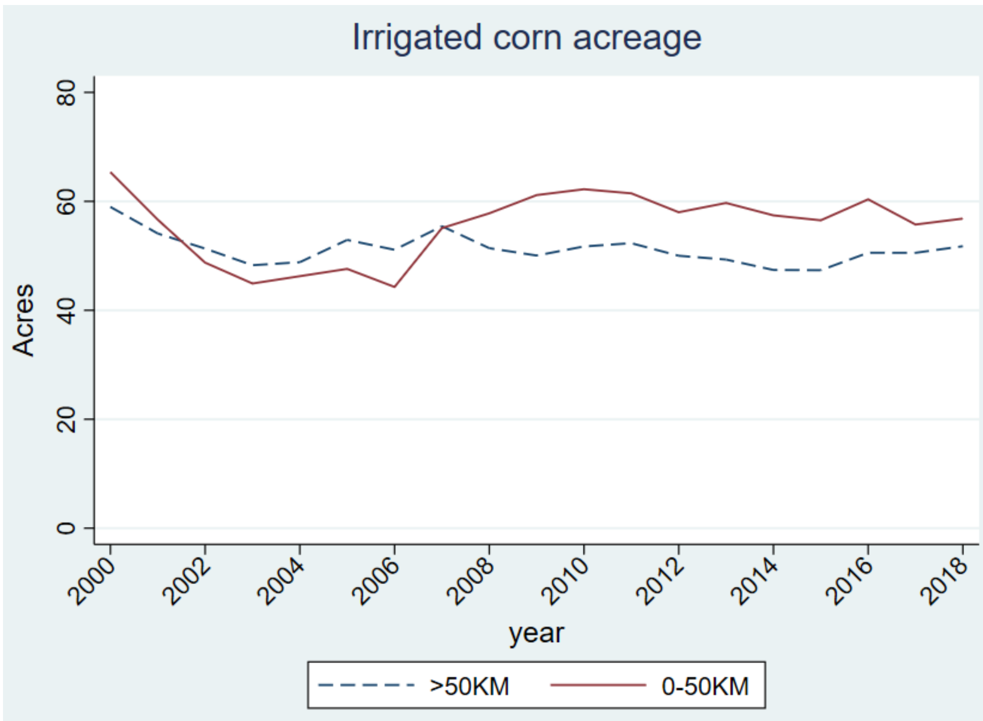

Fig. 4.6: Irrigated corn acreage per field over the HPA Kansas (2000-2018). Source: KGS, 2018.

Resulting from increases in irrigated acres per field, primarily in corn acreage within 50KM distances from ethanol plants. Moreover, given the fact that corn production accounts for 40% to 60% of the cultivated crop area in Kansas, the trend of total groundwater amount extracted from HPA in Kansas increased overtime. In particular, there was a shift in total water used from 2005 to 2010 at about more than double in response to increases in irrigated acres per filed and corn acreage in same period of time (fig. 4.7).

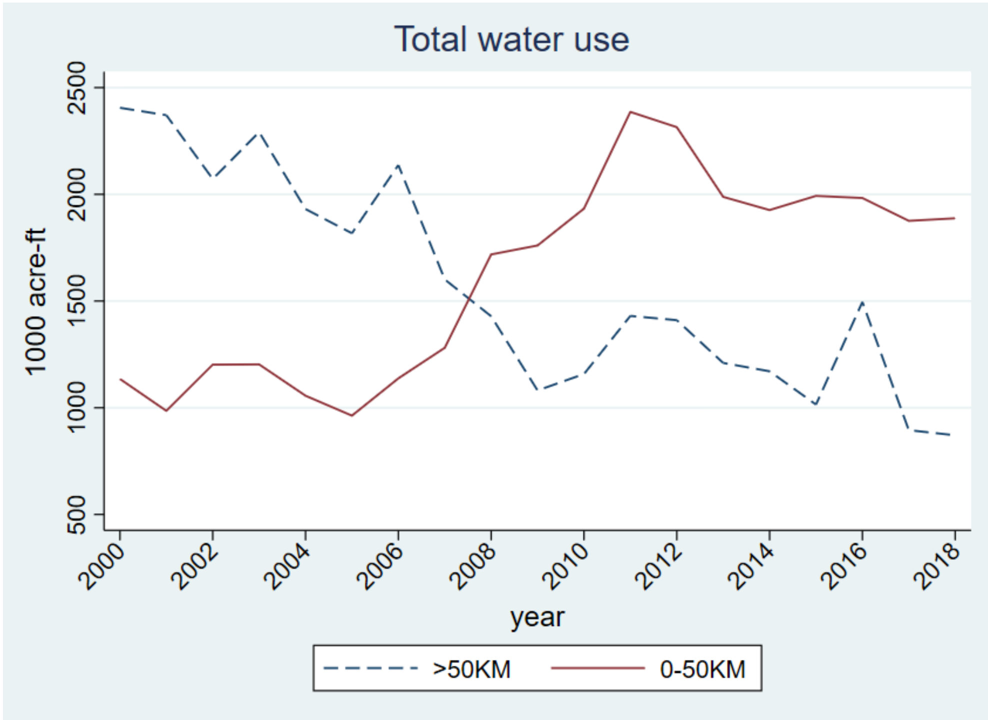

Fig. 4.7: Total groundwater used over HPA Kansas (2000-208). Source: KGS, 2018.

The number of ethanol plants in Kansas has increased from 3 plants in 2000 to 12 plants in 2013, while production capacity has increased from 38.5 to 527 million gallons in 2016. As the production capacity increased, average production capacity per field increased from about 0.84 million gallons in 2000 to 9.9 million gallons in 2009 for the 25KM neighborhood distance of fields around ethanol plant locations. Furthermore, within 50KM distance around ethanol plant location, the average production capacity per field increased from 2.2 million gallons in 2000 to 31.6 million gallons in 2009 (Table 4.1).

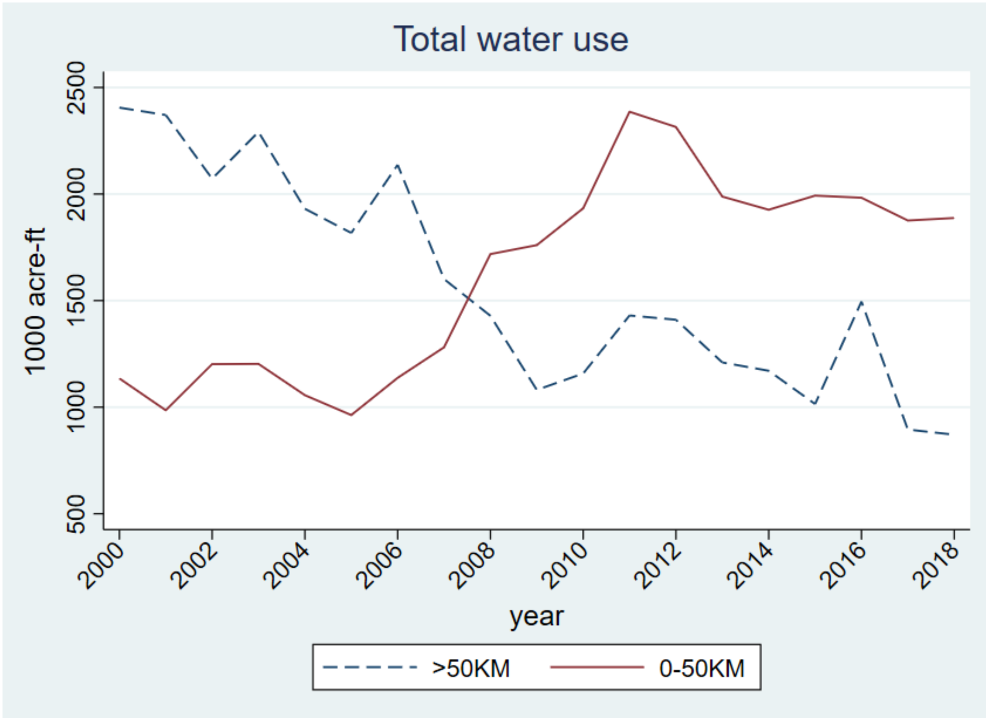

Fig. 4.8: Total groundwater used over HPA Kansas (2000-208). Source: KGS, 2018.

The number of ethanol plants in Kansas has increased from 3 plants in 2000 to 12 plants in 2013, while production capacity has increased from 38.5 to 527 million gallons in 2016. As the production capacity increased, average production capacity per field increased from about 0.84 million gallons in 2000 to 9.9 million gallons in 2009 for the 25KM neighborhood distance of fields around ethanol plant locations. Furthermore, within 50KM distance around ethanol plant location, the average production capacity per field increased from 2.2 million gallons in 2000 to 31.6 million gallons in 2009 (Table 4.1).

4.3 Methodology

This section provides a brief conceptual framework and empirical model of the ethanol market expansion impacts on local irrigation decisions in the Kansas HPA. First, we provide a description of water demand equation in order to examine the margins (extensive and intensive) in response to ethanol market expansion. Second, we examine the impact of ethanol plant locations on irrigation decisions and irrigated crop acreage. Finally, we model extensive and intensive margins with respect to irrigation water use as a function of the distance to an ethanol plant. Importantly, the model is able to capture the impacts of ethanol plants location and production capacity on total water use, which in turn affect groundwater stocks in the aquifer.

4.3.1 Conceptual Model

The distance between field[2] and ethanol plant will affect the net price received by grain producers due to shipping costs (Motamed et. al. 2016). Assume there is a representative groundwater irrigator such that his or her water demand for a particular field is subject to ethanol plant production capacity in year *t* and location, *k*. The irrigator chooses the optimal total irrigated acreage, *a*, and the optimal applied water intensity in acre/feet per acre *w*, given ethanol plant production capacity, *cap*, and location, *k*. In order to examine the margins of response to ethanol market expansion, following Hendricks and Peterson (2012) and Drysdale and Hendricks (2018), we decompose the effect of ethanol market expansion into the following three margins of adjustment: (i) extensive, a, (ii) intensive, w, and (iii) total irrigation water use, W,. Total water use as a function of ethanol plant production capacity and location can be represented as:

$$W_{it}(\boldsymbol{Z}_{it}, cap_{it}^{k}) = a_{it}(\boldsymbol{Z}_{it}, cap_{it}^{k})w_{it}(\boldsymbol{Z}_{it,}, cap_{it}^{k}) \tag{4.1}$$

where $\boldsymbol{Z}_{it}$ is a vector of weather conditions, irrigation technology, hydrological factors, and cap_{it}^{k} is ethanol plant and production capacity within location, *k*, that have affected irrigator *i* in year *t*.

[2] We use term field to represent groundwater diversion (well) location. Each well can serve one or more field for irrigation.

Differentiating equation (4.1) with respect to cap^k, and dividing by $W(cap^k)$, the percentage change in total water use is:

$$\frac{W'_{it}(cap^k)}{W_{it}(cap^k)} = \frac{a'_{it}(cap^k)}{a_{it}(cap^k)} + \frac{w'_{it}(cap^k)}{w_{it}(cap^k)} \tag{4.2}$$

Where $\frac{W'_{it}(cap^k)}{W_{it}(cap^k)}$ is percentage change in total water use; $\frac{a'_{it}(cap^k)}{a_{it}(cap^k)}$ is percentage change in the extensive margin; and $\frac{w'_{it}(cap^k)}{w_{it}(cap^k)}$ is percentage change in the intensive margin. Multiplying equation (4.2) by (cap^k) results in the following expression:

$$W'_{it}(cap^k)\frac{cap^k}{W_{it}(cap^k)} = a'_{it}(cap^k)\frac{cap^k}{a_{it}(cap^k)} + w'_{it}(cap^k)\frac{cap^k}{w_{it}(cap^k)} \tag{4.3}$$

This implies:

$$e^W = e^a + e^w \tag{4.4}$$

Where e^W is elasticity of the total water use; e^a is elasticity of the extensive; and e^w is elasticity of the intensive margins.

