CROP ACREAGE RESPONSE MODELING IN NORTH DAKOTA AND THE GREATER MIDWEST

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

DOCTOR OF PHILOSOPHY

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ABSTRACT

Our research consists of two papers. First paper focus on the trend of North Dakota (ND) crop acreage changes and include economic factors (expected prices of crops, input price, crop yield, revenue of crops) and climate factors (precipitation, minimum and maximum temperature, growing degree days, and palmer drought severity index). We are using Geographic Information System (GIS) database for cropland areas throughout ND for the years 1998 through 2013. But we are using five crops for our analysis. We use Seemingly Unrelated Tobit Left Censored Regression and Monte Carlo Simulation techniques for our analysis. We also include renewable fuel standard dummy (year 2005 and 2007). Findings suggest that prices of crop, yield, revenue, input price significant impact on crop acreage. Marginal effects of crop price increase by $1 to own acreage of barley, corn, soybean, wheat, and oilseeds ranges between 50 to 295 acres, 28 to 572 acres, -24 to 45 acres, -198 to -39 acres, and 7 to 48 acres throughout ND and statistically significant except soybean. Elasticity of own-price to acreage of barley, corn, soybean, wheat, and oilseeds are 1.16%, 1.23%, 0.17%, -0.16%, and 0.53%, respectively, and statistically significant except soybean.

Second paper mainly focus on three states ND, South Dakota (SD), and Minnesota (MN) causes of crop acres planted changes due to economic factors as well as weather factors. We are using Seemingly unrelated regression and Monte Carlo Simulation technique for that paper. We produce a balanced panel dataset with annual observations of the planted acreages of each of the five crops in each of the three states, along with the relevant price and yield variables for each crop and pertinent precipitation and temperature variables for each year in each state. Monte Carlo Simulation technique used to calculate own-price elasticity of MN state barley, corn, soybean, wheat, and sunflower to their own acreage are -0.506%, 0.197%, 0.116%, 0.566 %, and

11.34%, respectively; in SD state are -0.739%, 0.312%, 0.290%, 0.309%, and 1.72%, respectively and statistically significant except barley crop elasticity. This research findings will help forecast future agricultural land use trends & crop area response.

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First, I would like to thank Almighty Allah who gave me patience, support, and determination to accomplish the writing process. I would like to give thanks to the funding agency National Science Foundation, North Dakota EPSCoR Center for Regional Climate Studies for continuing my research and giving me the opportunity to work as a young researcher.

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I will always be grateful to my father, who passed away fifteen years ago, for encouraging me to seek higher learning. Finally, thanks to my husband and my daughter who sacrifice their time and continue to support me in my research efforts.

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LIST OF ABBREVIATIONS

CDL..Cropland Data Layer

CME...Chicago Mercantile Exchange

ERS ....Economic Research Service

GIS ....Geographic Information System

GMO ....Genetically Modified Crops

GDD..Growing Degree Days

GDP...Gross Domestic Product

MN ....Minnesota State

NASS ....National Agricultural Statistics Service

NRCS...Natural Resources Conservation Service

ND..North Dakota State

PDSI...Palmar Drought Severity Index

SD ....South Dakota State

SUREG ....Seemingly Unrelated Regression

SUTR ....Seemingly Unrelated Tobit Regression

SSURGO..Soil Survey Geographic Database

US ....United States

USGS ....United States Geological Survey

USDA...United States Department of Agriculture

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CHAPTER 1. GENERAL INTRODUCTION

According to the United States Department of Agriculture's Economic Research Service (USDA-ERS), the total number of US farmworkers on US farms are (self-employed, family farmworkers, and hired workers) 9.93 million in year 1950 whereas 3.19 million in year 2000. According to USDA, Agriculture Census 2012 report total number of farmers in US are 3.2 million occupied 2.1 million farms in year 2012. In 1960, US total farm population are 15,635,000, farm numbers 3,711,000, and average size of farms 303 acres whereas in year 1990 declined farm population 2,987,552, number of farms 2,143,150, but increased size of farms 461 acres. (Growing a Nation, the story of American Agriculture, 2014). According to (USDA) National Agricultural Statistics Service (NASS), report 2011, in US from the period 1994 to 2006, number of farm size dropped 2.20 million to 2.08 million whereas farm size dropped 441 acres to 418 acres from the period 1994 to 2010. According to (USDA), (NASS) 2017 report from the period 2009 through 2016 in US number of farms declined from 2.17 million to 2.06 million whereas farm size rose from 423 acres to 443 acres in the same period.

Farm size and farm population contributed largely to the agriculture in each state. There are three states in our study North Dakota (ND), South Dakota (SD), and Minnesota (MN). We include the changes of farm population, farm size, and farm numbers from the period 1960 to 2017. In ND, 24% people engaged in agriculture and 40 million acres land occupied by farms and ranching. In addition, 90% land area is in agriculture (Farm Flavor, North Dakota Agriculture 2018). There are about 17,509 farmers and 4,012 female farmers in ND as well as 27,578 family constitute farm ownership which is 91% (Farm Flavor, North Dakota Family Farms 2018). In addition, ND 30,961 farms impact on economy worth $10.9 billion per year (Farm Flavor, ND Agriculture 2018). In 1960, number of farms in ND are 53,710 whereas it dropped to 31,500 in year 2010 (North Dakota Studies 2018). About ninety-percent of land occupied in ND by farms and ranch land (NASDA, North Dakota Department of Agriculture (n.d.). According to Leistritz and Randal (1994) from the period 1960 through 1990 farm and ranch related direct employment in agriculture decreased by 48% in ND overall. In ND, 26.9% employment are created by farm and farm related whereas 27.6% in South Dakota (SD) (Leistritz and Randal 1994). From the period 2009 to 2010, ND number of farms dropped from 32,000 to 31,900 whereas farm size increased from 1,238 acres to 1,241 acres at the same period (USDA, NASS 2011). According to Farmland information center (2018) in year 2012 number of farms are 30,961 whereas in year 2002 it was 30,619 in ND. In year 2012, 35% of ND farms size was 1000 acres or more, greater than national average farm size in percentage (Farhang 2014). In 2012, ND average farm size was 1,250 acres (Farhang 2014). According to report of (USDA), (NASS) (2018) number of farms increased in ND in period 2016 and 2017 are 29,800 to 29,900 whereas farm size decreased from 1,312 to 1,308 acres in the same period.

In South Dakota (SD) state, agriculture contributed in state's economy worth $25.6 billion per year and about 19 million acres cropland in SD according to NASDA, SD Department of Agriculture, 2018. SD state ranked 10th, out of 50 states in producing 25 agricultural products (Farm Flavor, South Dakota Agriculture 2018). 98% of SD farms are family owned (SD Agriculture, the common thread, 2014). In year 2014, 2500 farms of SD are family operated which 100 years old (SD Agriculture, the common thread 2014). SD provided food for 155 people annually state-wise and for world (SD Agriculture, the common thread 2014). From the period 1960 through 1974, in SD state farm size increased from 781 acres to 1,046 acres and farm numbers declined by 26% from 1960 to 1974 (Jensen 1975). From the period 2002 to 2012, number of farms increased from 31,736 to 31,989 in SD (Farmland Information Center 2018).

31,989 farms contributed to SD state economy per year worth $10.1 billion (Farm Flavor, SD Agriculture 2018). From the period 2009 through 2010 in SD, number of farms increased from 31,500 to 31,800 whereas farm size decreased from 1,387 acres to 1,374 acres at the same period (USDA, NASS 2011). In the period 2016-2017, number and size of farms are 31,000 and 1,397 acres, respectively (USDA, NASS 2018).

Agriculture industry impact on Minnesota state's economy worth $75 billion per year and create employment for 340,000 people (Farm Flavor, Minnesota Agriculture 2018). In 1964, number of farms in Minnesota increased 26,809 as compare to 17,716 farms in 1945 and farm size 235 acres in year 1964 (Historic Context Study of Minnesota Farms (1820-1960) (n.d.). In Minnesota state, from the period 2016 through 2017 number of farms are 73,300 to 73,200 respectively as well as size of farms are 353 to 354 acres, respectively (USDA, NASS 2018). In Minnesota state number of farms declined from 80,839 to 74,542 between year 2002 to 2012 (Farmland Information Center 2018). In addition, 74,542 farms of MN have economic impact worth $21.2 billion per year and farms occupied around 26 million acres land (Farm Flavor, Minnesota Agriculture 2018). In the period, 2009-2010, number of farms and farm size are 81,000 and 332 acres, respectively (USDA, NASS 2011). From year 2012 to 2015, number of farms in Minnesota dropped from 74,500 to 73,600 whereas farms acres in the same period rose from 349 to 352 acres (USDA, NASS 2017).

Own and relative crop prices influence crop allocation decisions to see government support policies impact on agricultural sectors' crop production and prices (Holt 1999). Acreage response of rice with inputs costs and crop prices. Input prices (fuel and fertilizer price) changes may impact on producers' decision-making process to allocation of acreage (Ballard and Thomsen 2008). Soybeans and rice crop are substitute in production and these two crops can get affected if soybeans price changes as they use same machinery in their production process (Ballard and Thomsen 2008). In short run crop acreage own price elasticity is 0.69 whereas in long run 1.19. In addition, rice acreage cross price elasticity due to soybeans prices in the short run -0.33 whereas in long run -0.57. Besides that, increase input prices (fuel, fertilizer, and machinery) inversely relate to acreage decisions (Ballard and Thomsen 2008). Barr et al. (2011) calculates elasticity of land use supply to price in United States and Brazil. Their findings suggest elasticity of land use to price in United States inelastic in nature whereas in Brazil is elastic in nature (Barr et al. 2011). Existing literature found correlation of price-yield to crop acreage in farm level and county level (Finger 2012). Key findings suggest that, price and yield correlation is smaller in farm level (Finger 2012). As farm getting larger, correlation of price-yield is higher that means as maize and barley crop area increases by 1%, correlation of price to yield -0.02 and -0.08, respectively (Finger 2012). There is relation between crop insurance and land values. Key findings suggest that from 1997 to 2015, crop production and revenue of farm increases. As prices of crop decline, crop production and farm income will also go down. It also has some impact on crop subsidy and land values. As crop price goes down, then subsidy and land values also go down (Duffy 2016). Crop acreage of principal crops in US from 2007 to 2015 ranges between 320.4 to 318.5 million acres (Good and Irwin 2016). In addition, principal crop acreage increases in state of Minnesota, North Dakota, South Dakota, Nebraska, and Kansas. There acreage varied of principal crops year to year because of conservation reserve program (CRP) enrollment as well as double cropping system (Good and Irwin 2016). The variation of crop acreage annually due to price effects as well as corn and soybeans acreage increases in 2017 and 2018 as they forecasted (Good and Irwin 2016). There is relation between acreage response with future prices and government programs (Chavas, Pope, and Kao 1983).

Key findings of this study mention that government programs influence farmers' decision-making process of United states corn and soybeans production (Chavas, Pope, and Kao 1983). Results of this study suggest that future prices could not act as an important component to crop acreage when there are government programs (Chavas, Pope, and Kao 1983). Future prices forecast acreage response accurately in compare to other forecasting techniques in econometrics (Just and Rausser 1981). Output and input prices have impact on corn acreage (Hodjo, Acharya, and Blayney 2016). Finding show that output prices have negative effect on corn yields whereas positive effect on rice yields (Hodjo, Acharya, and Blayney 2016). Government program or nonprogram have relation with wheat acreage response with expected wheat price and price risk (Krause, Lee, and Koo 1995). Finding indicate us that expected wheat price negatively relate to government program wheat acreage response (Krause, Lee, and Koo 1995). In addition, price risk not involve in government program acreages response which ultimately increases government program acreage (Krause, Lee, and Koo 1995). Maize acreage responds with differential prices (producers' price in rural and retail price in urban market). Key findings suggested that urban retail price can explain acreage response most effectively (Honfoga 1993). Wheat acreage response to prices changes in USA (Burt and Worthington 1988). Findings suggest that wheat acreage response elasticity to mean price is 1.3 in Great plains whereas 1.5 in USA (Burt and Worthington 1988). There is variation of costs and yields in wheat production in USA regions (Vocke and Ali 2013). Results suggest that difference in production cost is due to machinery and fertilizer cost differences across regions in USA (Vocke and Ali 2013). Their survey report suggests that, if farms can gain $4.87 per bushel price of wheat yields, then 97% farms of USA able to mitigate all operating expenses during wheat production cost (Vocke and Ali 2013). Zulauf et al. (2018) shows compare of crop revenue to cost of production per acre in three different period 2002-2006, 2008-2013, and 2015-2016 of 9 crops. Key findings suggest that, out of 9 crops, 8 crops revenue to cost of production per acre are higher in the period 2008-2013 than that of 2003-2006. In addition, corn, rice, sorghum, and barley crop revenue to cost of production per acre is higher in 2015-2016 than that of 2003-2006 whereas decline revenue to cost of production per acre of soybean, peanuts, and oats crop and wheat and cotton crop no change in that period (Zulauf et al. 2018).

Iizumi et al. (2017) stablish relationship between yields growth to global temperature and socioeconomic changes (Iizumi et al. 2017). Finding suggested that due to warming trends of global temperature, there are no effect of yields of maize, soybean, and wheat crop in low income counties in low latitude location (Iizumi et al. 2017). But warming trends of global temperature cause negative effect of yields maize and soybean crop of high income countries in higher latitude location (Iizumi et al. 2017). Larson (2015) focus on price and climate effect on yields and crop acreage. Corn yield increases as corn price increases but due to corn ethanol production leads to change in land use (Larson 2015). For slow warm climate lead to decline of corn yield from 7% to 12% whereas for more warmer climate lead to almost 40% decline of corn yields (Larson, 2015). It also suggests that, due to variability of climate if farmers adopt different practices of crop then yield reduction only 10% (Larson 2015). Price increases of corn lead to increases in corn yield whereas soybean crop doesn't have such relation (Larson 2015). As growing season getting longer and warmer, good for crop yields whereas negative effect on crop yields as warm days increases (Larson 2015). Moreover, precipitation increases lead to decline of crop yield (Larson 2015). As farmers adopt different practices with crop price signal lead to have less negative effect of climate variation on crop acreage (Larson 2015). Corn and soybean yield respond with weather (Tannura, Irwin, and Good 2008). Results tells that, corn yields related to precipitation of June and July and temperatures of July and august whereas soybeans yield related to June, July, and August precipitation (Tannura, Irwin, and Good 2008). It also mentions that yield effect not only from weather but also from technology like genetically modified seed (Tannura, Irwin, and Good 2008). Rainfall is an important factor of corn and rice allocation as well as yields response (Hodjo, Acharya, and Blayney 2016).

The impact of demand for biofuel production led to increase price rise of food as well as effect of the Energy Independence and Security Act (EISA) of 2007 (Rosegrant 2008). The crop corn, maize, and soybean used for bioethanol production. As more ethanol production increased from maize, it led to raise food price because same land now used for production of ethanol instead of food (Rosegrant 2008). Due to increase demand and price of maize for ethanol production led consumers to choose substitute crop like rice and wheat as food (Rosegrant 2008). On the other hand, maize price hike make opportunity for producers to make more profit by growing, farmers who produce rice and wheat, will substitute with maize because of price incentive (Rosegrant 2008). This supply and demand side ultimately raise price of rice and wheat crop (Rosegrant 2008). Govinda et al. (2012) found that, effect of biofuel production increases on land use change, food supply, and food price Key findings suggest that, biofuel production increase lead to decline forest and pasture land into allocation of biofuel production as well as shortage of food supply (Govinda et al. 2012). Most developing countries like India and Sub Saharan African countries get affected from increases production of biofuel on shortage of food supply (Govinda et al. 2012).

Our research mainly focusses on North Dakota and greater Midwest states like South Dakota and Minnesota, crop acreage responses relate to economic factors and climatic factors. In our crop acreage responses modeling economic factors like the expected price of crops, input prices (fertilizer prices and farm level diesel prices), crop yields, soil texture, latitude, longitude, crop revenues, climate variables like precipitation, minimum and maximum temperature Palmar severity index, growing degree days, oil production, renewable fuel standard dummies and genetically modified crop dummies. We have two papers in this dissertation: crop acreage response modeling for North Dakota and another for North Dakota, South Dakota, and Minnesota. In the North Dakota paper, we divided whole ND into 1354 quadrangle. In the South Dakota, North Dakota, and Minnesota paper we are using state level data. In both papers we find that, major crops grown in these three states are corn, wheat, barley, and soybeans. Wheat is grown in major portions of North Dakota.

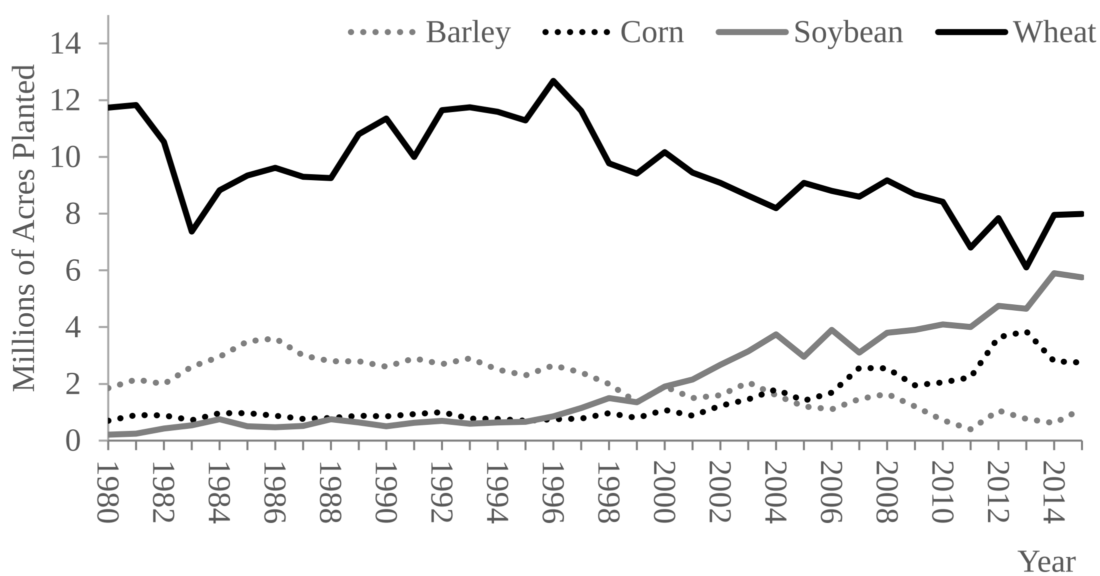


Figure 1.1. Planted acres of barley, corn, soybean, and wheat in North Dakota

From 1980 to 2015, wheat acres planted increased in comparison with other crops in ND. We find that from 1980 to 1998, barley acreage increased, but from 1998 to 2015, it started declining below corn and soybean acreage. Soybean acreage increased after 1999, and the rate is still being increasing compared with corn and barley acreage. Corn acreage increased after 2004 as compared with barley acreage (Fig. 1.1, USDA, National Agricultural Statistics Service 2017).

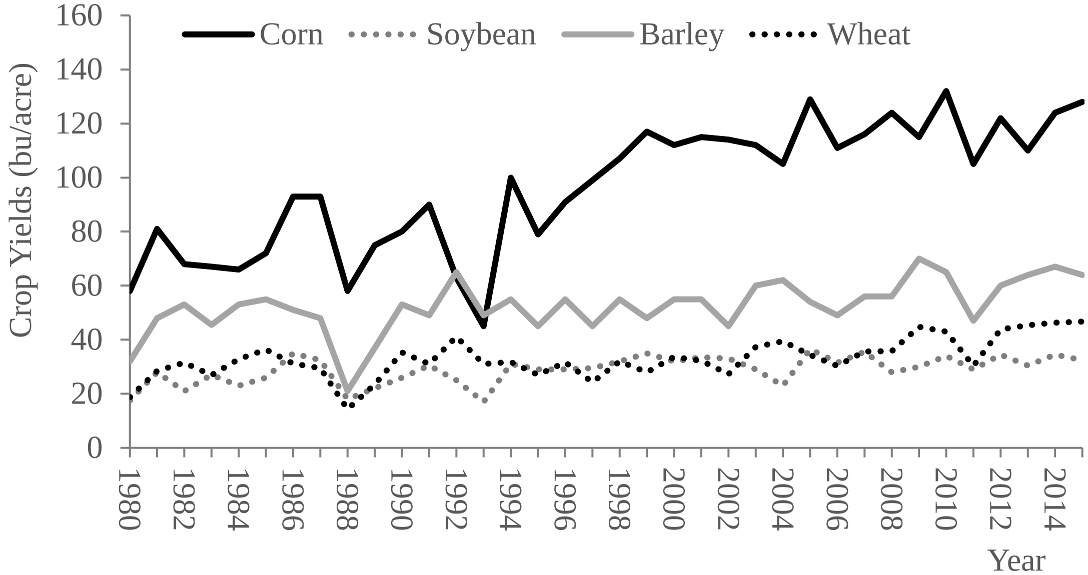


Figure 1.2. Barley, corn, soybean, and wheat yields in North Dakota (bushels/acre)

Corn yields in bushels per acre are higher as compare to other crops from the period 1980 through 2014 in ND. Corn yields increased from 1980 to 1992 by 58 to 49 bushels per acre; after that sharp decline, yields increased from 1993 to the present by 100 to 128 bushels. Barley yields in bushels per acre increased from 32 in 1980 to 48 in 1987; after that yields declined, but then increased from 53 bushels per acre in 1990 to 64 bushels per acre in 2015 (Fig. 1.2, USDA, National Agricultural Statistics Service 2017).

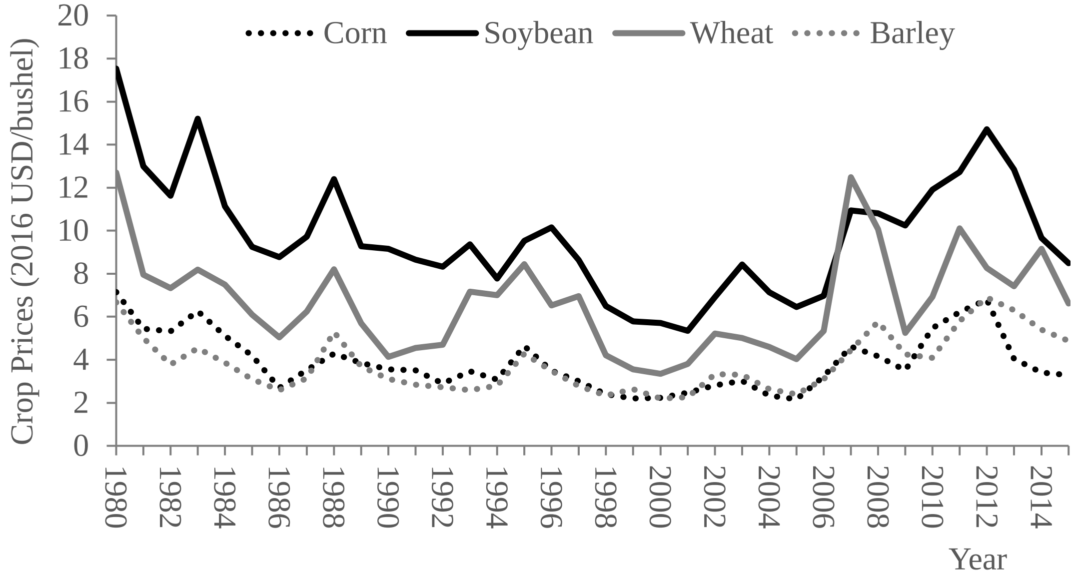


Figure 1.3. Inflation-adjusted prices of barley, corn, soybean and wheat in North Dakota (2016 USD/bushel)

Soybean prices increased from $9.36 per bushel in 1980 to $17.53 in 1993 in ND; there was a sharp price decline in 1996, but prices started to increase after 2006. Wheat prices were $12.70 per bushel in 1980, then spiked in 1988, 1995, and 2007 by $8.20, $8.44, and $12.49 per bushel, respectively; after 2007, prices followed a downward trend (Fig. 1.3 USDA, National Agricultural Statistics Service 2017).

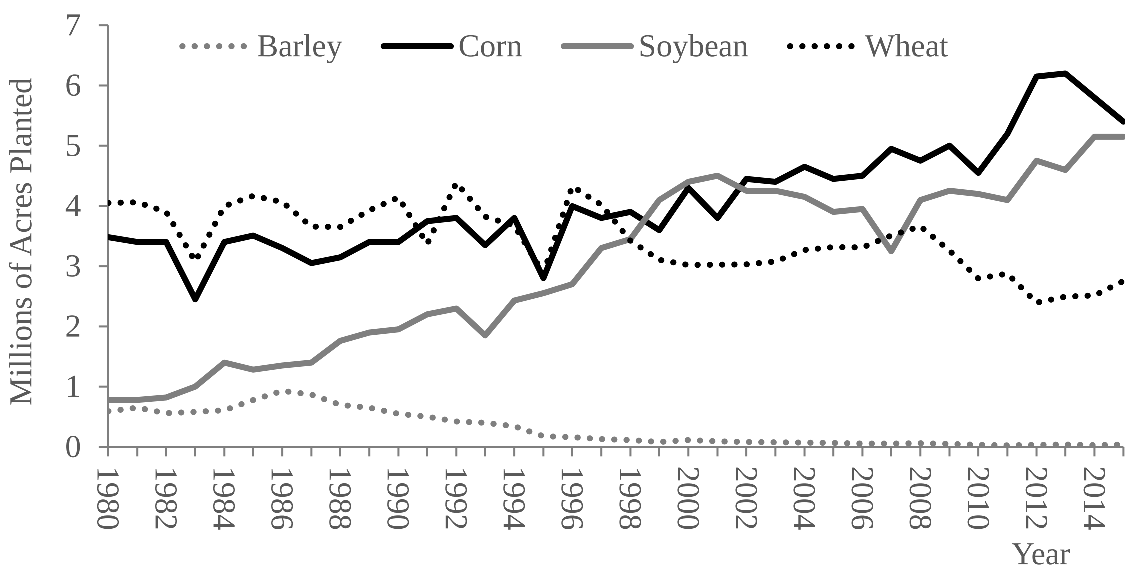


Figure 1.4. Planted acres of barley, corn, soybean, and wheat in South Dakota

Acres planted of wheat and corn increased from the 1980 through 1996 in SD. After 1996, wheat acreage started decreasing, and after 1998, corn acreage started increasing as the predominate crop in South Dakota (Fig. 1.4, USDA, National Agricultural Statistics Service 2017).

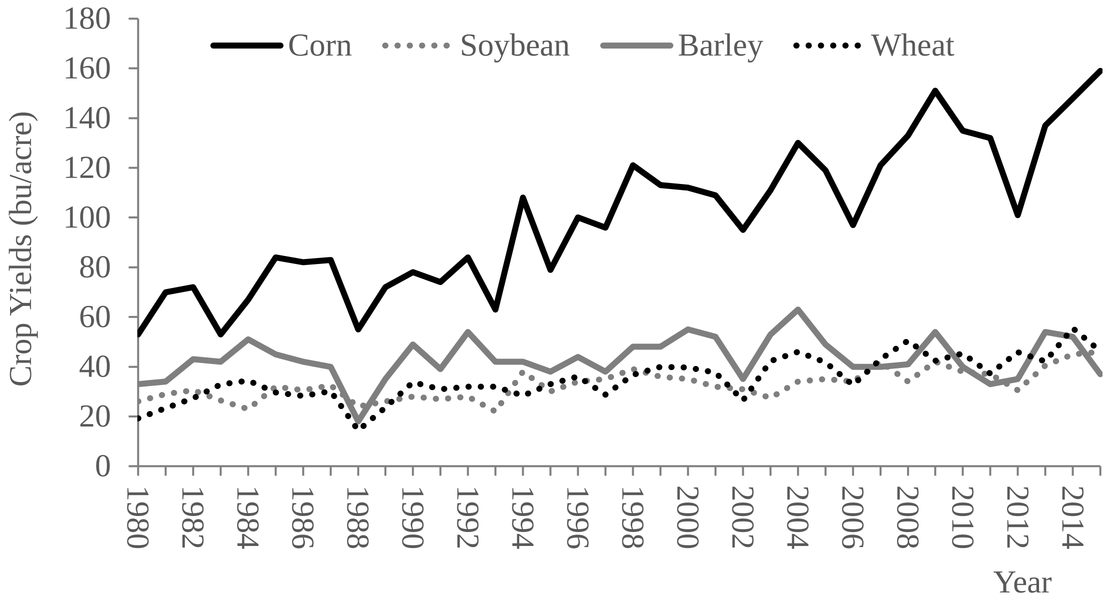


Figure 1.5. Barley, corn, soybean, and wheat yields in South Dakota (bushels/acre)

Corn yields increased from 1980 through 2015 by 53 to 159 bushels per acres in SD. Barley yields increased from 1980 through 2004 by 33 to 63 bushels per acres. But after 2006, barley yields decreased from 40 to 37 bushels per acre (Fig. 1.5, USDA, National Agricultural Statistics Service 2017).

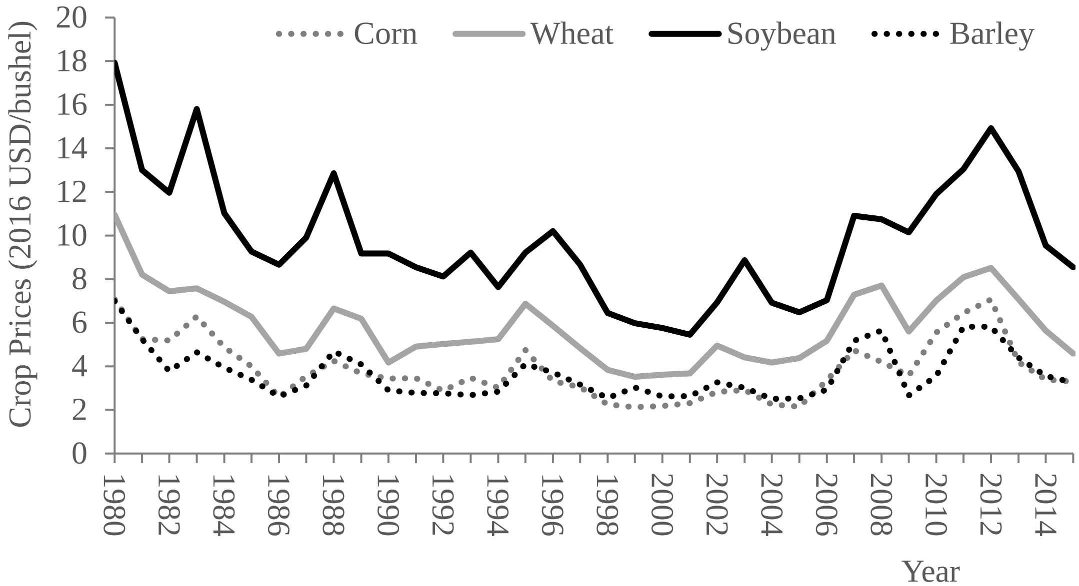


Figure 1.6. Inflation-adjusted prices of barley, corn, soybean and wheat in South Dakota (2016 USD/bushel)

Compared with other crops, soybean prices in South Dakota were still higher from 1980 through 2015 by $17.93 to $8.54 per bushel. Wheat prices from 1980 through 2012 ranged from $11 to $8.51 per bushel (Fig. 1.6, USDA, National Agricultural Statistics Service 2017).

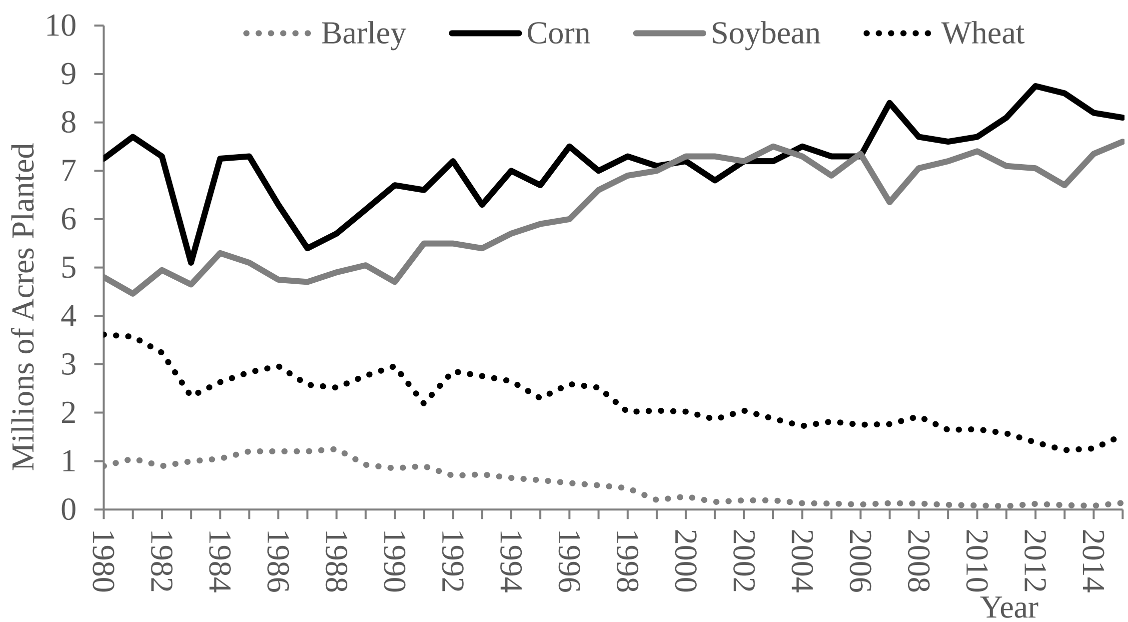


Figure 1.7. Planted acres of barley, corn, soybean, and wheat in Minnesota

Acres planted corn and soybeans increased from 1980 through 1998 in Minnesota. From 1998 through 2006, corn and soybean acreage increased at the same pace. But after 2006, corn acreage increased more than soybean acreage (Fig. 1.7, USDA, National Agricultural Statistics Service 2017).