4.3.2 Empirical Model

To implement our models, we use panel data methods to estimate the relationship between local ethanol markets and total water use (W_{it}), number of acres irrigated (a_{it}), and amount of water applied per acre (w_{it}). Therefore, from equation (4.2) we aim to estimate the following reduced form models:

$$W_{it} = \boldsymbol{\theta}^W \boldsymbol{x}_{it} + \beta^W cap_{it}^k + \lambda_f^W + \varepsilon_{it}^W \tag{4.5}$$

$$a_{it} = \boldsymbol{\theta}^a \boldsymbol{x}_{it} + \beta^a cap_{it}^k + \lambda_f^a + \varepsilon_{it}^a \tag{4.6}$$

$$w_{it} = \boldsymbol{\theta}^w \boldsymbol{x}_{it} + \beta^w cap_{it}^k + \boldsymbol{\gamma}^w \boldsymbol{C}_{it} + \lambda_f^w + \varepsilon_{it}^w \tag{4.7}$$

where $\boldsymbol{x}_{it}$ is a vector of observable field characteristics that vary through time (e.g., weather variables, depth to water, and energy price), $\boldsymbol{C}_{it}$ is a vector of variables indicating the share of irrigated acres devoted to different crops (alfalfa, corn, sorghum, soybeans, wheat, and other cops), and cap_{it}^{k} is the cumulative ethanol plant capacity within distance zone k to field i. λ_s is a vector of field fixed effect. We complete the model with an error term that is robust to heteroscedasticity in the residuals distribution, ε_{it}. From these models, we aim to estimate the total change in irrigation water use (β^{W}), extensive margin response (β^{a}), and intensive margin response (β^{w}) considering the ethanol plant location, k and production capacity. In addition, we aim to estimate the elasticities in equations (4.3) and (4.4). However, the relationship in equation (4.4) will not strictly hold in this application due to potential measurement error and differences in the number of observations between regressions.

Ethanol plant location and production capacity can affect irrigated crop acreage. We decompose equation (4.6) into multiple irrigated crop equations. We aim to estimate irrigated crop acreage response to ethanol market expansion using the following equations:

$$\boldsymbol{crop}_{it} = \boldsymbol{\theta}^{c}\boldsymbol{x}_{it} + \beta^{c}cap_{it}^{k} + \lambda_{f}^{c} + \varepsilon_{it}^{c} \tag{4.8}$$

where $\boldsymbol{crop}_{it}$ is a vector of variables indicating irrigated acres devoted to different crops (alfalfa, corn, sorghum, soybeans, wheat, and other cops). Equation (4.8) provides the response in irrigated crop acreage under different crops to local ethanol market expansion.

4.4 Data

To implement our empirical model, a field-level panel data subset of more than 427,000 observations over the HPA in Kansas from 2000-2018 is used in this study. The Kansas portion of the HPA provides an ideal study area because of the reliance on the HPA for irrigated production.

In addition, most of the ethanol plants in Kansas are located in this region (Fig. 4.1). The data used for our estimation are obtained from different sources. Table 4.2 shows descriptions for the data we use in this study.

Information about total groundwater use for irrigations, irrigated field, irrigated crop acreages, and irrigation technology come from the Water Information Management and Analysis System (WIMAS) of the Kansas Division of Water Resources. For depth to water, we use the information of monitoring wells measurements obtained from the Water Field Levels Database (WIZARD), which is provided by the Kansas Division of Water Resources. In order to have accurate measurement of depth to water, we use the average measurement for December at year *t-1* and January at year *t* to get depth to water measurement for year *t*. The reason behind considering these two months is to obtain static water levels that are not affected by in-season pumping.

Ethanol plant production capacity information was obtained from the Renewable Fuels Association (RFA) and Nebraska Energy Office (NEO). Data on ethanol plant locations in Kansas come from the National Renewable Energy Laboratory.

Energy cost is the prominent factor in determining marginal pumping cost for irrigators, and accounts for approximately 10% of the cost for growing corn in western Kansas (Pfeiffer and Lin 2014; KFMA 2019). In Kansas, the major energy sources for pumping irrigation water are natural gas, diesel, and electricity, which account for (~50%), (~25%), and (~22%) of irrigation energy use, respectively (Rogers, 2008; Pfeiffer and Lin, 2013; Sampson and Perry, 2019). We converted all measurements of natural gas, diesel, and electricity to The British thermal unit (BTU) to get price per BTU for all energy sources, then we average energy price for diesel and electricity to develop a price index. Following Sampson and Perry (2019), we use natural gas prices as energy price for farmers located in counties producing natural gas. Otherwise, we use the electricity and diesel price index in counties not producing natural gas. Energy prices are obtained from the U.S Energy Information (EIA). We expect farmers will decrease pumping in response to increased energy prices (Pfeiffer and Lin 2014).

For climate data, we calculated field-level growing degree-days (GDD), extreme degree-days (EDD), and total precipitation in the growing season. Weather variables were calculated using daily precipitation and maximum and minimum temperature from the PRISM database using the method provided by Schlenker and Roberts (2009). This method calculated measurements for grid areas of 25 square kilometers. We assign grid area measurements to the nearest groundwater diversion. GDD measures the exposure to heat within a range of temperatures (8C^{o}-30C^{o}). EDD measures the exposure to heat for temperatures exceeding the maximum in GDD (GDD>30). Both GDD and EDD are measured as accumulative degree-days within the growing season (April 1-September 30). Precipitation is calculated as the accumulative amount of precipitation within the growing season (Hendricks et. al., 2014). For soil characteristics, we use the Soil Survey Geographic database (SSURGO) metadata. From this website, we obtained county-level data for average slope, as well as silt and sand shares in the soil. Soil data is constant over time but varies across counties.

Water deficit, water demand, or water requirement refers to the amount of water lost via evapotranspiration (Ep), which includes evaporative water from soil and crops, as well as transpiration water from crops to the atmosphere (Gheewala et. al. 2017). Water deficit (WD) is evaporative demand not met by available water (Stephenson 1990). For simplicity, water deficit is calculated using the following formula:

$$WD_{it} = Ep_{it} - Prec_{it} \tag{4.9}$$

where WD_{it} is the water deficit in field i at year t and Ep_{it} is the evapotranspiration in field i at year t during the growing season. Evapotranspiration is obtained from the United States Geological Survey (USGS) for years 2001-2014 while for the rest of the time period obtained from Kansas Mesonet. Mesonet has one or more station in each county. we assign the nearest station to each field.

4.5 Empirical Model Estimation

The available data set was used to estimate the marginal effects of ethanol plant location and production capacity on total water use, extensive margin, intensive margin, and irrigated crop acreage. In addition, we estimate the respective elasticities with respect to ethanol capacity expansion. Following previous findings, we chose the 50KM as the focal neighborhood distance because fields located close to a plant will receive higher net grain prices due to shipment cost (Motamed et al. 2016). For completeness, we also explore a treatment group defined at 25KM.

4.5.1 Marginal Effect Estimations of Ethanol Plant

In order to quantify the impact on irrigation decision and irrigated cop acreage in response to ethanol plant location, *k*, we estimate equations (4.3)-(4.6) using neighborhood distance *k* = [25, 50] KM. To quantify the effect of having one or more plants within 50KM or 25KM, we use the cumulative number of ethanol plant within each neighborhood distance regardless of production capacity (table 3).

Table 3 shows that marginal effect total, extensive, intensive margin, and irrigated corn acreage increases when one or more new ethanol plant build close to field. Specifically, the amount of total water use increases by 12.36 acre/feet field when new plant built within the 25KM neighborhood while water use increases by 9.12 acre/feet per field within the 50KM neighborhood.

Total irrigated acres increase by 1.89 acres per field and water intensity increases by 0.92 acre/inch per acre per field within 25KM neighborhood while total irrigated acres increases by 1.06 acres and water intensity increases by 0.74 acre/inch per acre per field within 50KM neighborhood. For irrigated corn acreage, farmers increase the number of acres dedicated to irrigated corn by 3.22 acres per field within the 25KM neighborhood while irrigated corn acreage increases by 2.06 acres within 50KM. Furthermore, the results indicate a decrease in some other crops, specifically alfalfa, sorghum, and soybeans. Most coefficient estimates are statistically significant at the 0.01 significance level. Full OLS estimations for irrigation decision and irrigated crops can be found in the appendix.

4.5.2 Marginal Effect Estimations of Ethanol Production Capacity

Using the same neighborhood distances of 25KM and 50KM, we estimate marginal effect of ethanol production capacity on irrigation decisions and irrigated crop acreage (Table 4.4). Table 4 reports the set of marginal effects of total water use, extensive margin, intensive margin, and irrigated crop acreage to ethanol production expansion. Looking across columns of table 4, we find that ethanol market expansion in the neighborhoods of a field increased irrigation water use along all margins and corn acreage. However, all margins and corn acreage in neighborhood of 25KM exhibit larger magnitudes than other neighborhoods. In particular, a one-unit increase (1 million gallons) in ethanol production capacity increased total water use by about 0.26 acre-ft, increased irrigated acreage by 0.04 acres, and increased irrigation intensity by about 0.017 acre-inches/acre per field for the 25KM neighborhood. A one-unit increase (1 million gallons) in ethanol production capacity increased total water use by about 0.19 acre-ft., increased irrigated acreage by 0.026 acres, and increased irrigation intensity by about 0.014 acre-inches/acre per field for the 50KM neighborhood. All coefficient estimates are statistically significant at the 1%

significance level. The effect of ethanol production capacity on irrigated crop acreage show that for corn acreage, a one-unit increase (1 million gallons) in ethanol refining capacity increased corn acreage by 0.055 acres per field for the 25KM distance while it increased by 0.04 acres per field for the 50KM distance. As expected, increased ethanol capacity corresponds with decreases in alfalfa, sorghum, and soybeans acreage. This indicates that there is substitution in irrigated land between corn and other crops as ethanol markets expand.

4.5.3 Additional OLS Estimations

For other OLS estimates, which can be found in Tables 4.8-4.9 in the appendix, the irrigation technology coefficients exhibit almost similar results. Irrigation technology can be interpreted as average total water use and average irrigated acreage for irrigators using a particular technology relative to a producer who fallows fields. For total and extensive margin, irrigators using center pivot, center pivot with LEPA, and "other irrigation" (e.g., subsurface or other sprinkler systems) tend to irrigate the largest fields and use more water than flood irrigation. For the intensive margin, the coefficients on irrigation technology are interpreted as the impact of irrigation technology on water intensity. The results indicate that center pivot, LEPA, and "other irrigations" systems all have lower irrigation intensities than flood irrigation. This finding supports that using irrigation technologies can improve water management and water use efficiency over flood irrigation (Hofield 2001; Tsakmakis et. al. 2018).

Irrigation water price is the cost of pumping an inch of water per acre to the land surface, which depends on energy prices and the pumping lift or depth to water (Hendricks and Peterson, 2012). Moreover, energy is an important input used to extract groundwater for irrigation in western Kansas (Pfeiffer and Lin 2014; KFMA 2019). The combined effects of energy price and its interaction with depth to water capture the marginal cost of pumping for the user. The coefficient on energy price is statistically significant in all margins estimates at a 1% significance level. The negative sign of the energy price coefficients indicate that irrigators reduce their total water use and irrigation intensity as energy price goes up. Depth to water shows a negative impact in most of the margins estimates. However, the interaction between depth to water and energy price shows a negative impact for the pumping cost on total water use all neighborhoods models.

Regarding the climate variables, water deficit shows a positive and significant impact in all margins for all neighborhoods models. This indicates that, total water use, irrigated acreage, and irrigation intensity increases as water deficit increase since increase in water deficit indicate that the level of precipitation did not offset evapotranspiration (equation (4.9)). For the coefficients on favorable and detrimental heat levels, which is represented by growing degree-days (8C-30C) and growing degree-days (>30C), respectively. The positive relationship of GDD and EDD are statistically significant for the total, intensive, and direct intensive margin responses, providing evidence that irrigators do increase water applications in response to heat stress, while decreasing water applied within favorable heat levels (8C-30C). Moreover, the coefficient on EDD for total irrigated acreage is positive and significant, which indicates that irrigators increase the proportion of a field that is irrigated to mitigate the impact of heat stress.