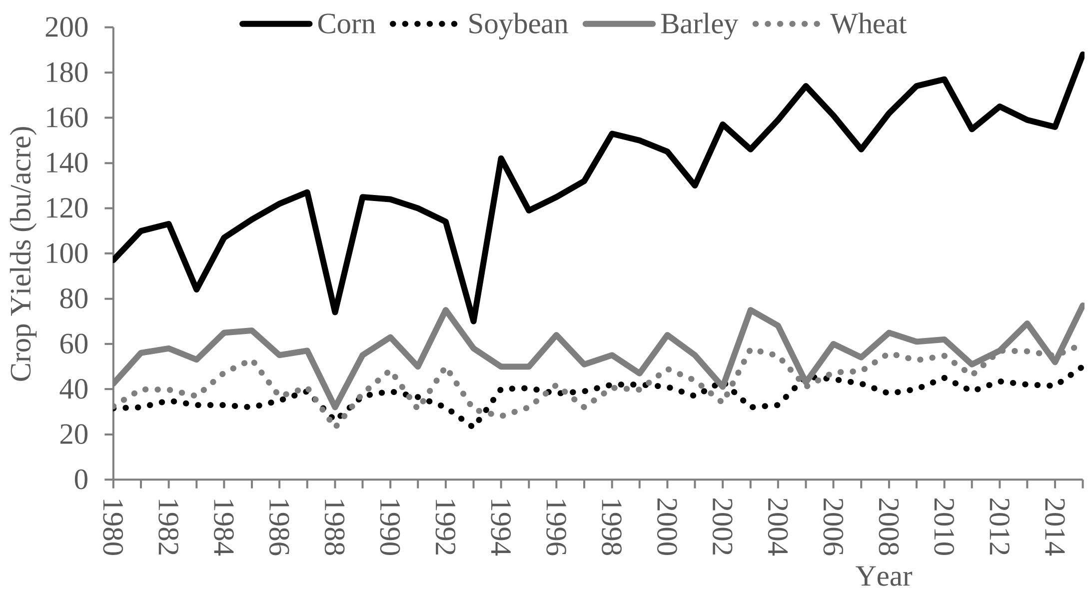


Figure 1.8. Barley, corn, soybean, and wheat yields in Minnesota (bushels/acre)

From 1980 through 2015, corn yields increased from 97 to 188 bushels per acre. Barley is still second largest position of all crops yields in Minnesota (Fig. 1.8, USDA, National Agricultural Statistics Service 2017).

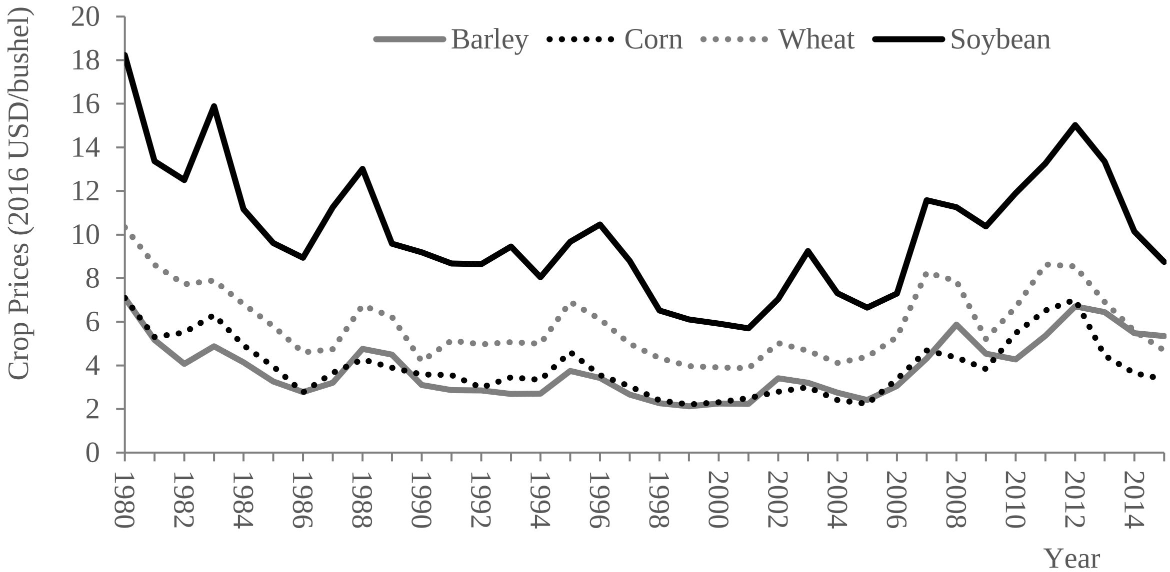


Figure 1.9. Inflation-adjusted prices of barley, corn, soybean and wheat in Minnesota (2016 USD/bushel)

Soybeans crop prices from 1980 through 2014 is still high which is 18 \$/bu to 8.75 \$/bu in MN. On the other hand, wheat price from 1980 through 2012, 10\$/bu to 8.53\$/bu (Fig. 1.9, USDA, National Agricultural Statistics Service 2017).

1.1. Objectives

1) To estimate how soil texture, expected crop price, input price, yield, lagged acreage, and major crop revenue respond to crop acreage in North Dakota.
2) To examine how geographical heterogeneity might affect each crop acreage response function in North Dakota.
3) To examine how temperature (minimum and maximum), precipitation, growing degree days (GDD), Palmer drought severity index (PDSI), oil production, and biofuel mandate impact crop acreage in North Dakota.
4) How planted acres change in North Dakota, South Dakota, and Minnesota due to crop price changes, crop yields, input price, crop revenues, and lagged acreage of crops.

5) How weather variables like annual precipitation, temperature (minimum and maximum), and genetically modified crop dummies cause shifting of acres planted in North Dakota, South Dakota, and Minnesota.

1.2. Dissertation Outline

Chapter 1 is the presentation of literature review of factors influence crop acreage response in North Dakota, South Dakota, and Minnesota. We mention the trend of crop acreage planted, yields, and prices of corn, soybeans, wheat, and barley from the year 1981 through 2015. We mention in following chapters two and three abstract, introduction, study area, data collection, methodology, empirical model, results, and conclusion of each paper. Chapter four includes conclusions of two papers. I include reference section at the end of chapter four.

Chapter 2. Crop Acreage Response Modeling in North Dakota. This chapter present major causes of crops acreage response modeling in North Dakota are economic factors and climate factors as well as geographical variation.

Chapter 3. Multiple Crop Acreage Response Due to Economic Factors and Weather: A Case Study On North Dakota, South Dakota, and Minnesota. Changes in crop acreage planted due to economic factors and climate factors in North Dakota, South Dakota, and Minnesota are assessed.

Chapter 4. General Conclusions and Future Research Implication. We explain conclusion and future research implication of two papers.

CHAPTER 2. CROP ACREAGE RESPONSE MODELING IN NORTH DAKOTA

2.1. Abstract

This study finds that cropland is not use for planting same crop for last sixteen year (Cropland data layer). The reason is couple of thing price signaling of major crops, yields response, revenue as well as change of climate trigger to produce some crops over others. Crop acreage response combinedly effect all those factors. This study analyzes prices of crops, yields response, crop acreage change, input prices (ammonium nitrate and farm level diesel retail oil price), revenue of crops, precipitation, temperature (minimum and maximum), growing degree days, palmar drought severity index, soil texture, biofuel policy which combinedly influence crop acreage response. We collect GIS based Cropland Data Layer from NASS from 1998 through 2013 year. We divided whole ND into 1355 quadrangle unit to see change of each crop acreage for last 16 years. We are using Seemingly Unrelated Left Censored Tobit Regression estimation method for our analysis. We are finding that own crop prices positively related to own crop acreages whereas other crop prices inversely related to that crop acreages. Yields of own crop positively relate to own crop acreage whereas another crop yields inversely relate to own crop acreage. Input prices of ammonium nitrate negatively relate to corn crop acreages. Because corn is input intensive crops. As nitrogen fertilizer price increases it could lead to substitute to soybeans crop to reduce production cost. Precipitation during May increases it leads to increases crop yields as well as crop acreages. Soil quality can cause productivity of crops. Temperature minimum and maximum positively relate crop acreages during growing season. Last year crop acreage positively relates to own crop acreages. Own and cross-price elasticity to crop acreage and marginal effects helps farmers decision to choose among alterative crop. Marginal effects of crop price increase by $1 to own acreage of barley, corn, soybean, wheat, and oilseeds ranges

between 50 to 295 acres, 28 to 572 acres, -24 to 45 acres, -198 to-39 acres, and 7 to 48 acres throughout ND and statistically significant except soybean. Elasticity of own-price to acreage of barley, corn, soybean, wheat, and oilseeds are 1.16%, 1.23%, 0.17%, -0.16%, and 0.53%, respectively, and statistically significant except soybean. This research findings will help forecast future agricultural land use trends & crop area response.

2.2. Introduction

Significant changes in agricultural land use have occurred in North Dakota over the last few years (Cropland data layer). Economic theory suggests farmers lean toward producing crops that will generate comparatively higher profits. Profits depend on the prices of inputs and outputs, as well as geophysical factors such as soil quality and climate that may confer a comparative advantage. Due to changes of agricultural technique (mix crop pattern, precision agriculture) in North Dakota in the period 1986, led to increases acreages of corn and soybeans in North Dakota overall (Boerboom et al. 2017). Grassland had been converted into corn and soy production due to doubling of commodity prices in western U.S. (Wright and Michael 2013). Also, the federal crop insurance and disaster program also acts as an incentive for a farmer's decision to convert land into cropland (Claassen et al. 2011). Moreover, land allocation decisions of producers for crop acreage, such as corn, soybeans, rice, and wheat, also depend on crop price changes and price volatility (Haile, Kalkuhl, and Von Braun 2015). Reitsma et al. (2015) concluded that the tripling of corn prices in South Dakota between 2006 and 2012, led to the conversion of 730,000 hectors of grassland to cropland. Choi and Helberger (1993) estimated the elasticity of crop yields' response to price changes and fertilizer use for corn, soybeans, and wheat. Their findings suggested that elasticity of fertilizer demand to crop prices are 0.47, 0.10, and 0.82, respectively whereas elasticity of yields to fertilizer for corn, wheat, and soybeans are

0.58,0.29, and 0.16, respectively. Additionally, Miao, Khanna, and Huang (2015) found that a price increase has a positive impact on corn yield, whereas no such effect is found for soybean yields. They determined that the price elasticities of corn yield and corn acreage were 0.23 and 0.45, respectively. Feng and Babcock's (2010) show that farmers increase their crop acreage for which commodity prices are expected to increase relative to other crops. An increase in fertilizer prices could affect corn yields because farmers then switch to other crops as corn needs more fertilizer for production (Feng and Babcock 2010). Input price increases and output prices of crops act inversely for crop acreage response (Feng and Babcock 2010). A farmer's decisions during planting and post-planting time also depend on expectations of output prices of crops (Irwin and Thraen 1994; Gouel 2010). Crop acreage planted (corn and soybeans) responds to price shocks more in the short run than the medium to long run (Hendricks, Aaron, and Daniel 2014). Perrin and Heady (1976) shows that acreage response is more dependent on output price, and input price and crop yield are more dependent on weather, climate, and technological change. Houck and Gallagher (1976) mentions that corn yield is responsive to input price. When fertilizer prices rose, there was significant influence on corn yield, except for weather and government programs. We can find very few studies conducted on barley and sunflower acreage in response to price changes and government programs. Recently, there has been more research on oilseeds such as sunflowers because of their multiple uses. Also, farmers prefer oilseeds due to changes in government target prices for wheat and barley (VanDyne, Blase, and Carlson 1990). Krause and Koo (1996) mentions that the acreage response of sunflowers and flaxseed is different from the wheat and barley acreage response due to expected prices and the impact of government programs. Haile, Brockhaus, and Kalkuhl (2016) estimates elasticity of crop acreage to price of four crops such as wheat, rice, corn, and soybean in major producing countries. Key findings suggest that, corn in United States, Argentina, and Brazil, wheat in United states, Russia, and Ukraine, soybean in United States, Ukraine, Brazil, and China more responsive to their own price (Haile, Brockhaus, and Kalkuhl 2016). In addition, it also suggests that some countries (Ukraine, Brazil, and India) crop (soybean and corn) acreage allocation are higher whether price changes or not changing at all in the long run (Haile, Brockhaus, and Kalkuhl 2016). Fertilizer price has positive and negative impact on crop acreage (Haile, Brockhaus, and Kalkuhl 2016). Iqbal and Babcock (2016) focuses on how global crop areas of corn, wheat, soybean, and rice response to prices in the short and long run whereas price volatility keep constant. Finding suggest that elasticity of global crop areas to price in short run is 0.024 whereas in the long run is 0.143 (Iqbal and Babcock 2016). It also mentions that, corn crop elasticities in the short run of global areas to own price effect is 0.100 whereas in the long run is 0.210, soybean in short run and long run are 0.213 and 0.631, respectively, wheat in the short run is 0.035, and rice in the short run 0.001 (Iqbal and Babcock 2016). Crop rotation has a great influence on crop yields. Continuous corn on the same land increases yields but not as much as a corn-soybeans rotation. Roth (2017) found that corn-soybeans rotation yields 5% to 20% more yields with same land than corn-corn rotation. It also finds that-corn soybeans rotation needs 40 lbs. less nitrogen fertilizer per acre. It also found that crop-soybeans rotation decreased input cost $25 per acre (Roth 2017). Hendricks et al. (2014) striking research topic relation of corn price and nitrogen losses in United States Corn belt. Their findings suggest that due to higher price of corn farmers prefer to plant corn next year and this year in the same land (Hendricks et al. 2014). As a result, more nitrogen fertilizer needs for corn growth which cause to pollute waterbodies (Hendricks et al. 2014). Their findings suggest that nitrogen loss to crop price inelastic in nature (Hendricks et al. 2014). In addition, corn and soybean price change led to more ethanol production (Hendricks et al. 2014). There is relation between crop returns and crop acreage decisions (“Relationship between….” 2013). In Midwest, due to relative price of corn and soybeans, corn acreage increases over the crop year 1995 through 2011(“Relationship between….” 2013). In Illinois, from 1995 to 2011, about 50% of crop rotation acreage allocated for soybeans crop but from 2007 to 2011, sharp increases in corn acreage (“Relationship between….” 2013). In addition, relative price of corn and crop budget tell that rate of returns higher for continuous corn rotation in Illinois (“Relationship between….” 2013). Key findings suggest that, low and higher corn acreage associated with higher and low rate of returns. Besides that, relative price of corn to soybean which make more profitable of corn than soybean (“Relationship between….” 2013). But, due to higher production cost of corn (seed and machinery) which make of returns of corn almost same to soybean (“Relationship between….” 2013). As a result, across states rotation choice are fifty- fifty for corn and soybean (“Relationship between….” 2013).

Soil texture acts as a contributing factor for crop yield and acreage response. Yields are higher in clay soils than in sandy soils in arid regions (Armstrong et al. 2009). Corn is a warm crop need sandy-loam soil, which is well-drained for its growth. Soil rich in nitrogen is good for growing corn crops. The pH level between 5.8 and 6.8 is good for corn growth. (Delp n.d.). For soybeans crop need mineral enriched soil that has nitrogen, phosphorous, and potassium nutrient. Slightly acidic soil is good for soybeans with a pH level of 6.5. Soybeans need loamy soil, which is well drained and fertile. Loamy soil consists of silt, sand, and clay particles (Septer n.d.). Wheat crops need a dry, cool climate. Well drained clay-loam soil is good for growing wheat. A rainfall of 750 to 1600 mm/year is good for wheat growth (“Ecological…” n.d.). Barley crop yields are higher in fine and coarse textured soil. Barley crops need a cool climate with sandy-loam soils that are well-drained with a 6.5 pH level (Simpson and Siddique 1994). According to Kandel, Knodel, and Lubenow (2015) North Dakota leads the United States with 85% canola production. Canola can be grown to all soil's types, but clay-loam soils are more suitable. Nitrogen and sulfur fertilizer are good for canola yields.

Temperature and precipitation have a profound impact on crop productivity. Growing degree days measure the daily minimum and maximum temperature, which helps farmers decide planting time as dependent on temperature (North Dakota Agricultural Weather Network Center (NDAWN) 2017). Temperatures between 50°F to 86°F are good for corn and soybean growth. Also, the lower limit temperature for canola is 41°F (NDAWN 2017). In addition, the lower limit temperature for barley and wheat is 42°F (Enz and Vasey 2005), and the upper limit temperature for wheat is 70°F (NDAWN 2017). Corn yields increase until 29°C, whereas soybean yields increase until 30°C. If temperatures exceed that limit, the yield will start to decline (Schlenker and Michael 2009). Spring planted small grains, such as wheat, barley, and oats, the yields decrease as temperature increases (Chmielewski and Kohn 1999). Furthermore, Lanning et al. (2010) found that wheat yields increase in Montana due to higher temperatures during March, whereas yields decrease with higher July temperatures. During growing season, if temperatures and precipitation are increasing, there are also some reverse effects because higher temperatures decrease yields. On the other hand, increases in precipitation might affect yields positively or negatively during the growing season. In addition, if precipitation increases during planting time, it causes a decrease of yields; whereas, increased precipitation after three to seven weeks of planting increases yields (Chmielewski and Kohn 1999; and Hakala et al. 2012). Hakala et al. (2012) found that higher precipitation during the late growing season has a negative impact on crop yields. For, soybeans production July rainfall and August temperature are an important factor (Hakala et al. 2012). Due to higher economic returns of corn and soybeans, changes in federal farm policy will positively influence farmers' decision-making processes regarding what crops they will prefer to plant (McMullen et al. 1997). Due to variability of precipitation and temperature, small grains like barley started to decline in yields and acreage planting. In addition, it also suggests that production of cool season crops like spring barley started to decline due to warmer temperatures (Klink et al. 2013). According to "How Might" (n.d.) in the next 100 years, average summer temperatures will start increasing in North Dakota an average of 3°F, and 4°F in other seasons. In addition, it also mentions that the expected number of days for precipitation and temperature will start increasing as well ("How Might" n.d.). Due to recent climate changes, New York state, once considered too cool to grow soybeans, farmers planted about 320, 000 acres of soybeans in 2013 (Weise 2013).

The biofuel mandate has an impact on crop acreage response. The Energy Policy Act of 2005 for Renewable Fuels Standard (RFS) mandate was introduced to use minimum renewable fuels as an alternative fuel in transportation to improve air quality (Millman et al. 2015). The Energy Independence and Security Act (EISA) of 2007 mandated that biofuel use needed to increase by 9 billion gallons to 36 billion gallons between 2008 and 2022 (USDA, ERS 2017). Corn is used to produce ethanol fuel as an additive to improve air quality (USDA, ERS 2017). Crop yield, crop acreage allocation, and bilateral trade have impact on land conversion due to demand for ethanol fuel (Keeney and Hertel 2009). Hertel, Tyner, and Birur (2010) mentioned global impact of biofuel mandate on land use in US and EU (Hertel, Tyner, and Birur 2010**)**. Their findings suggest that, due to oil price hike and greenhouse gas emissions abatement policy, ultimately increases demand for biofuel production (Hertel, Tyner, and Birur 2010**)**. In addition, impact of the Energy Independence and Security Act (EISA) of 2007 has raise food prices due to large corn crop used for ethanol production as well as reduction of corn crop used for food (Hertel, Tyner, and Birur 2010**)**. Oil rig operations in North Dakota have recently increased, and that will have an indirect effect on cropland acreage. Due to Bakken shale in western North Dakota, there has been a much greater demand for oil production. In addition, North Dakota become the largest oil producing states due to the increased Bakken shale oil production from 2007 to April 2014. During this period, average production ranged from 123,600 barrels per day to more than 1 million barrels per day. This higher oil production has led to increased demand for labor, goods, and services in the state (O'Neil, et al. 2015). Allred et al. (2015) suggested that since 2000, demand for oil and gas extraction in central North America has increased by an average of 50,000 new wells per year. Moreover, landowners or farmers have the option of receiving royalty payments due to their land use for oil drilling (Anderson 2012). Furthermore, if landowners receive higher revenues from drilling the same piece of land than they would with crop production, this can act as an externality for crop acreage response (Anderson 2012).

The Palmer drought severity index (PDSI) is a measure of drought conditions, depending on temperature and precipitation. The index was named for Wayne Palmer, a meteorologist who developed this method (Palmer 1965). The value of PDSI suggests that a negative value is drought condition, 0 is normal (Palmer 1965). The main objectives in our paper is how crop acreage respond to soil texture, expected crop prices, and input prices of major crops and geographical heterogeneity. We also try to determine how each crop acreage might be affected by climate variables like precipitation, maximum and minimum temperature, growing degree days, and PDSI.

2.3. Study Area

Our study area includes all of North Dakota. North Dakota agriculture contributes 38% of the state's economy, and about 94,285 people are employed in this sector. In addition, North Dakota is the second largest national wheat producing state, producing 15% of all U.S. wheat, equivalent to $1 billion annually (ND 2011). Wheat crop planted about 8 million acres in 2012 in ND (Farhang 2014). Most of the planted acres in North Dakota are dedicated to wheat, soybeans, barley, corn, sunflowers, and canola ("Major Crops of North Dakota and Livestock" 2010). Half of the total land area crop acres are used for wheat production. Wheat, the primary crop grown in North Dakota in acreage, is produced in every county. North Dakota is the leading producer of durum wheat and spring wheat. According to North Dakota Wheat Commission (n.d.) wheat is planted on an average of 9 million acres, yielding an average of 38 bushels per acre. According to "Farms in North Dakota" (2014) North Dakota is the leading producers of durum wheat and its mostly produced in northwestern part of that region. According to "Major Crops of North Dakota and Livestock" (2010) Sunflowers crop raised by Native Americans in the state. According to "Farms in North Dakota" (2014) majority of US sunflower produced in North Dakota State. According to "Major Crops of North Dakota and Livestock" (2010) Cass County, in the eastern part of the ND state, is the leading producer of soybeans. According to "Major Crops of North Dakota and Livestock" (2010) the first ND agricultural crop was corn, having been grown 300 years ago in the Upper Missouri Valley by Native American tribes. Although corn is mainly concentrated in southeastern ND counties, it is grown all over the state. In Ransom (2004) mentioned that corn needs moderate temperature for growing. Corn is considered a warm season crop. Due to recent changes in ND weather and higher rainfall in the eastern part, conditions are favorable for more corn grown during July and August. North Dakota often produces more barley than any other state (Ransom 2004)

2.4. Data Collection

2.4.1. GIS Data Collection Process

The dependent variables—acreages of each of the five crops—for this research are derived from the Cropland Data Layer (CDL), which is produced annually by the U.S. Department of Agriculture's (USDA) National Agricultural Statistics Service (NASS). The CDL is a geospatial database that classifies land use by crop at a 30-meter resolution. In North Dakota, the database is available each year from 1998 to 2013, which is the time period analyzed in this paper. The current study uses five land use classifications—barley, corn, oilseeds (combined sunflower, canola, and rapeseed), soybean, and wheat (combined hard red spring wheat, hard red winter wheat, and durum). The state is divided into 1355 cross-sectional units (about 50 square miles apiece) based on the United States Geological Survey (USGS) Quadrangle Index. Arc GIS software was used to tabulate the area of each of the five crops within each of the 1355 cross-sectional units each year from 1998 to 2013. Additionally, soil texture data for all of North Dakota was downloaded from the Soil Survey Geographic (SSURGO) database produced by the USDA, and the area of each of eight soil textures—clay, clay-loam, loam, loam-sand, sandy-loam, silt-loam, silty-clay, and silty-clay-loam—were tabulated for each of the 1355 cross-sectional units in ArcMap 10.5.

2.4.2. Economic Variables

When available, the expected price of each crop was proxied by futures contract prices. Prices of September futures contracts for corn, soybean, and hard red spring wheat from Chicago Mercantile Exchange (CME) on the 15th day of January, February, and March were downloaded from Quandl.com from 1998 through 2013. However, futures contracts are unavailable for barley and “oilseeds”, these expected prices were proxied by one-year lags of September barley and sunflower spot prices available from the USDA NASS Quick Stats database. All prices were adjusted for inflation using the Implicit GDP Price Deflator provided by the Federal Reserve’s Economic Research service with 2012 as the base year. One-year lags of county-level corn, soybean, barley, wheat, and sunflower yields were also collected from the USDA NASS Quick Stats database and were used as proxies for crop yield expectations. The United States Energy Information Administration tracks weekly Midwest retail diesel prices, which are used as an explanatory variable because diesel fuel represents a large proportion of the cost of crop production. Diesel price data were acquired for the last two weeks of February and the first two weeks of March from 1998 to 2013. Nitrogen fertilizer also accounts for a large proportion of the cost of crop production, so average United States farm prices of ammonium nitrate fertilizer for April from 1998 through 2013 were acquired from the United States Department of Agriculture, Economic Research Service, Fertilizer Use and Price 2017. All prices—including crop prices and input prices—were adjusted for inflation using the Implicit GDP Price Deflator provided by the Federal Reserve Economic Data (FRED) with 2012 as the base year. The latitude and longitude of each of the 1355 cross-sectional units were also recorded. Twenty-year averages (1970 to 1990) of climate variables were collected for each month, March through August, including monthly precipitation and monthly averages of daily maximum and minimum temperatures for each of North Dakota’s 53 counties from North Dakota State University’s Climate Change throughout the Dakota's database (https://www.ndsu.edu/climate). From the same database, the thirty-year county-level average of growing degree days (GDD) accumulated annually from May through October was also acquired, as were the county-level 30-year averages of the Palmer

Drought Severity Index (PDSI) for the months of March and April. County-level year-over-year change in oil production (barrels) was obtained from the North Dakota Drilling and Production Statistics from the periods 1996 through 2014. Two biofuel mandate indicator variables that indicate enactment of the 2005 rules and the 2007 rules, are also included as explanatory variables.

2.4.3. Descriptive Statistics

Descriptive statistics—including the mean, standard deviation, minimum, and maximum—for each variable are presented in table 2.1. Expected revenues for each crop are calculated for each year by multiplying the expected yield by the expected price. One-year lags and inverse distance weighted one-year lags of each of the crop acreages are also used to account for any constraints imposed by crop rotations and to account for any spatial correlation patterns among the quadrangles' crop coverages. Means of the lagged and spatially-weighted lagged acreages are not presented in table 2.1 because they are nearly identical to the average values of crop acreages used as dependent variables. Note that the minimum values for acreages of each crop are zero, indicating that—at least in some years in some cross-sections—each crop's acreage is censored at zero.

Table 2.1. Descriptive statistics for dependent and independent variables

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
Dependent Variables					
Crop acreage					
Barley (ac.)	21,664	716.66	1,055.62	0.00	10,969.61
Corn (ac.)	21,664	1,183.67	2,145.87	0.00	17,636.11
Oilseed (ac.)	21,664	1,538.49	1,983.18	0.00	15,816.70
Soybean (ac.)	21,664	2,386.95	3,894.96	0.00	23,735.72
Wheat (ac.)	21,664	6,152.71	4,174.06	0.00	23,777.53
Independent Variables					
Expected price					
Barley ($/bu.)	16	3.22	1.19	1.93	5.76
Corn ($/bu.)	16	4.15	1.35	2.75	6.39
Soybean ($/bu.)	16	9.35	3.06	5.84	15.11
Sunflower ($/cwt.)	16	17.48	6.08	11.61	18.82
Wheat ($/bu.)	16	5.62	2.46	3.67	13.24
Diesel ($/gal.)	16	2.45	0.91	1.23	4.07
Fertilizer ($/short ton)	16	375.78	108.04	237.74	539.36
Expected yield					
Barley (bu./ac.)	21,664	42.09	7.87	30.00	67.90
Corn (bu./ac.)	21,664	71.85	18.17	35.00	111.80
Soybean (bu./ac.)	21,664	20.10	9.95	0.00	36.50
Wheat (bu./ac.)	21,664	23.97	3.49	18.00	34.90
Expected revenue					
Barley ($/ac.)	21,664	145.22	69.68	58.05	487.66
Corn ($/ac.)	21,664	297.89	122.92	96.41	714.02
Soybean ($/ac.)	21,664	196.54	123.24	0.00	476.01
Wheat ($/ac.)	21,664	134.70	60.90	66.04	462.23
Daily maximum temp					
March Average (°F)	53	36.19	2.87	41.86	30.20
April Average (°F)	53	54.16	1.58	57.62	50.34
May Average (°F)	53	68.25	1.19	66.28	70.99
June Average (°F)	53	77.21	1.14	74.54	80.20
July Average (°F)	53	83.48	1.64	79.32	87.10
August Average (°F)	53	81.65	1.54	85.21	77.83

Table 2.1. Descriptive statistics for dependent and independent variables (continued)

Variable	**Observations**	**Mean**	**Standard deviation**	**Minimum**	**Maximum**
<u>**Independent Variables**</u>					
Daily minimum temp					
March Average (°F)	53	15.87	1.20	10.88	19.19
April Average (°F)	53	29.77	1.04	27.08	32.08
May Average (°F)	53	41.88	0.98	39.79	44.45
June Average (°F)	53	51.25	0.99	48.94	53.97
July Average (°F)	53	55.99	1.19	53.46	59.09
August Average (°F)	53	53.18	1.24	50.62	56.12
Total precipitation					
March Average (in.)	53	0.86	0.16	0.56	1.26
April Average (in.)	53	1.54	0.27	0.99	2.22
May Average (in.)	53	2.31	0.24	1.81	2.78
June Average (in.)	53	3.07	0.25	2.38	3.46
Total Precipitation					
July Average (in.)	53	2.39	0.32	1.65	2.95
August Average (in.)	53	2.05	0.42	1.37	2.76
Palmer Drought Severity					
Average Index March	53	0.19	0.55	-1.08	1.22
Average Index April	53	0.34	0.63	-1.17	1.40
Average Annual Growing Degree Days May to October	53	2,311.95	138.12	2,018.95	2,633.69
Change in oil extraction (bbl.)	304	224,155.40	1,500,568.00	-3,051,393.00	16,500,000.00
Latitude (decimal deg.)	1,355	47.48	0.87	46.06	48.94
Longitude (decimal deg.)	1,355	-100.47	2.04	-103.94	-96.69
Renewable Fuel Standard					
Indicates 2005-2013	16	0.56	0.51	0.00	1.00
Indicates 2007-2013	16	0.44	0.51	0.00	1.00
Soil Texture (Percent cover)					
Clay	1,355	0.20	2.05	0.00	35.03
Clay-loam	1,355	1.51	7.58	0.00	83.98
Silt-loam	1,355	11.57	23.80	0.00	100.00
Loam	1,355	66.83	36.14	0.00	100.00
Loam-sand	1,355	4.74	14.06	0.00	100.00
Sandy loam	1,355	8.97	16.75	0.00	94.98
Silty clay	1,355	3.04	12.41	0.00	100.00
Silty clay-loam	1,355	3.15	12.71	0.00	100.00

2.5. Theoretical Model

Our theoretical model is a cropland supply function for land allocation to each of 5 different crops. The study region comprises the entirety of North Dakota. According to economic theory, the amount of land allocated to a crop is a function of the explicit costs and benefits attributable to the crop, as well as the opportunity cost associated with forgoing other productive uses of the land—e.g. other crops. It is therefore assumed that farmers allocate (or supply) land to a crop according to the expected revenues for that crop, as well as those of alternative crops and land uses. The total area allocated to a crop is assumed to be based on farmers' expectations about the various determinants of revenue for each crop, among other things. A very general supply function for acreage of crop *i* can be written as follows:

$$A_{ik} = f(P_i, Y_{ik}, C_{ik}, \mathbf{P_j}, \mathbf{Y_{jk}}, \mathbf{C_{jk}}, \mathbf{W_k}, S_k; \boldsymbol{\beta}_\mathbf{i}) \tag{2.1}$$

where A_{ik} is the acreage of crop *i* supplied in area *k*, P_i is the expected price of crop *i*, Y_{ik} is the expected yield of crop *i* in area *k*, C_{ik} is the expected cost of producing crop *i* in area *k*; $\mathbf{P_j}$ is a vector of expected prices of all alternative crops, $\mathbf{Y_{jk}}$ is a vector of expected yields for all alternative crops at location *k*, $\mathbf{C_{jk}}$ is a vector of expected production costs for each of the *J* alternative crops in area *k*, $\mathbf{W_k}$ is the vector of expected weather events in production area *k*, S_k is soil attributes at location *k*, and $\boldsymbol{\beta}_\mathbf{i}$ is a vector of parameters relating the acreage of crop *i* in area *k* to the aforementioned explanatory variables. The law of supply signals the following expectations, *ceteris paribus*: (1) $\partial A_{ik}/\partial P_i > 0$; (2) $\partial A_{ik}/\partial Y_{ik} > 0$; (3) $\partial A_{ik}/\partial C_{ik} < 0$. That is, a crop's acreage should increase when its expected price increases and when its expected yield increases but should decrease when its production cost increases. It is difficult to form expectations about the cross-price derivatives, however, because substitutability and complementarity between any two crops may vary over time and space. Signs of derivatives with respect to expected weather variables are also difficult to predict generally, as weather varies over space and each crop has unique optimal growing conditions.