The coefficients on the crop share that only appear in the intensive margin equation, where the reference crop is “other crops”. For alfalfa, corn, and soybean irrigators apply more water per acre for both neighborhoods models. By comparison, water use intensities for sorghum and wheat significantly decrease when switching from “other crops” to sorghum and wheat.

4.5.4 Elasticity Estimations

For a better understanding of the irrigation decision response to ethanol production expansion, we also provide estimates of the elasticity of irrigation water use decisions with respect to ethanol plant production capacity within 25KM and 50KM neighborhood of a field (Table 4.5). All elasticities estimates show a significant impact at a 1% significance level. However, all elasticities estimates are in the inelastic range. Generally, the 50KM neighborhood model estimates show greater elasticities in all margins. In particular, we estimate a total water use elasticity of about 0.014 and 0.030 for the 25KM and 50KM neighborhood, respectively. This indicates that that a 10% increase in ethanol capacity leads to a 0.14% and 0.30% increase in total irrigation water use for the 25KM and 50KM neighborhood, respectively. At the extensive margin, a 10% increase in ethanol capacity leads to about a 0.017% and 0.049% increase in irrigated acreage for the 25KM and 50KM neighborhood, respectively. At the intensive margin, a 10% increase in ethanol capacity leads to about a 0.11% and 0.26% increase in acre-inches applied per acre for the 25KM and 50KM neighborhoods, respectively. Furthermore, 13% of the increase in total water use is due to increase in irrigated area for the 25KM and 50KM neighborhoods. For irrigated crops, the results indicate that a 10% increase in ethanol production capacity leads to increases in irrigated corn of 0.07% and 0.09% for 25KM and 50KM neighborhood, respectively.

As a robustness check, we estimate equations (4.5)-(4.7) using Seemingly Unrelated Regression Estimation (SURE). Given the fact in equation (4.1), the change in total water use is a result of the sum change in extensive and intensive margins. This fact brings the possibility that error term in equations (4.5)-(4.7) are correlated. We conducted a Breusch-Pagan test of independence (Gatignon, 2003). The results suggest that total, extensive, and intensive margin equation should be estimated as a system of equations. The results of SURE can be found in tables (4.14)-(4.17). All results coming from the SURE regression are consistent with the results of the OLS estimations. However, SURE estimations slightly are higher than those of OLS estimations. In addition, the elasticities of SURE estimations also higher than those of the OLS estimations.

Another potential concern is related to restrictions that might be imposed on irrigators. For instance, the HPA Kansas is managed by five Groundwater Management Districts (GMDs). Each GMD provides local water-use planning. Therefore, if GMDs impose different restrictions on irrigators, then our main estimations in tables (4.6)-(4.9) might overestimate the effects from the ethanol market. To control for this possibility, we estimates the equations in (4.5)-(4.7) with GMD and year fixed effects. Using GMD fixed effects and year fixed effects instead results in a slightly changes to our OLS results in tables (tables (4.18)-(4.21) in the Appendix).

4.6 Conclusion and discussion

Understanding the effects of biofuels policies on U.S. agriculture remains a priority for policy makers and researchers. In this chapter, we analyze local irrigation decisions in the Kansas portion of the HPA in response to ethanol market expansion. To identify the effects of ethanol market expansion, we exploit field-level data for years 2000-2018 on irrigation water use, irrigated acreage, and irrigated crop decisions. We adopt proximity of 25KM and 50KM neighborhoods of field from ethanol plant as treatment groups to capture the impact of ethanol plant location and capacity on irrigation behavior. In addition, we conducted irrigated crop acreage models to capture the impact of the ethanol market on cropping patterns. We find that ethanol plant location and production capacity has a positive and statistically significant effect on irrigated land and irrigation water use for local producers.

We estimate that the construction of a new ethanol plant increases total water use by 12.36 acre/feet and 9.12 acre/feet per field within 25KM and 50KM, respectively. In addition, we estimate that a 1-million-gallon increase in ethanol capacity leads to a 0.26 and 0.19 acre-ft increase in total water use per field for the 25KM and 50KM neighborhoods, respectively. Approximately 13% of total response in total water use is due to increases in irrigated acreage.

Furthermore, we estimate that a 10% increase in ethanol capacity increases irrigated corn by 0.7% and 0.9% for the 25KM and 50KM neighborhoods, respectively. Overall, our results increment off the existing literature on crop acreage response (e.g., Fatal and Thurman 2015; Miao 2016; Motamed et al. 2016; Wright et al. 2017; Li et al. 2018) by connecting irrigation behavior and irrigation water use to ethanol expansion. Increasing demand for ethanol feedstock to meet RFS mandates will require significant expansion of corn cropping, which will increase irrigation water demand, placing further stress on groundwater stocks.

Despite the advantage of using panel data to control for unobserved variation across space and time, there is still potential for omitted variables because the location of an ethanol plant is unlikely to be determined randomly across Kansas. In particular, the independent variable of interest (cap_{it}^{k}) in equations (4.5) – (4.8) may be correlated with the error term, resulting in biased estimation of the effect of ethanol market expansion on irrigation decisions. One way to account for this possible endogeneity is to identify an instrument that is correlated with ethanol capacity yet uncorrelated with irrigation water use.

Tables

Table 4.1: Number, total production capacity, and average production capacity of ethanol plants

Year	No. active plants	Statewide Capacity	capacity (25KM)	capacity(50KM)
2000	3	38.5	0.85	2.27
2001	3	38.5	0.87	2.33
2002	4	58.5	1.41	3.72
2003	4	73.5	1.31	3.43
2004	5	103.5	1.32	3.44
2005	5	166.5	1.43	3.73
2006	6	206.5	1.47	4.20
2007	7	316.5	6.84	19.98
2008	11	426.5	8.15	26.43
2009	11	491.5	9.95	31.62
2010	11	491.5	9.96	31.69
2011	11	491.5	9.86	31.16
2012	11	503.5	9.92	31.90
2013	12	503.5	9.92	31.88
2014	12	503.5	9.98	31.84
2015	12	504	9.96	31.84
2016	12	527	9.96	31.86
2017	12	527	9.96	31.80
2018	12	516	9.88	31.64
Note: Capacity in millions of gallons				

Table 4.2: Descriptive statistics of explanatory variables

Variable	Unit	Obs.	Mean	Std. Dev.
Total water used (Total)	Acre-feet	427,914	125.775	117.945
Acres irrigated (Extensive)	Acres	427,914	110.785	87.798
Irrigation intensity (Intensive)	Acre-in/acre	427,914	10.738	7.809
Ethanol capacity within 25KM	Millions of gallons	427,914	6.613	16.153
Ethanol capacity within 50KM	Millions of gallons	427,914	20.811	27.522
Center pivot (standard)	0,1	427,914	0.094	0.292
Center pivot with LEPA	0,1	427,914	0.566	0.496
Flood	0,1	427,914	0.061	0.239
Other Irrigation	0,1	427,914	0.066	0.248
Energy price	$/BTU	427,914	10.330	3.646
Depth to water	feet	427,914	129.989	91.906
Water deficit	Millimeters	427,914	477.669	97.675
Degree days (8C-30C) (GDD)	Degrees*days	427,914	6012.825	472.535
Degree days (>30C) (EDD)	Degrees*days	427,914	2447.621	161.889
Sand	% in soil	427,914	33.368	25.259
Silt	% in soil	427,914	43.579	19.472
Slope	%	427,914	2.319	3.086
alfalfa	0-1	427,914	0.086	0.234
corn	0-1	427,914	0.377	0.430
sorghum	0-1	427,914	0.054	0.154
soybeans	0-1	427,914	0.110	0.255
wheat	0-1	427,914	0.102	0.214
other	0-1	427,914	0.021	0.128

Table 4.3: Marginal effect of Irrigation decision and crop acreage to ethanol plant location

Marginal effect	25KM neighborhood	50KM neighborhood
Total	12.3652*** (0.7718)	9.1227*** (0.4786)
Extensive	1.8964** (0.4307)	1.0682*** (0.2952)
Intensive	0.9281*** (0.0529)	0.7459*** (0.0325)
Alfalfa	-1.5336** (0.5411)	-1.2405*** (0.3496)
Corn	3.2274*** (0.5920)	2.0621*** (0.4374)
Sorghum	-0.3697 (0.2277)	0.5470*** (0.1734)
Soybeans	-1.3866*** (0.3403)	-0.8435*** (0.2387)
Wheat	1.2898*** (0.3905)	1.5402*** (0.2741)

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Regressions included field fixed-effects

Table 4.4: Marginal effect of irrigation decision and crop acreage to ethanol production capacity

Variable	25KM	50KM
Total	0.2619*** (0.0174)	0.1945*** (0.0109)
Extensive	0.0437*** (0.0103)	0.0260*** (0.0055)
Intensive	0.0171*** (0.0010)	0.0143*** (0.0006)
Alfalfa	-0.0291*** (0.0091)	-0.0258*** (0.0056)
Corn	0.0555*** (0.0108)	0.0400*** (0.0078)
Sorghum	-0.0026 (0.0042)	0.0092*** (0.0030)
Soybeans	-0.0123** (0.0059)	-0.0066* (0.0040)
Wheat	0.0239*** (0.0078)	0.0195*** (0.0051)

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Regressions included field fixed-effects

Table 4.5:Elascticity estimations of irrigation decision and crop acreage to ethanol production capacity

Variable	25KM	50KM
Total	0.0139*** (0.0008)	0.0303*** (0.0015)
Extensive	0.0017*** (0.0005)	0.0049*** (0.0010)
Intensive	0.0112*** (0.0005)	0.0267*** (0.0010)
Alfalfa	-0.0139*** (0.0050)	-0.0258*** (0.0073)
Corn	0.0070*** (0.0014)	0.0096*** (0.0026)
Sorghum	-0.0022 (0.0035)	0.0301*** (0.0067)
Soybeans	-0.0055** (0.0026)	-0.0055 (0.0046)
Wheat	0.0097*** (0.0032)	0.0271*** (0.0053)

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Regressions included field fixed-effects

Appendix: Additional Tables

Table 4.6: OLS estimates of irrigation response to ethanol plant (25KM)

Variables	Total	Extensive	Intensive
Ethanol Plant	12.3654*** (0.7718)	0.8968** (0.4307)	0.9281*** (0.0529)
Center pivot	97.9895*** (1.1454)	115.6527*** (0.9527)	9.3894*** (0.0824)
Center pivot with LEPA	98.2578*** (1.0685)	115.0472*** (0.9249)	9.4584*** (0.0748)
Flood irrigation	82.3536*** (1.2875)	96.5256*** (1.1172)	9.9847*** (0.0987)
Other irrigation	101.2716*** (1.3228)	115.9035*** (1.1050)	9.5179*** (0.0877)
Depth to water	-0.1008*** (0.0109)	-0.0181*** (0.0063)	-0.0061*** (0.0007)
Energy price	-0.2675*** (0.0804)	0.0504 (0.0494)	-0.0788*** (0.0065)
Depth to water#Energy price	-0.0018*** (0.0006)	0.0001 (0.0004)	0.0002*** (0.0000)
Water deficit	0.0302*** (0.0014)	0.0002 (0.0009)	0.0028*** (0.0001)
Degree days 8C-30C	-0.0126*** (0.0045)	-0.0011 (0.0025)	-0.0017*** (0.0003)
Degree days>30C	0.0202 (0.0129)	0.0023 (0.0072)	0.0034*** (0.0010)
Alfalfa			2.6036*** (0.0804)
Corn			2.5093*** (0.0501)
Sorghum			-0.6454*** (0.0736)
Soybeans			1.8373*** (0.0534)
Wheat			-1.9976*** (0.0675)
Time trend	-1.6895*** (0.0364)	-0.1049*** (0.0248)	-0.1378*** (0.0026)
Constant	94.3880*** (5.7588)	24.8851*** (3.0916)	5.0819*** (0.4391)
Observations	427,914	427,914	427,914
R-squared	0.1501	0.3651	0.2801
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Regressions included field fixed-effects			