2.6. Methodology

A system of five acreage supply functions was estimated using seemingly unrelated Tobit regression (SUTR) using Simulated Maximum Likelihood. The SUTR model was developed by Arnold Zellner in 1962. Each equation (1) has its own unique dependent variable and (2) may include different explanatory variables among equations (Zellner, 1962). The SUTR model was selected for this dissertation for two reasons. Firstly, the dependent variables are censored at zero—i.e. no cross-sectional unit can have less than zero acres of any crop. This means a censored regression technique, such as Tobit Regression, is appropriate (Greene, 2003). Secondly, the five dependent variables—planted acres of each crop—are highly correlated with each other, as any area planted to one crop cannot be planted to any other crop in the same year. As a result of the correlation among the five dependent variables, the residuals may be correlated also. In the SUR model, error terms can be correlated across equations, and these cross-correlations are estimated (Davidson and MacKinnon,1993). The empirical model estimated for this research can be written as:

$$\begin{bmatrix} \mathbf{Z_{bt}} \\ \mathbf{Z_{ct}} \\ \mathbf{Z_{ot}} \\ \mathbf{Z_{st}} \\ \mathbf{Z_{wt}} \end{bmatrix} = \begin{bmatrix} \mathbf{X_t} & 0 & 0 & 0 & 0 \\ 0 & \mathbf{X_t} & 0 & 0 & 0 \\ 0 & 0 & \mathbf{X_t} & 0 & 0 \\ 0 & 0 & 0 & \mathbf{X_t} & 0 \\ 0 & 0 & 0 & 0 & \mathbf{X_t} \end{bmatrix} \begin{bmatrix} \boldsymbol{\beta}_\mathbf{b} \\ \boldsymbol{\beta}_\mathbf{c} \\ \boldsymbol{\beta}_\mathbf{o} \\ \boldsymbol{\beta}_\mathbf{s} \\ \boldsymbol{\beta}_\mathbf{w} \end{bmatrix} + \begin{bmatrix} \mathbf{U_{bt}} \\ \mathbf{U_{ct}} \\ \mathbf{U_{ot}} \\ \mathbf{U_{st}} \\ \mathbf{U_{wt}} \end{bmatrix}, \tag{2.2}$$

where $\mathbf{Z_{bt}}, \dots, \mathbf{Z_{wt}}$ are five 1,355 by 1 vectors of latent variables related to the acreages of barley, corn, oilseeds, soybean, and wheat, respectively, in all cross-sectional units in year *t*; $\mathbf{X_t}$ is a 1,355 by 60 matrix of the values of each of 60 explanatory variables in each cross-sectional unit in time *t*; $\boldsymbol{\beta}_\mathbf{b}, \dots, \boldsymbol{\beta}_\mathbf{w}$ are five 60 by 1 column vectors of parameters—including intercepts—

relating the explanatory variables to the vectors of latent variables; and $\mathbf{U_{bt}}, \ldots, \mathbf{U_{wt}}$ are five 1,355 by 1 vectors of errors at time *t*, which are distributed as follows:

$$\begin{pmatrix} \mathbf{U_{bt}} \\ \mathbf{U_{ct}} \\ \mathbf{U_{ot}} \\ \mathbf{U_{st}} \\ \mathbf{U_{wt}} \end{pmatrix} \sim N \left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{bb} & \sigma_{bc} & \sigma_{bo} & \sigma_{bs} & \sigma_{bw} \\ \sigma_{bc} & \sigma_{cc} & \sigma_{co} & \sigma_{cs} & \sigma_{cw} \\ \sigma_{bo} & \sigma_{co} & \sigma_{oo} & \sigma_{os} & \sigma_{ow} \\ \sigma_{bs} & \sigma_{cs} & \sigma_{os} & \sigma_{ss} & \sigma_{sw} \\ \sigma_{bw} & \sigma_{cw} & \sigma_{ow} & \sigma_{sw} & \sigma_{ww} \end{bmatrix} \right). \tag{2.3}$$

The observed data are the recorded acreages—the five 1,355 by 1 vectors $\mathbf{A_{bt}}$, $\mathbf{A_{ct}}$, $\mathbf{A_{ot}}$, $\mathbf{A_{st}}$, and $\mathbf{A_{wt}}$—which are related to the latent variables by the observation function:

$$\mathbf{A_{it}} = \begin{cases} \mathbf{Z_{it}} & \text{iff } \mathbf{Z_{it}} > 0 \\ 0 & \text{iff } \mathbf{Z_{it}} \leq 0 \end{cases}, \tag{2.4}$$

where each vector of variable values is as previously defined. Table 2.1 lists and provides descriptive statistics for the dependent variables—the five *Z* vectors—and the explanatory variables used in the *X* matrix. In this model, the *X* matrix is identical for each acreage response equation. Estimation of the SUTR models was carried out in STATA 14.2 using the mvtobit estimation procedure.

2.6.1. Spatially Distributed Time Lags

Because the dependent variables for this research are panel data with time series measurements at fixed locations over the 16 years of the study period, it is essential that any spatial relationships among the variables be considered to ensure efficient estimation of the parameter estimates of interest. Spatial econometrics differs from traditional econometrics for two reasons—spatial dependence and spatial heterogeneity (LeSage 1999). Spatial weighting allows researchers to separate the effects of the other independent variables from any spatial dependencies that may exist between dependent variables at nearby locations. Thus, inverse distance-weighted one-year time lags of the crop acreages are used as explanatory variables. The inverse distance weights matrix is a 1,355 by 1,355 square matrix in which each element is the inverse of the distance between two cross-sectional units, and the elements on the diagonal are all zero. This matrix denoted W, was obtained by inputting the latitudes and longitudes of all 1,355 quadrangles into the spatwmat routine in STATA 14.2. Once the inverse distance weights matrix was generated, it was multiplied by the vector of time-lagged acreages of each crop to obtain $WA_{i,t-1}$—a 1,355 by 1 vector of inverse distance-weighted, time-lagged acreages of crop *i* in year *t* to be used as independent variables. Since the spatial weight's matrix has zeros on the diagonal, the resulting vector does not include the standard time-lag of crop acreage, so one-year lags of crop acreages are included as separate independent variables.

2.6.2. Marginal Effects and Elasticities of Crop Prices

Of interest in this research are the marginal effects of expected prices—particularly crop prices—on the acreages of each crop and the own- and cross-price elasticities of acreage response. Based on the estimated system of Tobit equations described in equations 2.2 to 2.4, the expected acreage values, marginal effects, and elasticities can be calculated as follows:

$$\widehat{\mathbf{A}}_{\mathbf{it}} = \Phi\left(\mathbf{X_t}\widehat{\boldsymbol{\beta}}_{\mathbf{i}}/\hat{\sigma}_i\right)\left(\mathbf{X_t}\widehat{\boldsymbol{\beta}}_{\mathbf{i}} + \hat{\sigma}_i\left(\frac{\phi\left(\mathbf{X_t}\widehat{\boldsymbol{\beta}}_{\mathbf{i}}/\hat{\sigma}_i\right)}{\Phi\left(\mathbf{X_t}\widehat{\boldsymbol{\beta}}_{\mathbf{i}}/\hat{\sigma}_i\right)}\right)\right), \tag{2.5}$$

$$\widehat{\mathbf{M}}_{\mathbf{ijt}} = \left(\partial\mathbf{A}_{\mathbf{it}}/\partial P_{jt}\right)\Phi\left(\mathbf{X_t}\widehat{\boldsymbol{\beta}}_{\mathbf{i}}/\hat{\sigma}_i\right), \text{ and} \tag{2.6}$$

$$\widehat{\boldsymbol{\eta}}_{\mathbf{ijt}} = \widehat{\mathbf{M}}_{\mathbf{ijt}}\left(P_{jt}/\widehat{\mathbf{A}}_{\mathbf{it}}\right), \tag{2.7}$$

where $\widehat{\mathbf{A}}_{\mathbf{it}}$ is a 1,355 by one vector of expected acreages of crop *i* in all cross-sectional units in year *t*, Φ is the standard normal cumulative density function; $\mathbf{X_t}$ is a 1,355 by 60 matrix of the values of each of 60 explanatory variables in each cross-sectional unit in time *t*; $\widehat{\boldsymbol{\beta}}_{\mathbf{i}}$ is a 60 by one vector of estimated parameters relating the acreages of crop *i* to the values of the independent variables; $\hat{\sigma}_i$ is the estimated standard deviation of the error terms for crop *i*; $\widehat{\mathbf{M}}_{\mathbf{ijt}}$is a 1,355 by one vector of marginal effects of the price of crop *j* on the acreage of crop *i* at each location in year t; $\widehat{\boldsymbol{\eta}}_{\mathbf{ijt}}$ is a 1,355 by one vector of estimated price elasticities—or percent changes in acreage of crop i in response to a one percent change in the price of crop j. Notably, when $i = j$, $\widehat{\mathbf{M}}_{\mathbf{ijt}}$ and $\widehat{\boldsymbol{\eta}}_{\mathbf{ijt}}$ are own-price marginal effects and elasticities, respectively; however, when $i \neq j$, they are cross-price marginal effects and elasticities.

Because equations 2.6 and 2.7 are highly nonlinear, we estimate the standard errors for these estimated marginal effects and elasticities using Monte Carlo simulation. The method used is a variation of that developed by Krinsky and Robb (1986)—simulating random draws from the joint distribution of all the model parameter estimates. Roberts (2009) provides an easy-to-follow mathematical exposition of the Monte Carlo procedure used in this research. For each of the 21,664 observations, 1,000 random draws from the distribution of parameter estimates were created—resulting in about 21.7 million vectors of simulated parameter estimates. Once these simulated vectors were created, the values of $\widehat{\mathbf{M}}_{\mathbf{ijt}}$, and $\widehat{\boldsymbol{\eta}}_{\mathbf{ijt}}$ were calculated 1,000 times per site-year (by plugging in $\mathbf{X_t}$). Marginal effects and elasticities were then averaged over all years for each location, and one-tailed statistical significance tests were performed to determine which of the 1,355 cross-sectional units had marginal effects and elasticities that have been discernibly non-zero during the years 1998 to 2013.

2.7. Results and Discussion

In this section, the SUTR estimates are presented, as are the marginal effects of crop prices on crop acreages and the own- and cross price elasticities. Parameter estimates for each of the five estimated crop acreage response functions are presented in table 2.2. The Wald test statistic is 383,208.680, and is distributed χ^2 with 295 degrees of freedom, so it exceeds the critical value of 375.79 ($p = 0.001$), which indicates that the model estimated here performs significantly better than the null model. Furthermore, statistical tests indicate most of the individual parameter estimates are different from zero at $\alpha < 0.10$. The expected crop prices in the model are the prices of September corn and soybean futures contracts on 15 March—just before planting time—and the one-year lagged spot prices of barley and sunflower. Two alternative models were estimated using the prices of September corn and soybean futures contracts on 15 January and 15 February. The pseudo-log-likelihood function values of the three estimations indicated that September futures contract prices for corn and soybean on 15 March provided the best fit.

A few noteworthy inferences can be drawn directly from the parameter estimates in table 2.2. For example, the parameters for own-price, own-yield, and own-revenue are all statistically non-zero at $\alpha = 0.01$ or better—except in the case of the wheat own-price parameter estimate, which is not discernibly different from zero. Additionally, most of crop acreage cross-price, cross-revenue, and cross-yield parameters are statistically significant, which shows relationships exist between acreage of one crop and prices, yields, and revenues of the other crops. However, these commodity price parameter estimates should not be interpreted in isolation; it is needful to calculate the marginal effects of prices based on equation (2.6) due to censoring and interactions between expected crop prices and price yields—i.e. the revenue variables. On the other hand, parameter estimates for expected prices of diesel and ammonium nitrate fertilizer can be directly interpreted because these enter the models linearly. For example, higher diesel prices lead to lower acreages of barley and oilseeds, but higher acreages of corn, soybean, and wheat. Higher ammonium nitrate prices appear to cause barley and corn acreages to decrease, while leading to increases in acreages of oilseeds, soybean, and wheat. The varied signs and magnitudes of the parameter estimates for these input prices are related to the relative requirements of each crop for the two inputs included in the model. That is, increasing diesel and fertilizer prices cause farmers to switch crops to reduce input use, rather than substantially decreasing overall planted acreage.

Table 2.2. Seemingly unrelated Tobit regression results

	Model dependent variables (acres of barley, corn, oilseeds, soybean, and wheat)				
Independent variable	**Barley**	**Corn**	**Oilseeds**	**Soybean**	**Wheat**
Expected price					
Barley	405.212^{***a}	199.929***	-121.895**	-858.924***	519.916***
	(29.373)^{b}	(31.495)	(51.748)	(56.390)	(76.374)
Corn	58.848	-163.417***	-1082.868***	-1348.330***	-620.310***
	(42.957)	(46.409)	(76.170)	(85.214)	(112.079)
Soybean	68.813***	-106.356***	266.185***	98.665***	103.821**
	(17.634)	(19.041)	(31.225)	(36.156)	(45.930)
Sunflower	-28.882***	-0.400	47.493***	101.168***	-48.808***
	(2.880)	(3.094)	(5.845)	(5.501)	(7.476)
Wheat	7.240	-60.533***	-117.348***	27.435	4.631
	(20.101)	(21.293)	(35.239)	(38.824)	(52.279)
Diesel	-382.391***	191.404***	-362.376***	1313.931***	1031.072***
	(28.543)	(30.723)	(50.200)	(55.187)	(73.805)
Ammonium nitrate	-2.309***	-3.681***	3.265***	16.206***	16.992***
	(0.458)	(0.501)	(0.811)	(0.921)	(1.195)
Expected yield					
Barley	14.842***	-9.129***	59.878***	45.036***	21.812***
	(2.691)	(2.884)	(4.753)	(5.239)	(7.008)
Corn	-5.269***	-29.915***	-2.635	-11.349***	5.626
	(1.453)	(1.548)	(2.566)	(2.803)	(3.781)
Soybean	-16.449***	-31.497***	-48.088***	44.765***	-33.335***
	(2.750)	(3.013)	(4.882)	(5.629)	(7.180)
Wheat	-16.434***	12.690*	-166.591***	-2.935	187.863***
	(6.205)	(6.617)	(10.914)	(11.932)	(16.163)
Expected revenue					
Barley	-2.888***	1.978***	2.399**	-1.971*	-9.197***
	(0.566)	(0.601)	(0.997)	(1.073)	(1.475)
Corn	0.649**	6.676***	0.633	1.125*	-1.347*
	(0.304)	(0.322)	(0.536)	(0.582)	(0.791)
Soybean	2.023***	4.076***	5.933***	-3.890***	4.554***
	(0.291)	(0.317)	(0.516)	(0.585)	(0.758)
Wheat	-0.015	1.862***	2.500*	-4.742***	-5.793***
	(0.761)	(0.803)	(1.332)	(1.445)	(1.983)

Table 2.2. Seemingly unrelated Tobit regression results (continued)

Independent variable	Model dependent variables (acres of barley, corn, oilseeds, soybean, and wheat)				
	Barley	Corn	Oilseeds	Soybean	Wheat
Daily high temperature					
March average	-289.916***	0.831	162.657***	-908.263***	-304.259***
	(30.880)	(33.079)	(54.269)	(60.648)	(79.849)
April average	508.358***	165.931***	70.145	1170.921***	-62.294
	(44.891)	(47.731)	(78.877)	(85.209)	(116.417)
May average	-388.992***	-61.675	-1312.366***	217.520**	-261.553**
	(44.089)	(47.318)	(77.859)	(87.390)	(114.766)
June average	99.907*	38.679	1122.196***	-886.868***	-54.112
	(55.812)	(60.014)	(98.585)	(109.740)	(145.677)
July average	-138.252**	-104.260	-1378.523***	1501.275***	-84.183
	(62.140)	(66.865)	(109.633)	(120.229)	(161.777)
August average	202.511***	7.592	1141.919***	-724.977***	427.674***
	(43.508)	(47.326)	(77.075)	(88.774)	(113.115)
Daily low temperature					
March average	-62.667**	-52.443*	-850.796***	300.441***	527.768***
	(26.705)	(28.540)	(46.932)	(51.027)	(69.157)
April average	-33.663***	-30.245***	-30.713***	51.634***	-16.088***
	(1.409)	(1.500)	(2.492)	(2.792)	(3.668)
May average	-240.912***	95.029	1145.825***	-525.381***	-2142.337***
	(63.783)	(68.774)	(112.676)	(129.433)	(166.278)
June average	381.412***	-300.665***	-1289.189***	730.771***	2027.774***
	(70.587)	(76.545)	(124.820)	(146.953)	(183.831)
July average	-87.611	153.906**	799.523***	47.726	-1837.295***
	(59.698)	(65.210)	(106.010)	(127.973)	(155.991)
August average	56.127	108.783**	-318.879***	-240.083**	1266.973***
	(48.428)	(52.399)	(85.698)	(98.405)	(126.447)
Total monthly precipitation					
March average	-624.560***	496.929***	-3842.608***	-2695.829***	1109.721***
	(136.657)	(145.369)	(239.963)	(260.402)	(353.919)
April average	-262.534***	738.092***	1454.826***	256.137**	-831.261***
	(59.871)	(64.072)	(105.827)	(119.504)	(155.682)

Table 2.2. Seemingly unrelated Tobit regression results (continued)

	Model dependent variables (acres of barley, corn, oilseeds, soybean, and wheat)				
Independent variable	**Barley**	**Corn**	**Oilseeds**	**Soybean**	**Wheat**
Total monthly precipitation					
May average	-453.359***	-249.232***	1582.797***	-497.536***	1287.013***
	(75.130)	(81.126)	(132.845)	(138.355)	(196.211)
June average	463.070***	244.340***	419.997***	-282.476***	-832.172***
	(42.779)	(46.230)	(75.457)	(84.283)	(111.175)
July average	11.643	522.963***	-45.514	-352.437**	-76.216
	(69.246)	(75.187)	(122.944)	(141.823)	(180.550)
August average	682.672***	-267.638***	1828.802***	-314.633**	494.038***
	(66.777)	(72.152)	(118.147)	(131.347)	(174.419)
Palmer drought severity					
March	505.072***	1494.482***	2103.431***	1596.018***	1183.139***
	(119.69)	(126.635)	(209.878)	(225.803)	(310.003)
April	-112.850	-1741.603***	-2589.594***	-723.542***	-1045.702***
	(115.247)	(122.195)	(202.140)	(220.299)	(298.146)
Growing degree days (May through October)	1.491***	-0.718***	6.860***	-4.749***	1.996***
	(0.221)	(0.243)	(0.391)	(0.472)	(0.576)
Renewable fuel standard					
Dummy 1 (2005 RFS)	460.214***	759.918***	575.874***	-3598.303***	185.107
	(56.261)	(62.104)	(99.542)	(111.034)	(145.991)
Dummy 2 (2007 RFS)	-875.477***	-679.953***	138.204	1992.860***	-230.676
	(55.107)	(59.812)	(97.496)	(106.522)	(143.593)
Change in oil activity	-0.014^{***c}	-0.009^{**c}	-0.011^{c}	0.041^{***c}	-0.038^{***c}
	(0.004)	(0.004)	(0.007)	(0.008)	(0.011)
Soil texture proportion					
Clay loam	-1.641*	0.247	-1.982	-6.826***	17.487***
	(0.834)	(0.915)	(1.476)	(1.876)	(2.178)
Clay	-2.617	-0.809	1.224	6.330	-16.307**
	(2.781)	(3.002)	(4.953)	(5.670)	(7.239)
Silt loam	0.137	-0.502	-2.965***	-3.158***	-6.080***
	(0.304)	(0.331)	(0.541)	(0.655)	(0.790)
Silty clay	-0.392	-6.910***	-8.610***	4.836***	-2.875**
	(0.532)	(0.566)	(0.943)	(1.002)	(1.376)

Table 2.2. Seemingly unrelated Tobit regression results (continued)

	Model dependent variables (acres of barley, corn, oilseeds, soybean, and wheat)				
Independent variable	**Barley**	**Corn**	**Oilseeds**	**Soybean**	**Wheat**
Soil texture proportion					
Silty clay loam	-1.011*	-1.646***	-10.790***	-4.215***	-0.781
	(0.547)	(0.579)	(0.966)	(1.013)	(1.426)
Loam	0.387***	-0.876***	0.636***	0.766***	1.792***
	(0.112)	(0.120)	(0.198)	(0.216)	(0.291)
Loam sand	-1.837***	2.656***	-0.598	-6.972***	-6.552***
	(0.474)	(0.501)	(0.831)	(0.897)	(1.229)
Sandy loam	-0.873***	1.977***	-1.436***	-1.731***	-4.046***
	(0.253)	(0.271)	(0.447)	(0.488)	(0.657)
Lagged acreage					
Barley	0.295***	0.071***	0.433***	0.140***	0.475***
	(0.008)	(0.009)	(0.014)	(0.016)	(0.021)
Corn	0.035***	0.720***	0.103***	0.183***	0.041**
	(0.006)	(0.007)	(0.011)	(0.012)	(0.017)
Soybean	0.029***	0.104***	-0.059***	0.673***	0.144***
	(0.004)	(0.004)	(0.007)	(0.008)	(0.011)
Oilseeds	1.000***c	2.670**c	0.658***c	0.158c	-0.658***c
	(0.098)	(0.106)	(0.172)	(0.181)	(0.172)
Wheat	0.055***	0.007***	0.176***	0.061***	0.821***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)
Inverse distance-weighted lagged acreage					
Barley	-0.255***	-0.133***	-1.344***	-0.411***	-1.514***
	(0.034)	(0.037)	(0.060)	(0.065)	(0.088)
Corn	-0.140***	-0.554***	-0.646***	0.535***	-0.845***
	(0.033)	(0.035)	(0.057)	(0.063)	(0.084)
Soybean	-0.261***	0.049***	-0.577***	-0.239***	-1.50***
	(0.017)	(0.018)	(0.030)	(0.033)	(0.045)
Oilseeds	0.816***c	0.515**c	4.330***c	-9.150***c	-0.002***
	(0.194)	(0.209)	(0.342)	(0.365)	(0.001)
Wheat	-0.252***	-0.041***	-0.333***	0.086***	-1.304***
	(0.012)	(0.013)	(0.022)	(0.024)	(0.032)

Table 2.2. Seemingly unrelated Tobit regression results (continued)

	Model dependent variables (acres of barley, corn, oilseeds, soybean, and wheat)				
Independent variable	**Barley**	**Corn**	**Oilseeds**	**Soybean**	**Wheat**
Latitude	73.508**	-304.777***	69.180	-240.633***	811.879***
	(29.041)	(31.446)	(51.488)	(57.608)	(75.866)
Longitude	-6.658	120.184***	466.012***	453.777***	873.705***
	(17.337)	(18.821)	(30.698)	(35.028)	(45.194)
Constant	-14361.290***	27625.430***	47625.350***	15437.510***	72910.120***
	(3179.473)	(3406.710)	(5598.277)	(6173.616)	(8268.249)
Standard deviation of error terms	787.097***	835.507***	1393.261***	1458.544***	2064.350***
	(3.818)	(4.217)	(6.758)	(7.775)	(9.906)

N = 21664; Wald χ^2_{295} = 383,208.680

[a] The symbols ***, **, and * indicate statistical significance at $\alpha = 0.01$, $\alpha = 0.05$, and $\alpha = 0.10$, respectively.

[b] Numbers in parentheses are the standard errors of the parameter estimates.

[c] Parameter estimate, and standard error are scaled—multiplied by 1,000.

It is also clear that expected climatic conditions—i.e. 20-year averages of monthly averages of daily maximum temperature, daily minimum temperature, total precipitation, PDSI, and the 20-year average of annual growing degree days accumulated during the growing season are all related to, and likely play a causal role in farmers' aggregate crop selections, as does the prevalence of each of the varied soil types. Crop producers are fully aware of, and responsive to, local climate conditions and soil attributes, as expected. These are all geographically specific factors that affect the opportunity costs—and comparative advantage—a given farmer has in production of each of the five crops.

The variables related to transportation fuels (the RFS indicator variables and the oil activity variable) also appear to have substantial influence on farmers' crop selections. For example, the joint effects of the two RFS indicators on crop acreages are positive for corn and oilseeds, but negative for barley and soybean. The positive effect on corn acreage may be due to farmers' expectations of increased demand for corn related to the renewable fuel mandates. The increasing prevalence of oilseed acreage since the implementation of the RFS is probably related to increased forward-contracting of canola acreage—that is, demand for this oilseed has increased dramatically since North Dakota farmers began planting canola in earnest around 1999. Much of North Dakota's canola crop is sent across the Canadian border for crushing. The negative effects on barley and soybean acreages likely indicate that the RFS have induced farmers to switch from barley and soybean to corn, at least in some locations. The joint effect of the RFS variables on HRSW acreage is negative, but not statistically significant. Changes in oil production over time are also strongly related to farmers' crop selections in counties where oil extraction activities occur. New crude oil extraction activities have negative impacts on acreages of barley, corn, soybean, and wheat. On the other hand, the oil extraction activities have been positively correlated with acreage of oilseeds.

Parameter estimates for the lagged and spatially weighted lagged dependent variables are also statistically non-zero, except in the case of lagged acreage of oilseeds in the oilseeds acreage response function. These parameters indicate that cropping activities in each location are partially determined by the cropping activities of the preceding growing season in both the same location and in neighboring locations. One-year lags of own-acreage in each crop acreage response function are all positive, indicating that each 50 $mi.^2$ tends to have plantings of the same crops, at least to some degree, year after year. Interpretation of the spatially weighted acreage lags is more complex, especially since these weighted time lags are highly collinear with the simple time lags of acreage. While these variables account for rotational constraints and, maybe, the influence of neighboring farms on each other's activities, these parameters are not of interest in this research, so the collinearity does not present a statistical problem. Finally, note that the parameter estimates for latitude and longitude are generally statistically significant, except for longitude in the barley acreage response function and latitude in the oilseeds acreage response function, even after controlling for other site-specific factors such as soil types, precipitation, drought, and temperatures.

The cross-correlation of the regression error terms is presented in table 2.3. These values indicate how over-estimation of acreage of one crop at a location in a specific year correlates to under/over-estimation of acreage of other crops at the same location in the same year. All the cross-correlations, excepting that between barley and corn error terms, are statistically significant, which indicates that the SUTR estimation technique will yield more efficient parameter estimates than could have been achieved by estimating the five acreage response functions individually. Positive cross-correlations indicate that the two crops are likely to both be over-predicted (or both under-predicted) in the same year and location, as is the case for barley and oilseeds, corn and oilseeds, and wheat and oilseeds. Conversely, negative cross-correlations indicate that if the predicted acreage of one crop is too high, the predicted acreage of the other will be too low, and vice versa.

Table 2.3. Cross-correlations of errors from the five crop acreage response functions

	Barley	Corn	Oilseeds	Soybean	Wheat
Barley	1.000	0.002 (0.007)	0.101***[a] (0.007)[b]	-0.114*** (0.007)	-0.043*** (0.007)
Corn		1.000	0.035*** (0.007)	-0.043*** (0.007)	-0.119*** (0.007)
Oilseeds			1.000	-0.152*** (0.007)	0.061*** (0.007)
Soybean				1.000	-0.137*** (0.007)
Wheat					1.000

[a] The symbols ***, **, and * indicate statistical significance at $\alpha = 0.01$, $\alpha = 0.05$, and $\alpha = 0.10$, respectively.
[b] Numbers in parentheses are the standard errors of the estimated correlation coefficients.

2.7.1. Actual and Predicted Maps of Crop Acreage in Year 1998 and 2013

In this section, we discuss and illustrate the spatial distributions of actual and predicted acreages of each crop in 1998 and 2013—the first and the last years of the study period. Predicted acreages were calculated for each crop in each year based on equation 2.5 and were then mapped in ArcMap 10.5. A visual comparison of the maps of actual (Fig. 2.1) and predicted (Fig. 2.2) barley acreage in 1998 reveals that the model's predictions are biased low in places where most of North Dakota's barley is grown and biased high in places where relatively little barley is typically grown. Figure 2.3 shows the actual barley acreage in 2013, while figure 2.4 shows predicted barley acreage for the same year. Strikingly, from 1998 to 2013, barley acreage decreased almost everywhere in North Dakota (Compare Fig. 2.1 and Fig. 2.3). Comparing figure 2.2 to figure 2.4, reveals a similarly striking, statewide decline in predicted barley acreage during the study period. However, predicted barley acreages are again too low in places where most North Dakota barley was grown and too high in places where relatively little barley is grown. Yet, the model is quite successful, year after year, at predicting hot spots (north central and northeastern quadrangles, excluding the Red river Valley) and cold spots (almost everywhere else) for barley production in North Dakota.

Figures 2.5, 2.6, 2.7, and 2.8 show the actual and predicted acreage values for corn in 1998 (Fig. 2.5, Fig. 2.6) and in 2013 (Fig. 2.7, Fig. 2.8). Comparison of figures 2.5 and 2.7 reveals that corn acreage has increase substantially in North Dakota from 1998 to 2013, especially making inroads in the southeastern region, spreading from the southern Red River Valley. The predicted corn acreages correspond quite well to the actual acreages in both 1998 (compare Fig 2.5 and Fig. 2.6) and in 2013 (compare Fig. 2.7 and Fig. 2.8), and both actual and predicted corn acreage increased substantially between 1998 and 2013. The estimated corn supply function appears to predict corn acres very well based on the comparisons of maps in figures 2.5 to 2.8.

Actual soybean acreages and predicted soybean acreages for each quadrangle are shown for 1998 and 2013 in figures 2.9, 2.10, 2.11, and 2.12. Comparing the predicted acreages to the actual acreages reveal that the model predictions—at least in 1998 and 2013—match the actual acreages quite well, and that the model clearly identifies and predicts areas of dense soybean production as over time as soybean production intensifies and spreads from the southern Red River Valley toward the northwest.

Actual and predicted acreages of wheat for 1998 and 2013 are shown in figures 2.13, 2.14, 2.15, and 2.16. In 1998, wheat acreage was widely distributed, including throughout the Red River Valley, though there were a few locations—especially in and around Theodore

Roosevelt National Park and Williston, ND, in the southwest and a few patches of low wheat acreage in south central and southeastern portions of the state. Predicted and actual wheat acreage in 1998 have a very similar spatial distribution pattern, though the predicted wheat acres are lower than actual acres in locations with high wheat acres and higher than actual acres in areas with low wheat density. From 1998 to 2013, wheat acreage drastically decreased in the southeastern portion of the state—especially in the southern Red River Valley, where corn and soybean acreage have made incursions into areas formerly densely planted to wheat (compare Fig. 2.13 and Fig. 2.15). The predicted wheat acreages in figures 2.14 and 2.16 show the same spatial pattern of declining wheat acreage in the southeast as the actual wheat acreages.

Actual and predicted acreages of oilseeds from 1998 are in figure 2.17 and figure 2.18, respectively. The actual acreages are higher than the predicted acreages in areas most densely planted to oilseeds and lower than actual acreages in areas with low density oilseed plantings, but the predicted acreages in 1998 do not closely match spatial pattern of the actual acreages (compare Fig. 2.17 and Fig. 2.18). However, by 2013 the actual and predicted oilseeds acreages both drastically declined in the southeast, where corn and soybean acreages have grown most during the study period (Fig. 2.19 and Fig 2.20).