Table 4.7: OLS estimates of irrigation response to ethanol plant (50KM)

Variables	Total	Extensive	Intensive
Ethanol Plant	9.1222*** (0.4786)	1.0674*** (0.2952)	0.7459*** (0.0325)
Center pivot	98.1669*** (1.1483)	115.6747*** (0.9533)	9.4075*** (0.0825)
Center pivot with LEPA	98.3226*** (1.0708)	115.0472*** (0.9247)	9.4658*** (0.0749)
Flood irrigation	82.3025*** (1.2933)	96.5086*** (1.1172)	9.9831*** (0.0989)
Other irrigation	101.4647*** (1.3251)	115.9167*** (1.1049)	9.5356*** (0.0878)
Depth to water	-0.1011*** (0.0109)	-0.0187*** (0.0063)	-0.0062*** (0.0007)
Energy price	-0.1420* (0.0810)	0.0638 (0.0494)	-0.0687*** (0.0065)
Depth to water#Energy price	-0.0021*** (0.0006)	0.0001 (0.0004)	0.0002*** (0.0000)
Water deficit	0.0331*** (0.0015)	0.0006 (0.0009)	0.0031*** (0.0001)
Degree days 8C-30C	-0.0120*** (0.0046)	-0.0010 (0.0025)	-0.0016*** (0.0003)
Degree days>30C	0.0170 (0.0130)	0.0018 (0.0072)	0.0031*** (0.0010)
Alfalfa			2.6078*** (0.0807)
Corn			2.5086*** (0.0502)
Sorghum			-0.6606*** (0.0736)
Soybeans			1.8363*** (0.0534)
Wheat			-2.0074*** (0.0675)
Time trend	-1.8900*** (0.0398)	-0.1347*** (0.0274)	-0.1551*** (0.0029)
Constant	95.2490*** (5.7791)	25.0347*** (3.0932)	5.1579*** (0.4402)
Observations	427,914	427,914	427,914
R-squared	0.1506	0.3652	0.2808

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Regressions included field fixed-effects

Table 4.8: OLS estimates of irrigation response to ethanol capacity (25KM)

Variables	Total	Extensive	Intensive
Ethanol capacity	0.2639*** (0.0148)	0.0486*** (0.0086)	0.0182*** (0.0009)
Center pivot	97.9026*** (1.1442)	115.6443*** (0.9525)	9.3846*** (0.0823)
Center pivot with LEPA	98.1348*** (1.0671)	115.0278*** (0.9245)	9.4523*** (0.0747)
Flood irrigation	82.1924*** (1.2873)	96.4993*** (1.1173)	9.9765*** (0.0987)
Other irrigation	101.1786*** (1.3209)	115.8858*** (1.1047)	9.5138*** (0.0876)
Depth to water	-0.1008*** (0.0109)	-0.0186*** (0.0063)	-0.0060*** (0.0007)
Energy price	-0.2129*** (0.0804)	0.0553 (0.0495)	-0.0749*** (0.0065)
Depth to water#Energy price	-0.0020*** (0.0006)	0.0001 (0.0004)	0.0002*** (0.0000)
Water deficit	0.0310*** (0.0014)	0.0003 (0.0009)	0.0029*** (0.0001)
Degree days 8C-30C	-0.0119*** (0.0045)	-0.0010 (0.0025)	-0.0016*** (0.0003)
Degree days>30C	0.0178 (0.0129)	0.0020 (0.0072)	0.0032*** (0.0010)
Alfalfa			2.6074*** (0.0803)
Corn			2.5073*** (0.0501)
Sorghum			-0.6480*** (0.0735)
Soybeans			1.8345*** (0.0534)
Wheat			-1.9998*** (0.0674)
Time trend	-1.7405*** (0.0365)	-0.1156*** (0.0247)	-0.1404*** (0.0026)
Constant	96.4047*** (5.7554)	25.1428*** (3.0918)	5.2142*** (0.4386)
Observations	427,914	427,914	427,914
R-squared	0.1512	0.3652	0.2807

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Regressions included field fixed-effects

Table 4.9: OLS estimates of irrigation response to ethanol capacity (50KM)

Variables	Total	Extensive	Intensive
Ethanol capacity	0.1832*** (0.0089)	0.0259*** (0.0055)	0.0137*** (0.0005)
Center pivot	98.0068*** (1.1472)	115.6571*** (0.9528)	9.3954*** (0.0825)
Center pivot with LEPA	98.1269*** (1.0694)	115.0168*** (0.9241)	9.4532*** (0.0749)
Flood irrigation	82.2579*** (1.2970)	96.4950*** (1.1177)	9.9834*** (0.0989)
Other irrigation	101.5445*** (1.3248)	115.9275*** (1.1050)	9.5428*** (0.0878)
Depth to water	-0.1026*** (0.0109)	-0.0193*** (0.0063)	-0.0062*** (0.0007)
Energy price	-0.0078 (0.0809)	0.0853* (0.0494)	-0.0593*** (0.0065)
Depth to water#Energy price	-0.0027*** (0.0006)	-0.0000 (0.0004)	0.0001*** (0.0000)
Water deficit	0.0345*** (0.0015)	0.0009 (0.0009)	0.0031*** (0.0001)
Degree days 8C-30C	-0.0101** (0.0046)	-0.0007 (0.0025)	-0.0015*** (0.0003)
Degree days>30C	0.0112 (0.0130)	0.0009 (0.0072)	0.0027*** (0.0010)
Alfalfa			2.6113*** (0.0806)
Corn			2.5063*** (0.0501)
Sorghum			-0.6654*** (0.0735)
Soybeans			1.8326*** (0.0534)
Wheat			-2.0071*** (0.0674)
Time trend	-1.9803*** (0.0400)	-0.1560*** (0.0272)	-0.1596*** (0.0029)
Constant	99.4438*** (5.7828)	25.6772*** (3.0940)	5.4593*** (0.4400)
Observations	427,914	427,914	427,914
R-squared	0.1519	0.3652	0.2816

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Regressions included field fixed-effects

Table 4.10: OLS estimates of irrigated crop acreage response to ethanol plant (25KM)

Variables	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Ethanol plant	-1.2335** (0.5411)	3.2271*** (0.5920)	-0.3697 (0.2277)	-1.3862*** (0.3403)	1.2900*** (0.3905)
Center pivot	13.0687*** (0.4502)	45.6920*** (0.6970)	11.4887*** (0.3083)	12.2696*** (0.3436)	25.2692*** (0.5134)
Center pivot with LEPA	13.3081*** (0.3694)	45.2090*** (0.5832)	11.4235*** (0.2473)	12.8100*** (0.2488)	24.0645*** (0.4430)
Flood irrigation	10.5988*** (0.4011)	27.8688*** (0.6563)	15.4112*** (0.3485)	13.1840*** (0.3487)	21.5752*** (0.4819)
Other irrigation	14.7342*** (0.4311)	29.0874*** (0.7292)	14.2092*** (0.3401)	14.7837*** (0.3577)	25.1881*** (0.5181)
Depth to water	-0.0336*** (0.0056)	-0.0270*** (0.0078)	0.0174*** (0.0034)	-0.0206*** (0.0037)	0.0195*** (0.0051)
Energy price	0.0217 (0.0381)	0.0156 (0.0629)	-0.0289 (0.0251)	-0.1503*** (0.0381)	0.2189*** (0.0371)
Depth to water#Energy price	0.0010*** (0.0003)	0.0006 (0.0005)	0.0000 (0.0002)	0.0009*** (0.0002)	-0.0012*** (0.0003)
Water deficit	-0.0015** (0.0006)	0.0015 (0.0012)	-0.0057*** (0.0005)	0.0022*** (0.0007)	-0.0072*** (0.0007)
Degree days 8C-30C	0.0004 (0.0021)	-0.0015 (0.0037)	-0.0031* (0.0016)	-0.0037 (0.0023)	0.0030 (0.0022)
Degree days>30C	-0.0024 (0.0059)	0.0064 (0.0105)	0.0099** (0.0046)	0.0083 (0.0066)	-0.0068 (0.0063)
Time trend	-0.3249*** (0.0176)	0.0800*** (0.0272)	-0.0092 (0.0121)	0.0308** (0.0146)	-0.0564*** (0.0174)
Constant	12.2960*** (2.6603)	13.1043*** (4.6205)	-6.1785*** (2.0709)	8.0326*** (2.9319)	-3.9204 (2.6904)
Observations	427,914	427,914	427,914	427,914	427,914
R-squared	0.0221	0.0376	0.0188	0.0082	0.0325

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Regressions included field fixed-effects

Table 4.11: OLS estimates of irrigated crop acreage response to ethanol plant (50KM)

Variables	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Ethanol plant	-1.2405*** (0.3496)	2.0621*** (0.4374)	0.5470*** (0.1734)	-0.8435*** (0.2387)	1.5402*** (0.2741)
Center pivot	13.0179*** (0.4490)	45.7004*** (0.6959)	11.4823*** (0.3089)	12.2857*** (0.3434)	25.2884*** (0.5133)
Center pivot with LEPA	13.2986*** (0.3687)	45.2423*** (0.5827)	11.4287*** (0.2471)	12.7950*** (0.2487)	24.0724*** (0.4431)
Flood irrigation	10.6111*** (0.4009)	27.8825*** (0.6571)	15.4054*** (0.3484)	13.1682*** (0.3488)	21.5704*** (0.4822)
Other irrigation	14.7073*** (0.4307)	29.1239*** (0.7288)	14.2077*** (0.3399)	14.7491*** (0.3578)	25.1972*** (0.5182)
Depth to water	-0.0327*** (0.0056)	-0.0269*** (0.0078)	0.0158*** (0.0034)	-0.0206*** (0.0037)	0.0189*** (0.0051)
Energy price	0.0107 (0.0380)	0.0315 (0.0628)	-0.0308 (0.0251)	-0.1564*** (0.0380)	0.2273*** (0.0370)
Depth to water#Energy price	0.0010*** (0.0003)	0.0005 (0.0005)	0.0001 (0.0002)	0.0009*** (0.0002)	-0.0012*** (0.0003)
Water deficit	-0.0019*** (0.0006)	0.0018 (0.0012)	-0.0054*** (0.0005)	0.0020*** (0.0007)	-0.0069*** (0.0007)
Degree days 8C-30C	0.0000 (0.0021)	-0.0016 (0.0037)	-0.0029* (0.0016)	-0.0036 (0.0023)	0.0029 (0.0022)
Degree days>30C	-0.0012 (0.0059)	0.0064 (0.0105)	0.0092** (0.0046)	0.0083 (0.0066)	-0.0065 (0.0062)
Time trend	-0.2974*** (0.0178)	0.0642** (0.0282)	-0.0252** (0.0128)	0.0360** (0.0150)	-0.0735*** (0.0182)
Constant	75.0157 (49.9612)	-91.2252 (327.5205)	357.3855*** (40.6768)	-1,031.0884*** (327.7214)	169.6572* (91.4622)
Observations	427,914	427,914	427,914	427,914	427,914
R-squared	0.0221	0.0375	0.0189	0.0082	0.0327

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Regressions included field fixed-effects

Table 4.12: OLS estimates of irrigated crop acreage response to ethanol capacity (25KM)