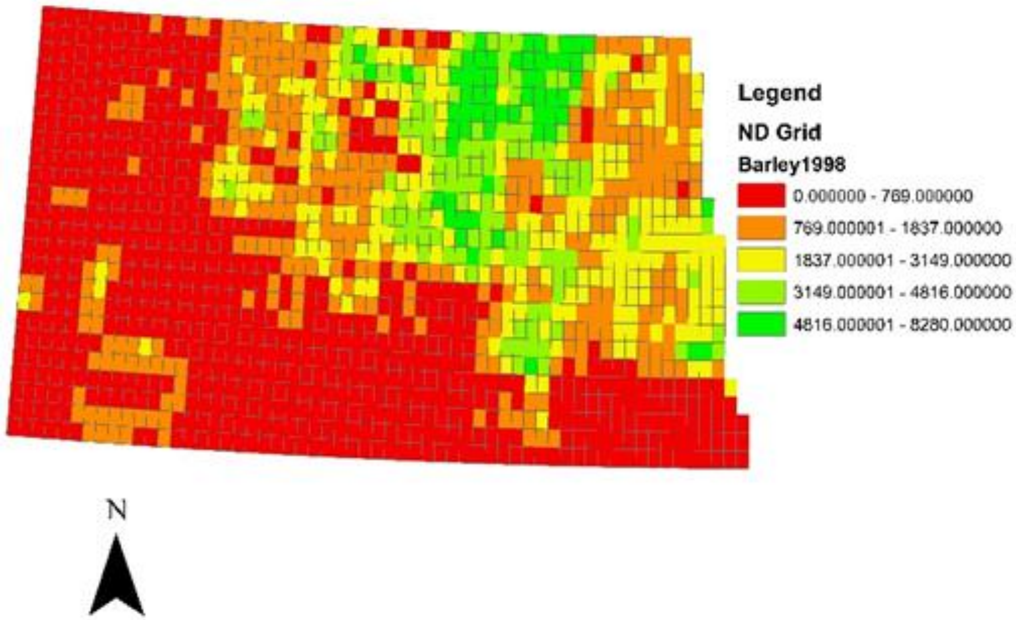


Figure 2.1. Actual barley acreage in year 1998

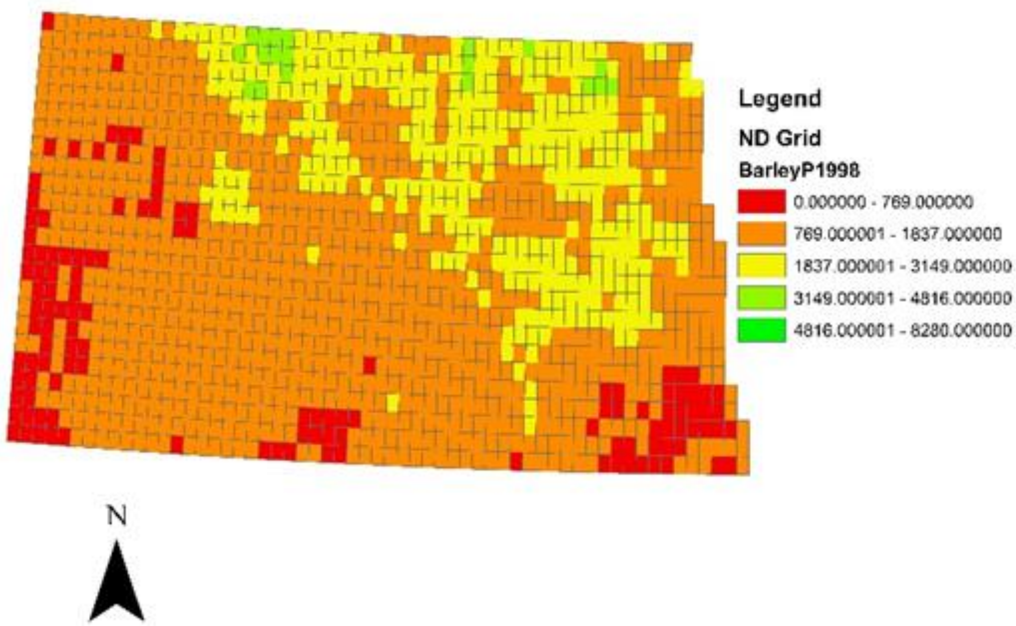


Figure 2.2. Predicted barley acreage in year 1998

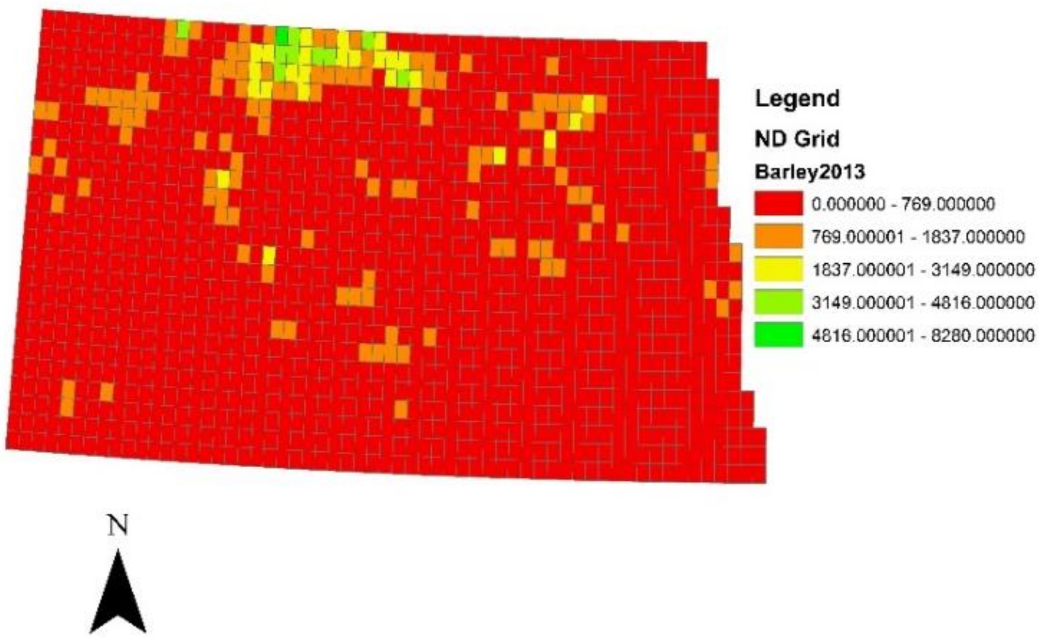


Figure 2.3. Actual barley acreage in year 2013

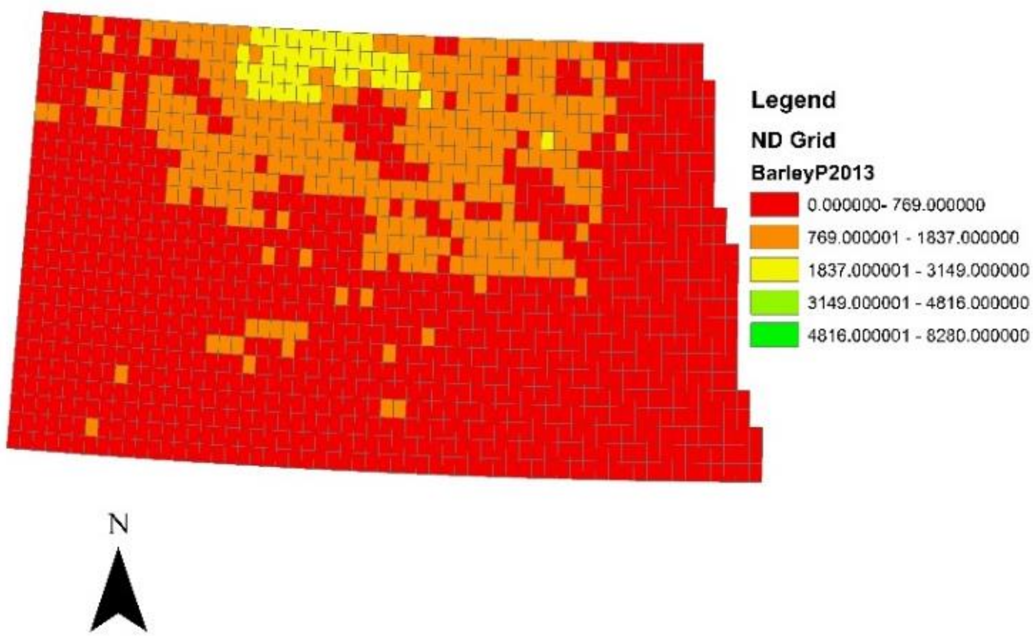


Figure 2.4. Predicted barley acreage in year 2013

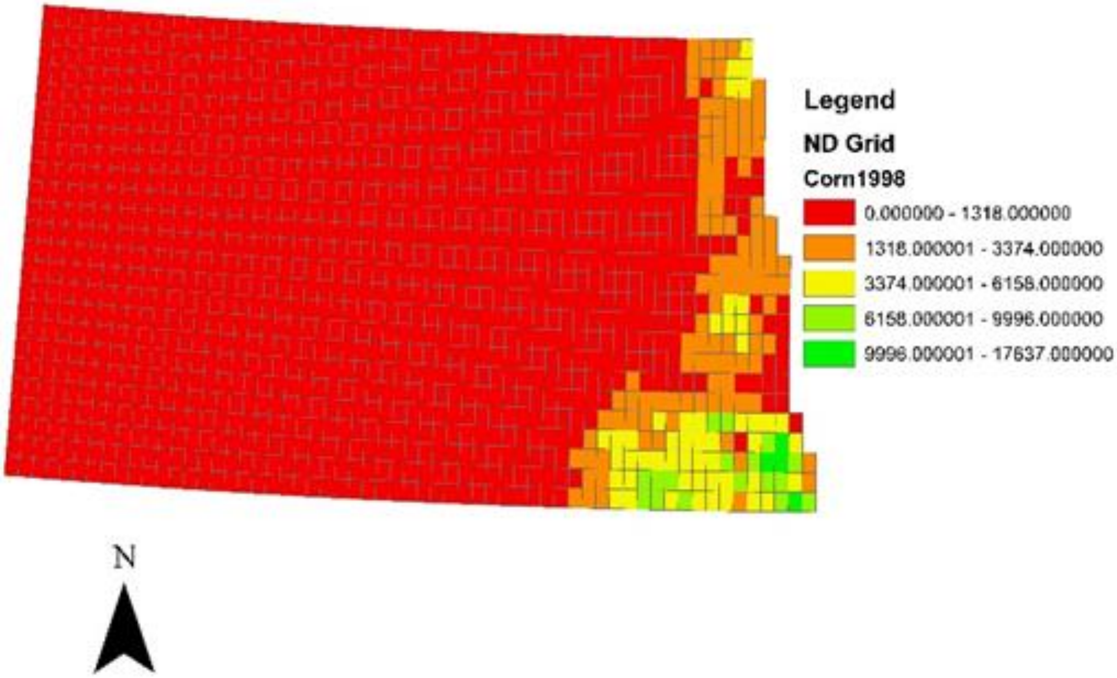


Figure 2.5. Actual corn acreage in year 1998

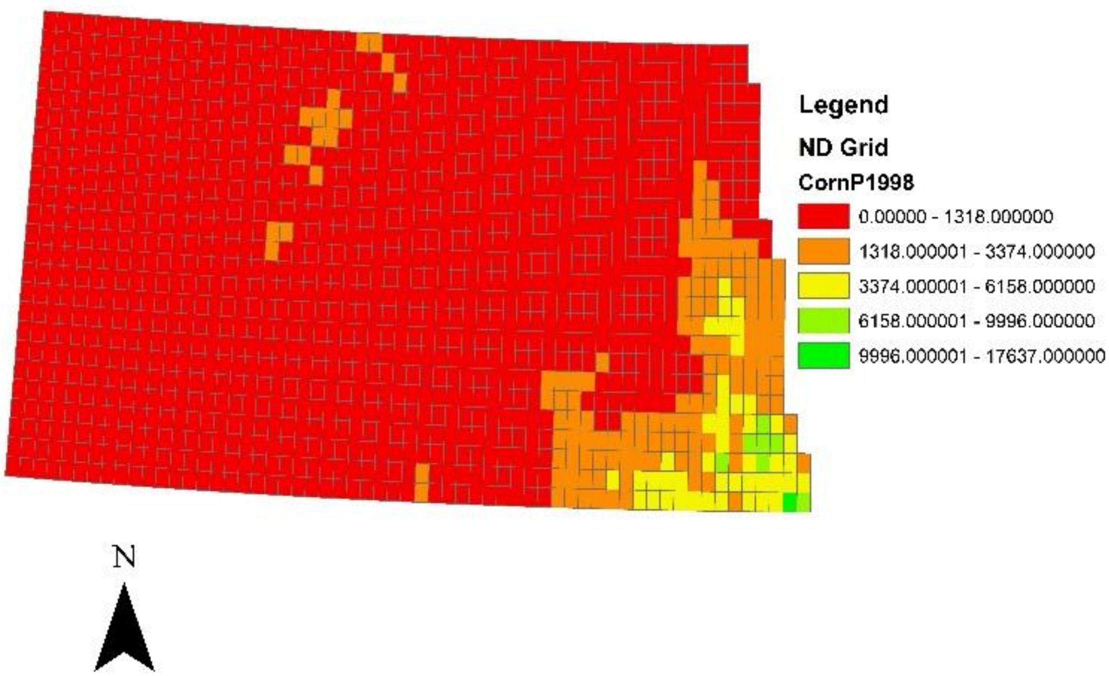


Figure 2.6. Predicted corn acreage in year 1998

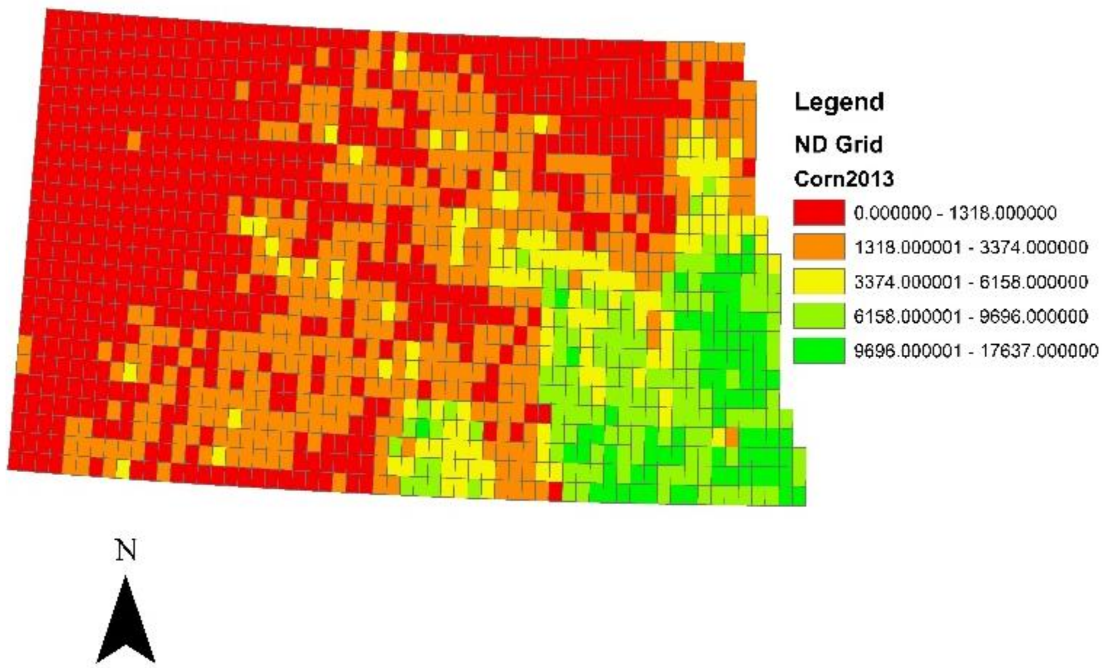


Figure 2.7. Actual corn acreage in year 2013

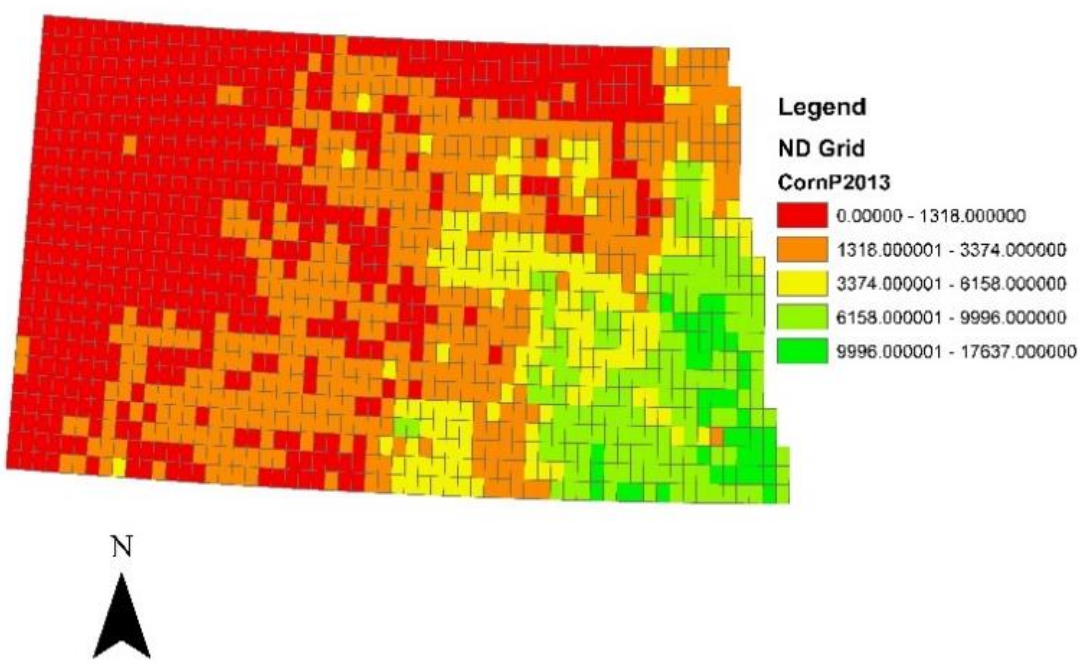


Figure 2.8. Predicted corn acreage in year 2013

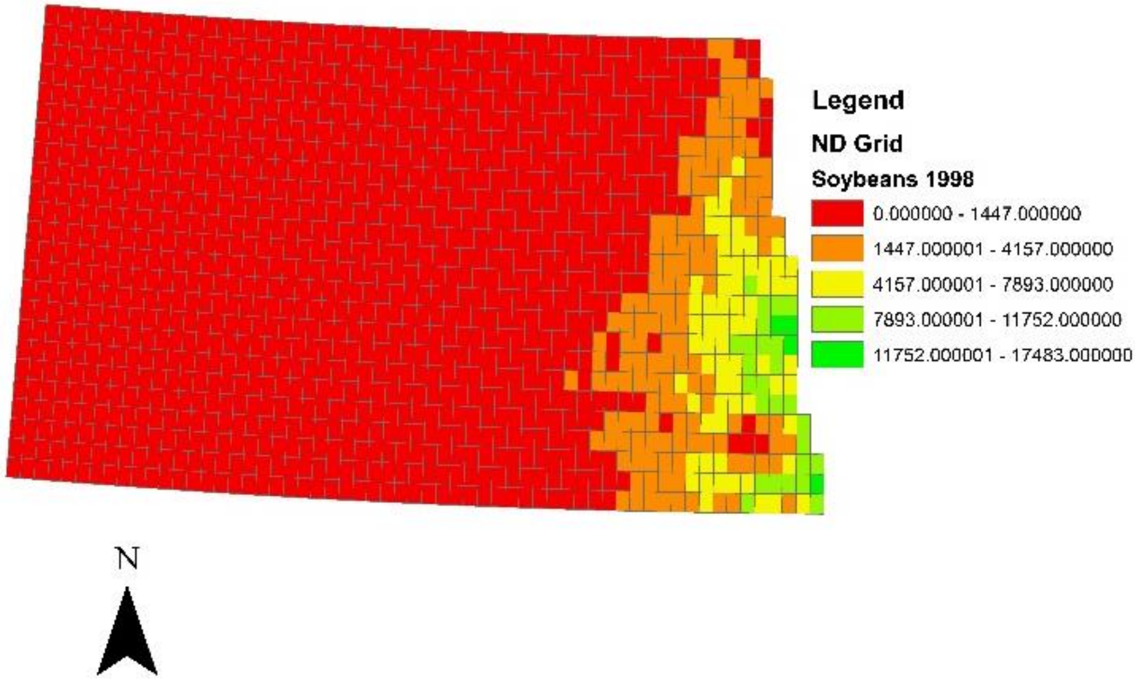