Variables	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Ethanol capacity	-0.0251*** (0.0091)	0.0555*** (0.0108)	-0.0026 (0.0042)	-0.0123** (0.0059)	0.0239*** (0.0078)
Center pivot	13.0771*** (0.4502)	45.6723*** (0.6971)	11.4901*** (0.3083)	12.2755*** (0.3436)	25.2610*** (0.5131)
Center pivot with LEPA	13.3190*** (0.3696)	45.1919*** (0.5833)	11.4213*** (0.2473)	12.8044*** (0.2488)	24.0557*** (0.4427)
Flood irrigation	10.6130*** (0.4011)	27.8474*** (0.6562)	15.4079*** (0.3485)	13.1755*** (0.3488)	21.5640*** (0.4818)
Other irrigation	14.7421*** (0.4312)	29.0785*** (0.7292)	14.2060*** (0.3401)	14.7742*** (0.3577)	25.1826*** (0.5180)
Depth to water	-0.0336*** (0.0056)	-0.0263*** (0.0078)	0.0171*** (0.0034)	-0.0215*** (0.0037)	0.0196*** (0.0051)
Energy price	0.0164 (0.0380)	0.0284 (0.0629)	-0.0300 (0.0251)	-0.1546*** (0.0380)	0.2242*** (0.0371)
Depth to water#Energy price	0.0010*** (0.0003)	0.0005 (0.0005)	0.0001 (0.0002)	0.0010*** (0.0002)	-0.0012*** (0.0003)
Water deficit	-0.0016*** (0.0006)	0.0017 (0.0012)	-0.0057*** (0.0005)	0.0022*** (0.0007)	-0.0071*** (0.0007)
Degree days 8C-30C	0.0003 (0.0021)	-0.0014 (0.0037)	-0.0031* (0.0016)	-0.0037 (0.0023)	0.0031 (0.0022)
Degree days>30C	-0.0022 (0.0059)	0.0060 (0.0105)	0.0099** (0.0046)	0.0083 (0.0066)	-0.0070 (0.0063)
Time trend	-0.3207*** (0.0175)	0.0766*** (0.0272)	-0.0116 (0.0121)	0.0238 (0.0146)	-0.0590*** (0.0174)
Constant	12.1097*** (2.6576)	13.4727*** (4.6197)	-6.1767*** (2.0714)	8.0105*** (2.9322)	-3.7533 (2.6900)
Observations	427,914	427,914	427,914	427,914	427,914
R-squared	0.0222	0.0377	0.0188	0.0082	0.0325

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Regressions included field fixed-effects

Table 4.13: OLS estimates of irrigated crop acreage response to ethanol capacity (50KM)

Variables	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Ethanol capacity	-0.0258*** (0.0056)	0.0400*** (0.0078)	0.0092*** (0.0030)	-0.0066* (0.0040)	0.0295*** (0.0051)
Center pivot	13.0346*** (0.4492)	45.6780*** (0.6960)	11.4756*** (0.3088)	12.2998*** (0.3433)	25.2726*** (0.5131)
Center pivot with LEPA	13.3223*** (0.3690)	45.2106*** (0.5827)	11.4216*** (0.2471)	12.7989*** (0.2486)	24.0574*** (0.4428)
Flood irrigation	10.6232*** (0.4008)	27.8662*** (0.6572)	15.4030*** (0.3484)	13.1618*** (0.3489)	21.5666*** (0.4821)
Other irrigation	14.7087*** (0.4308)	29.1220*** (0.7287)	14.2074*** (0.3398)	14.7489*** (0.3577)	25.1965*** (0.5182)
Depth to water	-0.0326*** (0.0056)	-0.0270*** (0.0078)	0.0159*** (0.0034)	-0.0214*** (0.0037)	0.0193*** (0.0051)
Energy price	-0.0032 (0.0379)	0.0500 (0.0627)	-0.0268 (0.0251)	-0.1575*** (0.0379)	0.2355*** (0.0370)
Depth to water#Energy price	0.0010*** (0.0003)	0.0004 (0.0005)	0.0001 (0.0002)	0.0010*** (0.0002)	-0.0012*** (0.0003)
Water deficit	-0.0020*** (0.0006)	0.0020* (0.0012)	-0.0054*** (0.0005)	0.0022*** (0.0007)	-0.0069*** (0.0007)
Degree days 8C-30C	-0.0002 (0.0021)	-0.0013 (0.0037)	-0.0028* (0.0016)	-0.0036 (0.0023)	0.0030 (0.0022)
Degree days>30C	-0.0006 (0.0059)	0.0056 (0.0105)	0.0090* (0.0046)	0.0081 (0.0066)	-0.0068 (0.0062)
Time trend	-0.2893*** (0.0177)	0.0533* (0.0281)	-0.0259** (0.0127)	0.0249* (0.0150)	-0.0729*** (0.0181)
Constant	73.5874 (49.9361)	-89.3004 (327.1974)	357.6073*** (40.6036)	-1,029.8789*** (329.1191)	169.8908* (90.9340)
Observations	427,914	427,914	427,914	427,914	427,914
R-squared	0.0222	0.0376	0.0189	0.0082	0.0326

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Regressions included field fixed-effects

Table 4.14: SUR estimates of irrigation response to ethanol plant (25KM)

Variables	Total	Extensive	Intensive
Ethanol Plant	17.9342*** (0.4171)	10.0023*** (0.2881)	0.6100*** (0.0242)
Center pivot	150.5051*** (0.5150)	138.5155*** (0.3557)	12.6343*** (0.0344)
Center pivot with LEPA	152.0199*** (0.3417)	138.2307*** (0.2360)	12.6906*** (0.0260)
Flood irrigation	107.8482*** (0.6139)	99.0106*** (0.4240)	12.7545*** (0.0396)
Other irrigation	149.8776*** (0.5836)	142.6994*** (0.4030)	12.0433*** (0.0372)
Depth to water	0.1637*** (0.0064)	0.0832*** (0.0044)	0.0018*** (0.0004)
Energy price	-1.0145*** (0.0932)	-0.6646*** (0.0644)	-0.0860*** (0.0054)
Depth to water#Energy price	0.0017*** (0.0006)	0.0048*** (0.0004)	0.0001*** (0.0000)
Water deficit	0.0112*** (0.0019)	-0.0082*** (0.0013)	0.0020*** (0.0001)
Degree days 8C-30C	-0.0483*** (0.0057)	-0.0115*** (0.0039)	-0.0029*** (0.0003)
Degree days>30C	0.1279*** (0.0163)	0.0336*** (0.0112)	0.0074*** (0.0009)
Alfalfa			1.5021*** (0.0247)
Corn			1.2088*** (0.0191)
Sorghum			-0.8828*** (0.0322)
Soybeans			0.6487*** (0.0236)
Wheat			-1.4600*** (0.0259)
Time trend	-1.2898*** (0.0344)	0.1804*** (0.0237)	-0.1230*** (0.0020)
Constant	-30.3150*** (7.8070)	-22.9085*** (5.3919)	-0.2158 (0.4526)
Observations	427,914	427,914	427,914
R-squared	0.4397	0.5348	0.5900

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Regressions included county fixed-effects

Table 4.15: SUR estimates of irrigation response to ethanol plant (50KM)

Variables	Total	Extensive	Intensive
Ethanol Plant	10.4875*** (0.2907)	3.1956*** (0.2009)	0.5703*** (0.0168)
Center pivot	150.4460*** (0.5153)	138.5680*** (0.3561)	12.6230*** (0.0343)
Center pivot with LEPA	152.2850*** (0.3417)	138.4525*** (0.2361)	12.6914*** (0.0260)
Flood irrigation	108.6741*** (0.6140)	99.4735*** (0.4243)	12.7800*** (0.0396)
Other irrigation	150.4411*** (0.5838)	142.9963*** (0.4034)	12.0616*** (0.0372)
Depth to water	0.1586*** (0.0064)	0.0814*** (0.0044)	0.0015*** (0.0004)
Energy price	-0.8308*** (0.0934)	-0.6097*** (0.0645)	-0.0759*** (0.0054)
Depth to water#Energy price	0.0011** (0.0006)	0.0045*** (0.0004)	0.0001*** (0.0000)
Water deficit	0.0173*** (0.0019)	-0.0064*** (0.0013)	0.0023*** (0.0001)
Degree days 8C-30C	-0.0452*** (0.0057)	-0.0099** (0.0039)	-0.0028*** (0.0003)
Degree days>30C	0.1147*** (0.0163)	0.0278** (0.0113)	0.0069*** (0.0009)
Alfalfa			1.5080*** (0.0247)
Corn			1.2105*** (0.0191)
Sorghum			-0.8794*** (0.0322)
Soybeans			0.6522*** (0.0236)
Wheat			-1.4589*** (0.0259)
Time trend	-1.5014*** (0.0361)	0.1724*** (0.0249)	-0.1391*** (0.0021)
Constant	-23.7781*** (7.8137)	-20.7690*** (5.3991)	0.1284 (0.4524)
Observations	427,914	427,914	427,914
R-squared	0.5007	0.5700	0.6051

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Regressions included county fixed-effects

Table 4.16: SUR estimates of irrigation response to ethanol production capacity (25KM)

Variables	Total	Extensive	Intensive
Ethanol Plant	0.3717*** (0.0087)	0.1695*** (0.0060)	0.0142*** (0.0005)
Center pivot	150.8473*** (0.5149)	138.7154*** (0.3559)	12.6438*** (0.0344)
Center pivot with LEPA	152.1177*** (0.3415)	138.3175*** (0.2360)	12.6910*** (0.0260)
Flood irrigation	108.1803*** (0.6137)	99.2408*** (0.4241)	12.7626*** (0.0396)
Other irrigation	150.1667*** (0.5834)	142.8442*** (0.4031)	12.0528*** (0.0372)
Depth to water	0.2256*** (0.0038)	0.1309*** (0.0019)	0.0032*** (0.0002)
Energy price	-0.1948*** (0.0700)	-0.0555 (0.0432)	-0.0661*** (0.0036)
Depth to water#Energy price	0.0113*** (0.0019)	-0.0085*** (0.0013)	0.0020*** (0.0001)
Water deficit	-0.0483*** (0.0057)	-0.0125*** (0.0039)	-0.0029*** (0.0003)
Degree days 8C-30C	0.1270*** (0.0163)	0.0363*** (0.0112)	0.0072*** (0.0009)
Degree days>30C			1.5056*** (0.0247)
Alfalfa			1.2116*** (0.0191)
Corn			-0.8850*** (0.0322)
Sorghum			0.6517*** (0.0236)
Soybeans			-1.4622*** (0.0259)
Wheat	-1.3545*** (0.0346)	0.1721*** (0.0239)	-0.1264*** (0.0020)
Time trend	-0.0046*** (0.0003)	0.1572*** (0.0249)	-0.0395*** (0.0021)
Constant	-35.6862*** (7.7538)	-28.8145*** (5.3487)	-0.2513 (0.4486)
Elasticity	0.0185*** (0.0005)	0.0107*** (0.0004)	0.0073*** (0.0003)
Observations	427,914	427,914	427,914
R-squared	0.5012	0.5704	0.6049

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Regressions included county fixed-effects

Table 4.17: SUR estimates of irrigation response to ethanol production capacity (50KM)

Variables	Total	Extensive	Intensive
Ethanol Plant	0.3038*** (0.0057)	0.1484*** (0.0039)	0.0117*** (0.0003)
Center pivot	150.4152*** (0.5144)	138.4909*** (0.3556)	12.6281*** (0.0343)
Center pivot with LEPA	152.2211*** (0.3411)	138.3676*** (0.2358)	12.6944*** (0.0260)
Flood irrigation	108.4467*** (0.6129)	99.3608*** (0.4237)	12.7727*** (0.0396)
Other irrigation	150.2242*** (0.5828)	142.9030*** (0.4029)	12.0531*** (0.0372)
Depth to water	0.1537*** (0.0064)	0.0783*** (0.0044)	0.0014*** (0.0004)
Energy price	-0.6321*** (0.0934)	-0.4781*** (0.0645)	-0.0712*** (0.0054)
Depth to water#Energy price	0.0009* (0.0006)	0.0044*** (0.0004)	0.0001*** (0.0000)
Water deficit	0.0212*** (0.0019)	-0.0033** (0.0013)	0.0024*** (0.0001)
Degree days 8C-30C	-0.0443*** (0.0057)	-0.0093** (0.0039)	-0.0028*** (0.0003)
Degree days>30C	0.1085*** (0.0163)	0.0236** (0.0112)	0.0067*** (0.0009)
Alfalfa			1.5074*** (0.0247)
Corn			1.2100*** (0.0191)
Sorghum			-0.8853*** (0.0322)
Soybeans			0.6512*** (0.0236)
Wheat			-1.4592*** (0.0259)
Time trend	-1.8561*** (0.0370)	-0.0807*** (0.0256)	-0.1458*** (0.0021)
Constant	-16.5993** (7.8017)	-16.1690*** (5.3932)	0.3102 (0.4525)
Elasticity	0.0491*** (0.0009)	0.0280*** (0.0007)	0.0215*** (0.0006)
Observations	427,914	427,914	427,914
R-squared	0.5026	0.5711	0.6054

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Regressions included county fixed-effects

Table 4.18: OLS estimates of irrigation response to ethanol plant (GMDs) (25 KM)

Variables	Total	Extensive	Intensive
Ethanol Plant	11.17*** (0.301)	3.210*** (0.208)	0.623*** (0.0167)
Center pivot	156.0*** (0.524)	140.0*** (0.363)	12.17*** (0.0414)
Center pivot with LEPA	158.0*** (0.341)	140.5*** (0.236)	12.15*** (0.0350)
Flood irrigation	104.2*** (0.615)	95.30*** (0.425)	12.29*** (0.0456)
Other irrigation	153.0*** (0.594)	143.5*** (0.411)	11.73*** (0.0426)
Depth to water	0.228*** (0.00586)	0.144*** (0.00405)	0.00101*** (0.0003)
Energy price	-0.718*** (0.0902)	-0.674*** (0.0624)	-0.0615*** (0.00499)
Depth to water#Energy price	0.00538*** (0.0005)	0.00714*** (0.0003)	0.000300*** (2.97e-05)
Water deficit	0.0703*** (0.0024)	0.0132*** (0.0016)	0.00490*** (0.0001)
Degree days 8C-30C	-0.104*** (0.0052)	-0.0565*** (0.00361)	-0.00412*** (0.0002)
Degree days>30C	0.293*** (0.0151)	0.163*** (0.0104)	0.0104*** (0.000835)
Alfalfa			4.101*** (0.0427)
Corn			3.101*** (0.0332)
Sorghum			-3.231*** (0.0559)
Soybeans			1.366*** (0.0409)
Wheat			-4.401*** (0.0450)
Constant	-170.2*** (6.429)	-100.0*** (4.446)	-3.117*** (0.356)
Observations	427,914	427,914	427,914
R-squared	0.470	0.544	0.638

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Regressions included GMD fixed effects and year fixed-effects

Table 4.19: OLS estimates of irrigation response to ethanol plant (GMDs) (50 KM)

Variables	Total	Extensive	Intensive
Ethanol Plant	8.309*** (0.201)	2.135*** (0.146)	0.515*** (0.0117)
Center pivot	160.8*** (0.539)	140.3*** (0.363)	12.14*** (0.0414)
Center pivot with LEPA	160.4*** (0.350)	140.9*** (0.235)	12.14*** (0.0349)
Flood irrigation	101.7*** (0.631)	95.45*** (0.425)	12.31*** (0.0456)
Other irrigation	155.1*** (0.613)	143.6*** (0.411)	11.73*** (0.0426)
Depth to water	0.346*** (0.00561)	0.132*** (0.00404)	0.000661** (0.000323)
Energy price	-2.276*** (0.0795)	-0.759*** (0.0625)	-0.0526*** (0.00499)
Depth to water#Energy price	0.00323*** (0.000548)	0.00783*** (0.000372)	0.000250*** (2.97e-05)
Water deficit	-0.00318** (0.00148)	0.0191*** (0.00168)	0.00503*** (0.000135)
Degree days 8C-30C	-0.0885*** (0.00535)	-0.0636*** (0.00362)	-0.00379*** (0.000289)
Degree days>30C	0.332*** (0.0156)	0.181*** (0.0105)	0.00919*** (0.000836)
Alfalfa			4.096*** (0.0427)
Corn			3.132*** (0.0332)
Sorghum			-3.169*** (0.0559)
Soybeans			1.403*** (0.0409)
Wheat			-4.355*** (0.0450)
Constant	-305.4*** (6.444)	-103.1*** (4.453)	-2.080*** (0.356)
Observations	427,914	427,914	427,914
R-squared	0.433	0.543	0.638

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Regressions included GMD fixed effects and year fixed-effects

Table 4.20: OLS estimates of irrigation response to ethanol capacity (GMDs) (25 KM)

Variables	Total	Extensive	Intensive
Ethanol Plant	0.418*** (0.00717)	0.163*** (0.00497)	0.0165*** (0.000398)
Center pivot	155.9*** (0.523)	139.9*** (0.362)	12.17*** (0.0414)
Center pivot with LEPA	157.6*** (0.340)	140.3*** (0.236)	12.15*** (0.0349)
Flood irrigation	104.2*** (0.613)	95.26*** (0.425)	12.30*** (0.0456)
Other irrigation	152.9*** (0.593)	143.5*** (0.411)	11.73*** (0.0426)
Depth to water	0.224*** (0.00582)	0.145*** (0.00403)	0.000420 (0.000322)
Energy price	-0.612*** (0.0900)	-0.623*** (0.0623)	-0.0588*** (0.00499)
Depth to water#Energy price	0.00562*** (0.000535)	0.00714*** (0.000371)	0.000325*** (2.97e-05)
Water deficit	0.0696*** (0.00243)	0.0117*** (0.00168)	0.00506*** (0.000135)
Degree days 8C-30C	-0.107*** (0.00521)	-0.0562*** (0.00361)	-0.00439*** (0.000289)
Degree days>30C	0.295*** (0.0151)	0.162*** (0.0104)	0.0109*** (0.000835)
Alfalfa			4.139*** (0.0426)
Corn			3.101*** (0.0332)
Sorghum			-3.242*** (0.0559)
Soybeans			1.371*** (0.0409)
Wheat			-4.400*** (0.0450)
Constant	-160.2*** (6.415)	-96.39*** (4.442)	-2.680*** (0.355)
Elasticity	0.0194*** (0.0004)	0.0113*** (0.000298)	0.00691*** (0.000244)
Observations	427,914	427,914	427,914
R-squared	0.473	0.545	0.638

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Regressions included GMD fixed effects and year fixed-effects

Table 4.21: OLS estimates of irrigation response to ethanol capacity (GMDs) (50 KM)

Variables	Total	Extensive	Intensive
Ethanol Plant	0.388*** (0.00500)	0.163*** (0.00347)	0.0142*** (0.000278)
Center pivot	154.9*** (0.522)	139.5*** (0.362)	12.12*** (0.0414)
Center pivot with LEPA	157.5*** (0.339)	140.2*** (0.235)	12.13*** (0.0349)
Flood irrigation	104.7*** (0.611)	95.43*** (0.424)	12.31*** (0.0455)
Other irrigation	152.3*** (0.591)	143.2*** (0.410)	11.69*** (0.0425)
Depth to water	0.200*** (0.00579)	0.136*** (0.00401)	-0.000535* (0.000321)
Energy price	-0.168* (0.0900)	-0.431*** (0.0625)	-0.0431*** (0.00500)
Depth to water#Energy price	0.00487*** (0.000534)	0.00680*** (0.000370)	0.000299*** (2.96e-05)
Water deficit	0.0736*** (0.00241)	0.0130*** (0.00167)	0.00524*** (0.000134)
Degree days 8C-30C	-0.106*** (0.00519)	-0.0556*** (0.00360)	-0.00438*** (0.000288)
Degree days>30C	0.273*** (0.0150)	0.152*** (0.0104)	0.0102*** (0.000834)
Alfalfa			4.147*** (0.0426)
Corn			3.102*** (0.0332)
Sorghum			-3.213*** (0.0558)
Soybeans			1.379*** (0.0409)
Wheat			-4.353*** (0.0450)
Constant	-111.3*** (6.435)	-75.69*** (4.464)	-0.915** (0.357)
Elasticity	0.0570*** (0.0008)	0.0316*** (0.000657)	0.0211*** (0.0005)
Observations	427,914	427,914	427,914
R-squared	0.475	0.546	0.638

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Regressions included GMD fixed effects and year fixed-effects

Chapter 5 - Conclusion

Agriculture represents a major use of land across the globe. Half of the world's habitable land is used for agriculture. In addition, water is an essential factor for life on the planet. Besides being key to human survival, water for irrigation is considered the primary factor for raising the productivity of lands around the world. About 20% of the world's croplands are irrigated, but they produce around 40% of the global crop supply. Thus, farmers' decisions with regards to water use in the face of water scarcity is an important topic with economic and environmental implications. Agricultural land decisions are affected by economic factors (e.g., output and input prices) and environmental factors (e.g., climate, soil characteristics, water quality, water availability, ecology). Government policies can have direct and indirect impacts on farmers' cropping patterns and land use decisions. Land use decisions can have a direct impact on groundwater use and availability for crop production. The primary source of irrigation water in Kansas is the High Plains aquifer (HPA), which underlies about 175,000 square miles, in parts of eight states. The HPA has been extensively used for agricultural irrigation in Kansas began in the 1930s and 1940s. Prolonged pumping from this aquifer has led to declining water levels, especially in the southwestern part of the aquifer. Decreases in aquifer levels between 2000 and 2017 ranged from 5 feet to more than 80 feet in southwestern Kansas. In Kansas, groundwater is the source of water for 98% of all irrigated fields (Hendricks and Peterson, 2012).

In this dissertation, we examined the impact of agricultural land use in Kansas in the context of water scarcity, biofuel expansion, and government policy. The specific objectives are to: (i) examine how water scarcity impacts irrigated crop acreage decisions along different dimensions using an acreage response framework based on the multinomial logit framework. (ii) develop an acreage response modeling framework based on the nested logit framework and land budgeting in the context of water scarcity; (iii) quantify the impact of ethanol market expansion due to the RFS mandate on irrigation decisions along different margins. The study area is the HPA in Kansas using field-level and county-level data set.

Given the finding results in this dissertation, we find that water scarcity plays a significant role in shaping agricultural land use. In the second essay, it shown that water scarcity factors have both direct effects on irrigated production and indirect effects on other land uses, such as dryland crop production. Direct effects of water scarcity factors result in reallocation of irrigated land, while indirect effects results in reallocation among broader land use categories. Elasticity estimates show that producers respond significantly to different water scarcity factors, including natural gas prices, depth to water, water deficit, and amount of water permitted for extraction.

Since many acreage response studies combine irrigated and non-irrigated acreage as one dependent variable, results may not provide correct magnitude shifts in water or land use decisions when water scarcity factors change, which could have an impact on suggestions for policy. Knowing the magnitude of the shifts in acreage decisions as a result in changes to water scarcity factors can help policy-makers and producers' design policies that better promote water conservation and maintain farmer welfare. The NMNL model provided a flexible framework for this purpose, capturing the direct and indirect impact of water scarcity factors on agricultural land use.

For the impact of government policy (e.g. RFS) on irrigation decisions, we estimate that the construction of a new ethanol plant increases total water use per field within 25KM and 50KM. In addition, we estimate that a 1-million-gallon increase in ethanol capacity leads to increase in total water use per field for the 25KM and 50KM neighborhoods. Approximately 13% of total response in total water use is due to increases in irrigated acreage. Increasing demand for ethanol feedstock to meet RFS mandates will require significant expansion of corn cropping, which will increase irrigation water demand, placing further stress on groundwater stocks.

Our study focuses on the Kansas HPA due to its importance irrigated crop production in Kansas. A useful extension of these studies would be to include all irrigated regions of the country. For future study, we suggest considering the NMNL framework to analyze the land-use change among additional uses, suchas forest and residential development use to provide a better more holistic understanding of land use chage as response to climate change and population growth. In addition, we suggest including the impacts of ethanol production expansion on nitrogen loss and the its impacts on water quality.

References

Angrist, J. D., & Pischke, J. S. (2008). Mostly harmless econometrics: An empiricist's companion. Princeton university press.

Association of American Railroads. (2020). "Ethanol: Freight Rail Delivers Renewable Fuels." Retrieved March 9, 2020, from https://www.aar.org/article/freight-rail-ethanol/.

Babcock, B. A. (2012). The impact of US biofuel policies on agricultural price levels and volatility. China Agricultural Economic Review, 4(4), 407-426.

Bailey, Kenneth W., and Abner W. Womack. Wheat acreage response: a regional econometric approach. No. 244132. Food and Agricultural Policy Research Institute (FAPRI), 1985.

BecKMan, J. and G. Nigatu (2017). Global Ethanol Mandates: Opportunities for US Exports of Ethanol and DDGS. Economic Research Service of the US Department of Agriculture.

Bergtold, J. S., A. C. Sant'Anna, N. Miller, S. Ramsey and J. E. Fefield (2017). Chapter 2.2.1 - Water Scarcity and Conservation Along the Biofuel Supply Chain in the United States: From Farm to Refinery. Competition for Water Resources. J. R. Ziolkowska and J. M. Peterson, Elsevier: 124-143.

Bhalla, Priya. "Impact of declining groundwater levels on acreage allocation in Haryana." Economic and political weekly (2007): 2701-2707.

Bigelow, Daniel P., and Allison Borchers. Major Uses of Land in the United States, 2012. United States, Department of Agriculture, Economic Research Service, 2017.

Blackwell III, J. Lloyd. "Estimation and testing of fixed-effect panel-data systems." Stata Journal 5.2 (2005): 202-207.

Brown, J. C., E. Hanley, J. Bergtold, M. Caldas, V. Barve, D. Peterson, R. Callihan, J. Gibson, B. Gray, N. Hendricks, N. Brunsell, K. Dobbs, J. Kastens and D. Earnhart. 2014. Ethanol plant location and intensification vs. extensification of corn cropping in Kansas. Applied Geography 53: 141-148 DOI: https://doi.org/10.1016/j.apgeog.2014.05.021.

Buchanan, Rex, Robert W. Buddemeier, and B. Brownie Wilson. The high plains aquifer. Kansas Geological Survey, 2001.

Buchanan, Rex, Robert W. Buddemeier, and B. Brownie Wilson. The high plains aquifer. Kansas Geological Survey, 2001.

Bullock, Donald G. "Crop rotation." Critical reviews in plant sciences 11.4 (1992): 309-326.

Carpentier, Alain, and Elodie Letort. "Multicrop production models with Multinomial Logit acreage shares." Environmental and Resource Economics 59.4 (2014): 537-559.

Carpentier, Alain, and Elodie Letort. "Multicrop production models with Multinomial Logit acreage shares." Environmental and Resource Economics 59.4 (2014): 537-559.

Carter, C., G. Rausser and A. Smith (2012). The Effect of the US Ethanol Mandate on Corn Prices. Available at: https://www.ourenergypolicy.org/wp-content/uploads/2013/07/The-Effect-oftheUS-Ethanol-Mandate-on-Corn-Prices-.pdf.

Damkjaer, S., & Taylor, R. (2017). The measurement of water scarcity: Defining a meaningful indicator. Ambio, 46(5), 513-531.

De Gorter, H., Drabik, D., & Just, D. R. (2013). How biofuels policies affect the level of grains and oilseed prices: Theory, models and evidence. Global Food Security, 2(2), 82-88.

Delucchi, MarkA. "Impacts of biofuels on climate change, water use, and land use." Annals of the New York Academy of Sciences 1195.1 (2010): 28.

Deschenes, O., and M. Greenstone. 2007. “The Economic Impact of Climate Change: Evidence from Agricultural Output and Random Fluctuation in Weather”. The American Economic Review 97(1):354-385.

Drukker, David M. "Testing for serial correlation in linear panel-data models." Stata Journal 3.2 (2003): 168-177.

Drysdale, K. M. and N. P. Hendricks. 2018. Adaptation to an irrigation water restriction imposed through local governance. Journal of Environmental Economics and Management 91: 150-165 DOI: https://doi.org/10.1016/j.jeem.2018.08.002.

Duffy, Patricia A., Kasazi Shalishali, and Henry W. Kinnucan. "Acreage response under farm programs for major southeastern field crops." Journal of Agricultural and Applied Economics 26.2 (1994): 367-378.

Fatal, Y. S. and W. N. Thurman. 2015. The Response of Corn Acreage to Ethanol Plant Siting. Journal of Agricultural and Applied Economics 46(2): 157-171 DOI: 10.1017/S1074070800000717.

Fernández-Cirelli, Alicia, et al. "Environmental effects of irrigation in arid and semi-arid regions." Chilean Journal of Agricultural Research 69 (2009), Nr. SUPPL. 1 69.SUPPL. 1 (2009): 27-40.

Fingerman, K. R., Torn, M. S., O’Hare, M. H., & Kammen, D. M. (2010). Accounting for the water impacts of ethanol production. Environmental Research Letters, 5(1), 014020.

Franzluebbers, A. J., et al. "Soil organic C and N pools under long-term pasture management in the Southern Piedmont USA." Soil Biology and Biochemistry 32.4 (2000): 469-478.

Gatignon, Hubert .Statistical analysis of management data. Boston, MA: Kluwer Academic Publishers, 2003.

Gensch, Dennis H., and Wilfred W. Recker. "The multinomial, multiattribute logit choice model." Journal of Marketing Research 16.1 (1979): 124-132.

Gheewala, S. H., Silalertruksa, T., Nilsalab, P., Lecksiwilai, N., Sawaengsak, W., Mungkung, R., & Ganasut, J. (2017). Water stress index and its implication for agricultural land-use policy in Thailand. International journal of environmental science and technology, 1-14.

Graveline, N., & Mérel, P. (2014). Intensive and extensive margin adjustments to water scarcity in France's Cereal Belt. European Review of Agricultural Economics, 41(5), 707-743.

Gruca, Thomas S., and Devanathan Sudharshan. "Equilibrium characteristics of multinomial logit market share models." Journal of Marketing Research 28.4 (1991): 480-482.

Haile, Mekbib G., Matthias Kalkuhl, and Joachim von Braun. "Inter-and intra-seasonal crop acreage response to international food prices and implications of volatility." Agricultural Economics 45.6 (2014): 693-710.

Hargreaves, G. H. and Z. A. Samani. 1982. Estimating Potential Evapotranspiration. Journal of the Irrigation and Drainage Division 108(3): 225-230.

Hausman, C., Auffhammer, M., & Berck, P. (2012). Farm acreage shocks and crop prices: an SVAR approach to understanding the impacts of biofuels. Environmental and Resource Economics, 53(1), 117-136.

Havlin, J. L., et al. "Crop rotation and tillage effects on soil organic carbon and nitrogen." Soil Science Society of America Journal 54.2 (1990): 448-452.

Hecox, G., P. Macfarlane, B. Wilson and O. A. Assessment. 2002. Calculation of Yield for High Plains Fields: Relationship between saturated thickness and field yield. Kansas Geological Survey Open File Report 24.

Hendricks, N. P. 2018. Potential Benefits from Innovations to Reduce Heat and Water Stress in Agriculture. Journal of the Association of Environmental and Resource Economists 5(3): 545-576 DOI: 10.1086/697305.

Hendricks, Nathan P., Aaron Smith, and Daniel A. Sumner. "Crop supply dynamics and the illusion of partial adjustment." American Journal of Agricultural Economics (2014): aau024.

Hendricks, Nathan P., and Jeffrey M. Peterson. "Fixed effects estimation of the intensive and extensive margins of irrigation water demand." Journal of Agricultural and Resource Economics (2012): 1-19.

Hodjo, Manzamasso, Ram N. Acharya, and Don Blayney. Corn and Rice Yield and Acreage Response to Prices, Policy and Climate Factors in Togo. No. 230082. Southern Agricultural Economics Association, 2016.

Hoekstra, A. Y., Mekonnen, M. M., Chapagain, A. K., Mathews, R. E., & Richter, B. D. (2012). Global monthly water scarcity: blue water footprints versus blue water availability. PLoS One, 7(2), e32688.

Hofield, Terry A. "Enhancing water use efficiency in irrigated agriculture." Agronomy journal 93.2 (2001): 281-289.

Huang, Haixiao, and Madhu Khanna. "An econometric analysis of US crop yield and cropland acreage: implications for the impact of climate change." AAEA annual meeting, Denver, Colorado. 2010.

Hudson, J. C. (1994). Making the corn belt: A geographical history of middle-western agriculture, Indiana University Press.

Kansas Farm manegment Association. 2019 Enterprise Summary: Irrigated Corn - Northwest. (available at https://www.agmanager.info/2019-enterprise-summary-irrigated-corn-northwest).

Kenny, Joan F., and Kyle E. Juracek. Irrigation Trends in Kansas, 1991-2011. US Department of the Interior, US Geological Survey, 2013.

Kettle, Nathan, Lisa Harrington, and John Harrington. "Groundwater depletion and agricultural land use change in the high plains: a case study from Wichita County, Kansas." The Professional Geographer 59.2 (2007): 221-235.

Khorshed Alam. 2015. “Farmers’ adaptation to water scarcity in drought-prone environments: A case study of Rajshahi District, Bangladesh”. Agricultural Water Management 148 (2015): 196–206.

Kline, J. D. (2005). Forest and farmland conservation effects of Oregon’s (USA) land-use planning program. Environmental Management, 35(4), 368-380.

Klonaris, Stathis, and David Hallam. "Conditional and unconditional food demand elasticities in a dynamic multistage demand system." Applied Economics 35.5 (2003): 503-514.

Lade, G. 2019. E15 Demand and Small Refinery Waivers: A Battle over Long-Run Market Share. Agricultural Policy Review Fall 2019: 12-15.

Langpap, C. and J. Wu. 2011. Potential Environmental Impacts of Increased Reliance on Corn-Based Bioenergy. Environmental and Resource Economics 49(2): 147-171 DOI: 10.1007/s10640-010-9428-8.

Lanning-Rush, J. L. (2016). Irrigation water use in Kansas, 2013. U.S. Geological Survey Data Series 981. Obtained from: https://pubs.usgs.gov/ds/0981/ds981.pdf.

Lark, T. J., J. Meghan Salmon and H. K. Gibbs. 2015. Cropland expansion outpaces agricultural and biofuel policies in the United States. Environmental Research Letters 10(4): 044003 DOI: 10.1088/1748-9326/10/4/044003.

Lee-Gammage, S. (2018). What is land use and land use change? (Foodsource: building blocks). Food Climate Research Network,University of Oxford.
Li, Hongmin, and Woonghee Tim Huh. "Pricing multiple products with the multinomial logit and nested logit models: Concavity and implications." Manufacturing & Service Operations Management 13.4 (2011): 549-563.
Liebman, Matt, and Elizabeth Dyck. "Crop rotation and intercropping strategies for weed management." Ecological applications 3.1 (1993): 92-122.
Liu, J., Hertel, T. W., Taheripour, F., Zhu, T., & Ringler, C. (2013). Water scarcity and international agricultural trade.
Liu, J., Yang, H., Gosling, S. N., Kummu, M., Flörke, M., Pfister, S., ... & Alcamo, J. (2017). Water scarcity assessments in the past, present, and future. Earth's future, 5(6), 545-559.
Liu, X., S. K. HoeKMan and A. Broch. 2017. Potential water requirements of increased ethanol fuel in the USA. Energy, Sustainability and Society 7(1): 18 DOI: 10.1186/s13705-017-0121-4.
Lopez, L., & Weber, S. (2017). Testing for Granger causality in panel data. The Stata Journal, 17(4), 972-984.
Lubowski, Ruben N., Andrew J. Plantinga, and Robert N. Stavins. "What drives land-use change in the United States? A national analysis of landowner decisions." Land Economics 84.4 (2008): 529-550.
Lubowski, Ruben N., Andrew J. Plantinga, and Robert N. Stavins. "Land-use change and carbon sinks: econometric estimation of the carbon sequestration supply function." Journal of Environmental Economics and Management 51.2 (2006): 135-152.
Majumdar, Indrajit, et al. "Effect of population pressure on forest land use change in alabama: a nested logit approach." International Journal of Ecological Economics and Statistics 14.P09 (2009): 77-93.
McGuire, V. L. (2014). Water-level changes and change in water in storage in the High Plains aquifer, predevelopment to 2013 and 2011–13: US Geological Survey Scientific Investigations Report 2014–5218, 14 p. US Geological Survey, Reston, Virginia, USA.
McIntosh, Christopher S., and Kamil H. Shideed. "The effect of government programs on acreage response over time: the case of corn production in Iowa." Western Journal of Agricultural Economics (1989): 38-44.
McIntosh, Christopher S., and Kamil H. Shideed. "The effect of government programs on acreage response over time: the case of corn production in Iowa." Western Journal of Agricultural Economics (1989): 38-44.
McPhail, L. L., & Babcock, B. A. (2012). Impact of US biofuel policy on US corn and gasoline price variability. Energy, 37(1), 505-513.
Miao, R. 2016. Impact of Ethanol Plants on Local Land Use Change. Agricultural and Resource Economics Review 42(2): 291-309 DOI: 10.1017/S106828050000438X.
Miao, R., Khanna, M., and H. Huang. 2015. “Responsiveness of Crop Yield and Acreage to Prices and Climate”. American Journal of Agricultural Economics 98(1):191-211.
Michael Babcock, Josh Holmgren and Eugene R. Russell Sr. (2009). Impact of Kansas Ethanol Production on Kansas Transportation. Report No. K-Tran: KSU-09-4. Obtained from https://engg.ksu.edu/files/transport/imported/Reports/2009/KSU094_Final_Rev.pdf, Kansas Department of Transportation
Miller, Douglas J., and Andrew J. Plantinga. "Modeling land use decisions with aggregate data." American Journal of Agricultural Economics 81.1 (1999): 180-194.

Molden, D. (2007). Water for Food, Water for Life: A Comprehensive Assessment of Water Management in Agriculture. London: Earthscan, and Colombo: International Water Management Institute.

Moore, Michael R., and Donald H. Negri. "A multicrop production model of irrigated agriculture, applied to water allocation policy of the Bureau of Reclamation." Journal of Agricultural and Resource Economics (1992): 29-43.

Motamed, M., L. McPhail and R. Williams. 2016. Corn Area Response to Local Ethanol Markets in the United States: A Grid Cell Level Analysis. American Journal of Agricultural Economics 98(3): 726-743 DOI: 10.1093/ajae/aav095.

National Research Council. (2012). Renewable fuel standard: potential economic and environmental effects of US biofuel policy. National Academies Press.

Natural Resources Conservation Service, Washington, DC. 15 January 2016 < http://www.nrcs.usda.gov/Internet/NRCS_RCA/reports/nri_nat.html>.

Nerlove, M. (1956). Estimates of the elasticities of supply of selected agricultural commodities. Journal of Farm Economics, 38(2), 496-509.

Olen, Beau, and JunJie Wu. "Impacts of Water Scarcity and Climate on Land Use for Irrigated Agriculture in the US West Coast." 2015 AAEA & WAEA Joint Annual Meeting, July 26-28, San Francisco, California. No. 205719. Agricultural and Applied Economics Association & Western Agricultural Economics Association, 2015.

Olesen, J. E., & Bindi, M. (2002). Consequences of climate change for European agricultural productivity, land use and policy. European journal of agronomy, 16(4), 239-262.

Paul, B., & Rashid, H. (2016). Climatic hazards in coastal Bangladesh: non-structural and structural solutions. Butterworth-Heinemann.

Pedro-Monzonís, M., Solera, A., Ferrer, J., Estrela, T., & Paredes-Arquiola, J. (2015). A review of water scarcity and drought indexes in water resources planning and management. Journal of Hydrology, 527, 482-493.

Pfeiffer, Lisa, and CY Cynthia Lin. "The Effects of Energy Prices on Groundwater Extraction in Agriculture in the High Plains Aquifer." American Journal of Agricultural Economics (2014).

Pfeiffer, Lisa, and CY Cynthia Lin. "The Effects of Energy Prices on Groundwater Extraction in Agriculture in the High Plains Aquifer." American Journal of Agricultural Economics (2013).

Pfeiffer, Lisa, and C-Y. Cynthia Lin. "Groundwater pumping and spatial externalities in agriculture." Journal of Environmental Economics and Management 64.1 (2012): 16-30.

Pimentel, D., Marklein, A., Toth, M., Karpoff, M., Paul, G., McCormack, R., ... & Krueger, T. (2008). Biofuel impacts on world food supply: use of fossil fuel, land and water resources. Energies, 1(2), 41-78.

Piroli, G., & Ciaian, P. (2012). Land use change impacts of biofuels: Near-VAR evidence from the US. Ecological Economics, 84, 98-109.

Ramsey, Steven M. (2017). Advances in land-use and stated-choice modeling using neural networks and discrete-choice models (Doctoral dissertation). Knsas State University http://hdl.handle.net/2097/35802.

Renewable Fuel Association (RFA) (2018). Ethanol Strong, Ethanol Industry Outlook. Available at https://ethanolrfa.org/wp-content/uploads/2018/02/NECfinalOutlook.pdf.

Renewables Fuels Association. "Pocket guide to ehanol." (2014).

Richards, Timothy J. "A nested logit model of strategic promotion." Quantitative Marketing and Economics 5.1 (2007): 63-91.

Rijsberman, F. R. (2006). Water scarcity: fact or fiction? Agricultural water management, 80(1-3), 5-22.

Rogers, Danny H., Mahbub Alam, and L. Kent Shaw. Kansas irrigation trends. Agricultural Experiment Station and Cooperative Extension Service, Kansas State University, 2008.

Rosegrant, M. W. (2008). Biofuels and grain prices: impacts and policy responses (pp. 1-4). Washington, DC: International Food Policy Research Institute.

Roumasset, James, and Christopher A. Wada. Groundwater Economics without Equations. No. 2014-8. 2014.

S. Patricia Batres-Marquez. (2018). "Looking at Current Ethanol Production: Top Five States." Retrieved April 12, 2020, from https://www.agmrc.org/renewable-energy/renewable-energy-climate-change-report/renewable-energy-climate-change-report/june-2018-report/looking-at-current-ethanol-production-top-five-states.

Saddiq, M., Fayaz, M., Hussain, Z., Shahab, M., & Ullah, I. "Acreage response of sugarcane to price and non-price factors in Khyber Pakhtunkhwa." International Journal of Food and Agricultural Economics 2.3 (2014): 121.

Sampson GS, Perry ED. (2019). Peer effects in the diffusion of water-saving agricultural technologies. Agricultural Economics, ;1–14.

Sampson, G. S., & Perry, E. D. (2019). The Role of Peer Effects in Natural Resource Appropriation–The Case of Groundwater. American Journal of Agricultural Economics, 101(1), 154-171.

Scanlon, B. R., C. C. Faunt, L. Longuevergne, R. C. Reedy, W. M. Alley, V. L. McGuire and P. B. McMahon. 2012. Groundwater depletion and sustainability of irrigation in the US High Plains and Central Valley. Proceedings of the National Academy of Sciences 109(24): 9320 DOI: 10.1073/pnas.1200311109.

Schlenker, W., W. M. Hanemann and A. C. Fisher. 2006. The impact of global warming on US agriculture: an econometric analysis of optimal growing conditions. Review of Economics and statistics 88(1): 113-125.

Schlenker, Wolfram, and Michael J. Roberts. "Nonlinear temperature effects indicate severe damages to US crop yields under climate change." Proceedings of the National Academy of sciences 106.37 (2009): 15594-15598.

Shi, X., Mao, J., Thornton, P. E., Hoffman, F. M., & Post, W. M. (2011). The impact of climate, CO2, nitrogen deposition and land use change on simulated contemporary global river flow. Geophysical Research Letters, 38(8).

Sophocleous, Marios. "groundwater management practices, challenges, and innovations in the High Plains aquifer, USA—lessons and recommended actions." Hydrogeology Journal 18.3 (2010): 559-575.

Stephenson, N. L. (1990). Climatic control of vegetation distribution: the role of the water balance. The American Naturalist, 135(5), 649-670.

Stewart, L. and D. M. Lambert. 2011. Spatial heterogeneity of factors determining ethanol production site selection in the U.S., 2000–2007. Biomass and Bioenergy 35(3): 1273-1285 DOI: https://doi.org/10.1016/j.biombioe.2010.12.020.

Taheripour, F., T. W. Hertel and J. Liu. 2013. The role of irrigation in determining the global land use impacts of biofuels. Energy, Sustainability and Society 3(1): 4 DOI: 10.1186/2192-0567-3-4.

Tsakmakis, Ioannis D., et al. "Impact of irrigation technologies and strategies on cotton water footprint using AquaCrop and CROPWAT models." Environmental Processes 5.1 (2018): 181-199.

Wallander, S., R. Claassen and C. Nickerson. 2011. The ethanol decade: an expansion of US corn production, 2000-09. USDA-ERS Economic Information Bulletin(79).

Wang, Jing, et al. "Land-use changes and policy dimension driving forces in China: Present, trend and future." Land use policy 29.4 (2012): 737-749.

Watkins, Kevin. "Human Development Report 2006-Beyond scarcity: Power, poverty and the global water crisis." UNDP Human Development Reports (2006).

Weersink, A., Cabas, J.H., and E. Olale, 2010. "Acreage Response to Weather, Yield, and Price". Canadian Journal of Agricultural Economics 58(2010):57-72.

White, C. (2014). 28. Understanding water scarcity: Definitions and measurements. Global water: Issues and insights, 161.

Wiggins, Vince, and Brian Poi. "Testing for panel-level heteroscedasticity and autocorrelation." Stata Corp FAQs. Retrieved on April 3 (2003): 2008.

Winter, Jonathan M., et al. "Representing water scarcity in future agricultural assessments." Anthropocene 18 (2017): 15-26.

Wooldridge, J. M. (2012). Econometric analysis. Pearson Addison Wesley press.

Wright, C. K., B. Larson, T. J. Lark and H. K. Gibbs. 2017. Recent grassland losses are concentrated around U.S. ethanol refineries. Environmental Research Letters 12(4): 044001 DOI: 10.1088/1748-9326/aa6446.

Wu, JunJie, and B. Wade Brorsen. "The impact of government programs and land characteristics on cropping patterns." Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie 43.1 (1995): 87-104.

Wu, JunJie, and Kathleen Segerson. "The impact of policies and land characteristics on potential groundwater pollution in Wisconsin." American Journal of Agricultural Economics 77.4 (1995): 1033-1047.

Wu, JunJie, and Richard M. Adams. "Micro versus macro acreage response models: Does site-specific information matter?" Journal of Agricultural and resource Economics (2002): 40-60.

Wu, JunJie. "Slippage effects of the conservation reserve program." American Journal of Agricultural Economics 82.4 (2000): 979-992.

Yan, B., Fang, N. F., Zhang, P. C., & Shi, Z. H. "Impacts of land use change on watershed streamflow and sediment yield: An assessment using hydrologic modelling and partial least squares regression." Journal of Hydrology 484 (2013): 26-37.

Young, M. D., and Christine Esau. "Investing in water for a green economy." Services, infrastructure, policies and management. UNEP (2013).

Zellner, Arnold, and Henri Theil. "Three-stage least squares: simultaneous estimation of simultaneous equations." Econometrica: Journal of the Econometric Society (1962): 54-78.

Zellner, Arnold. "An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias." Journal of the American Statistical Association 57.298 (1962): 348-368.