Figure 2.9. Actual soybean acreage in year 1998

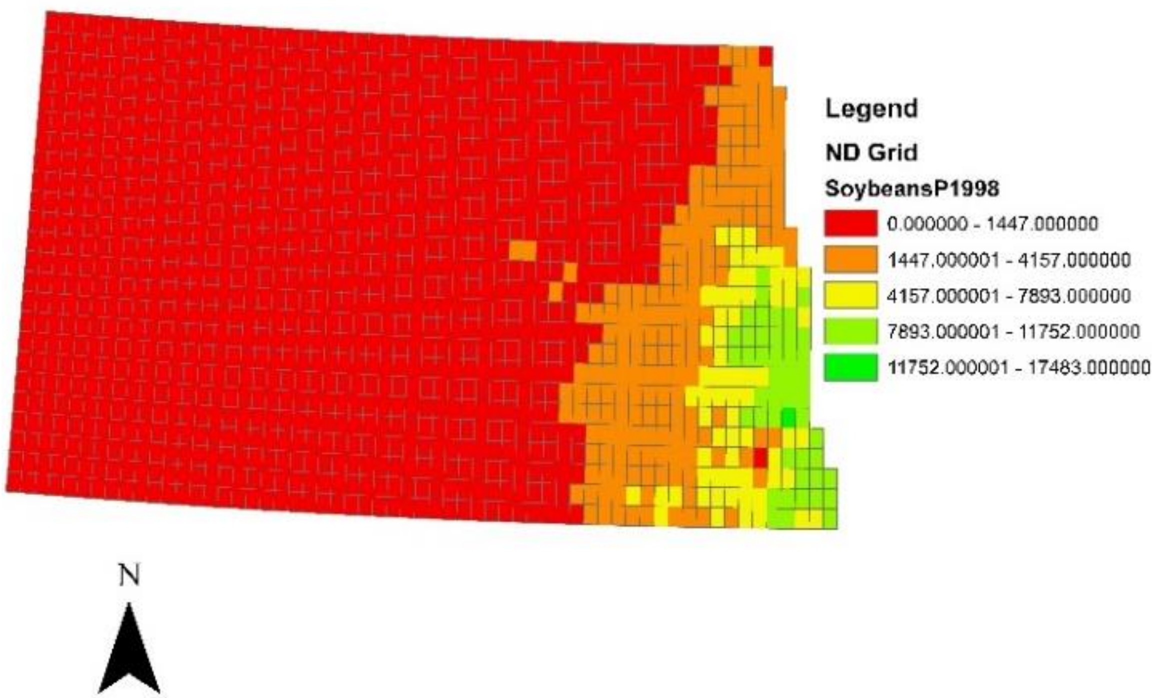


Figure 2.10. Predicted soybean acreage in year 1998

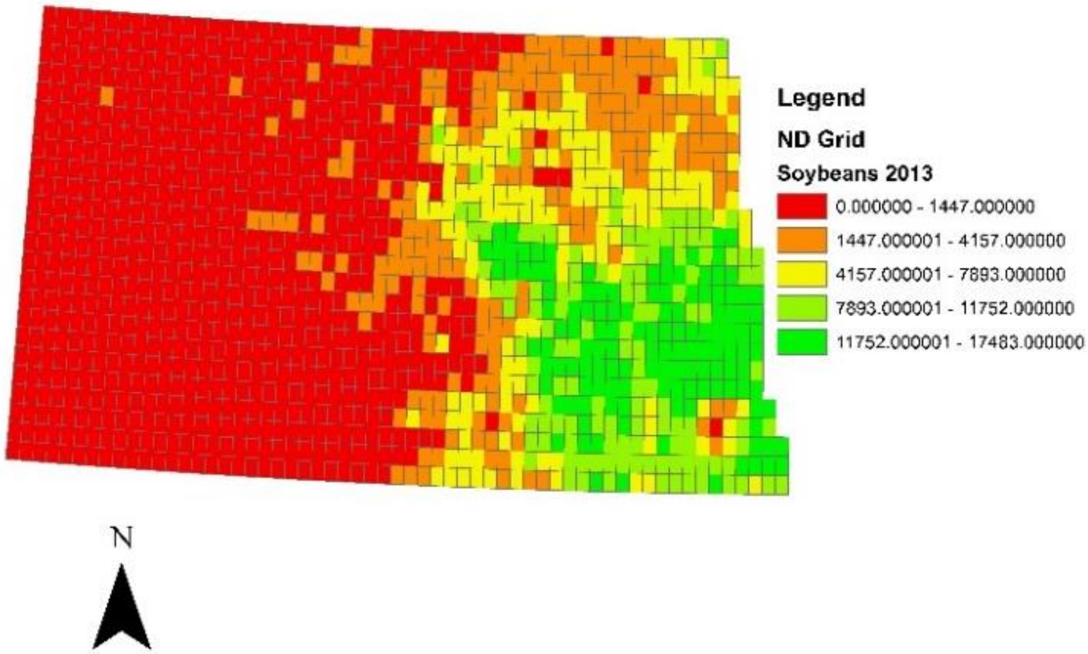


Figure 2.11. Actual soybean acreage in year 2013

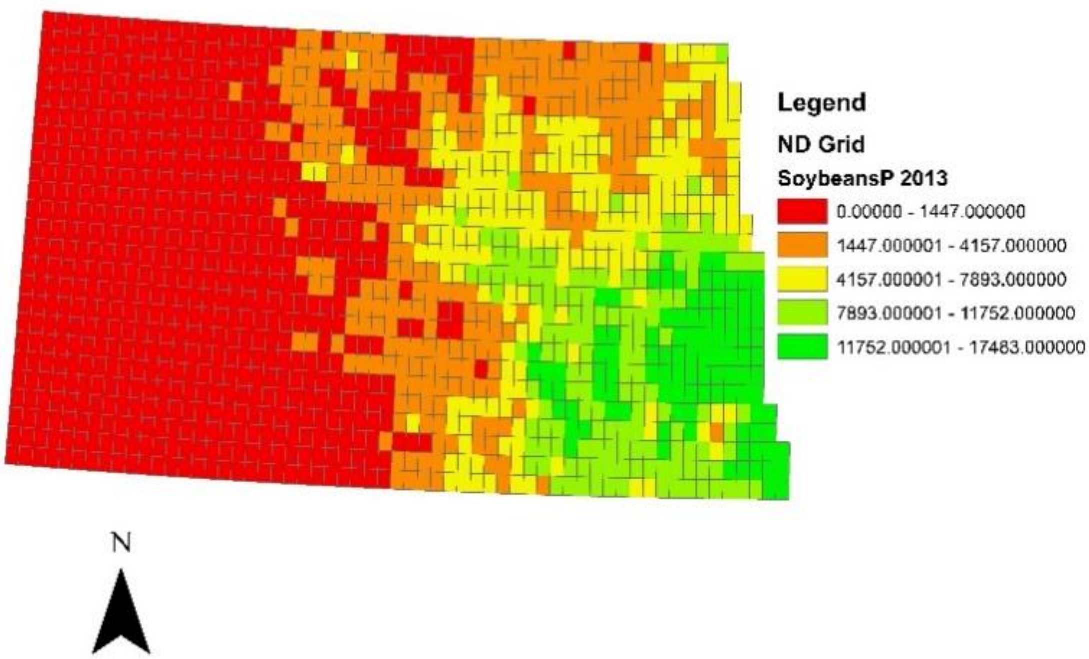


Figure 2.12. Predicted soybean acreage in year 2013

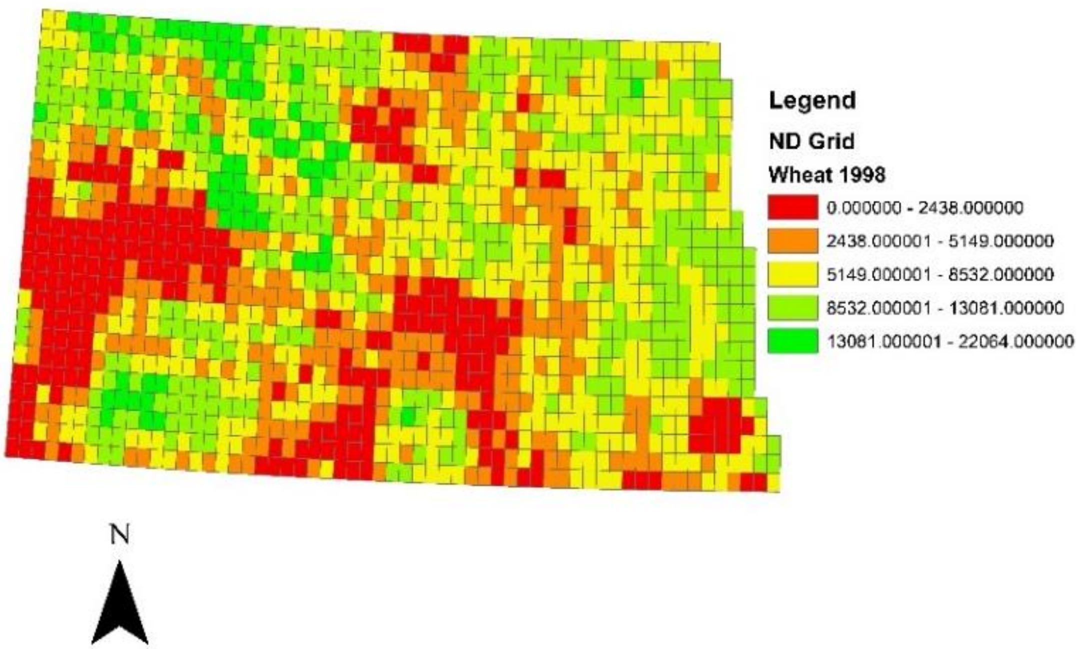


Figure 2.13. Actual wheat acreage in year 1998

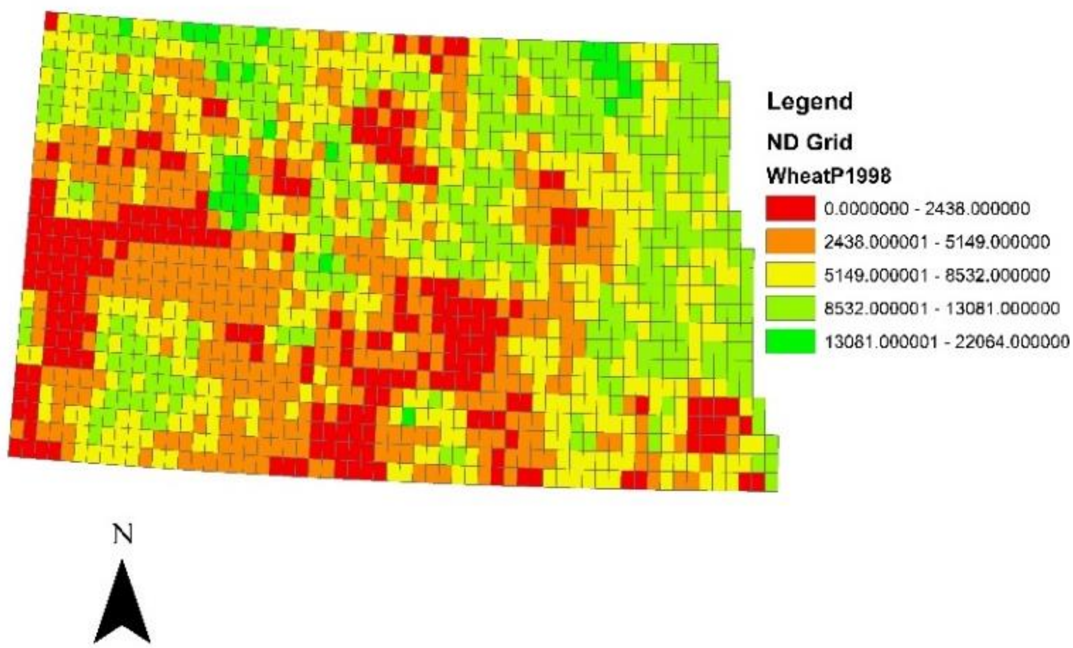


Figure 2.14. Predicted wheat acreage in year 1998

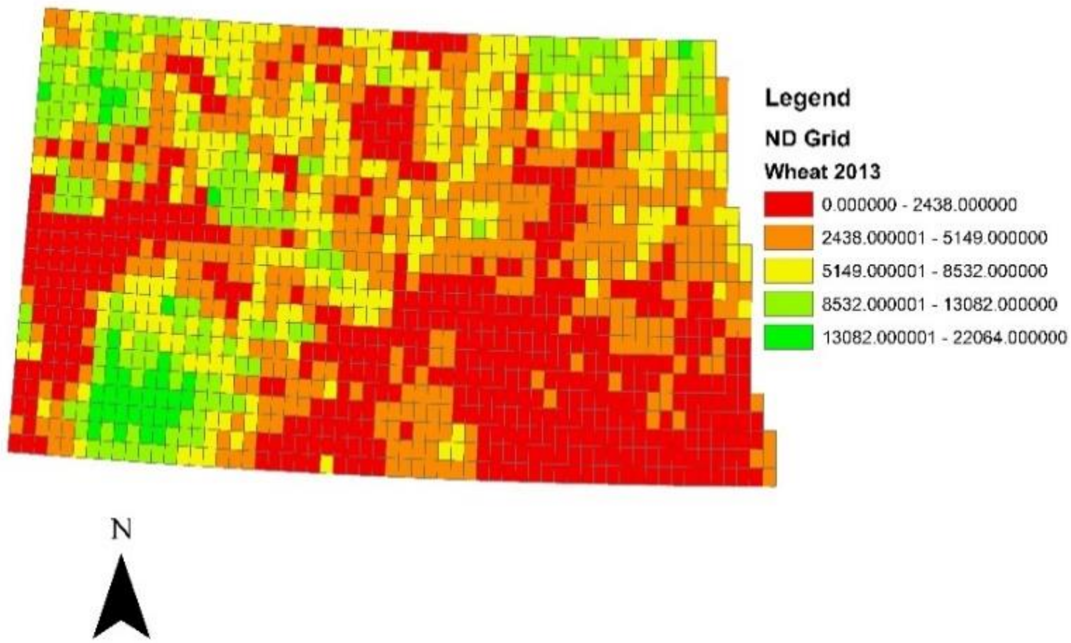


Figure 2.15. Actual wheat acreage in year 2013

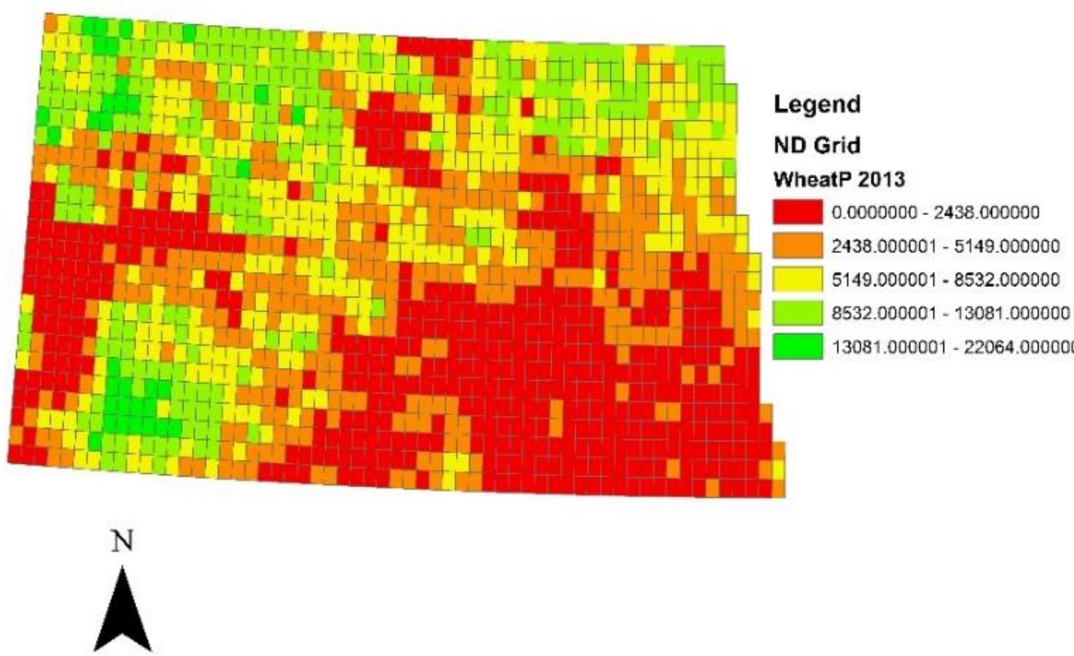


Figure 2.16. Predicted wheat crop in year 2013

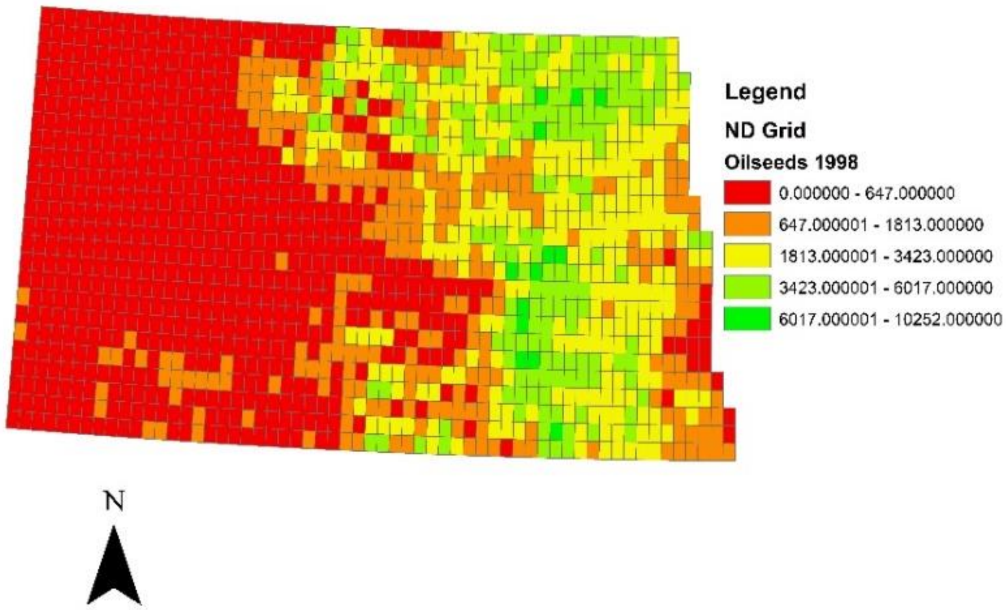


Figure 2.17. Actual oilseeds acreage in year 1998

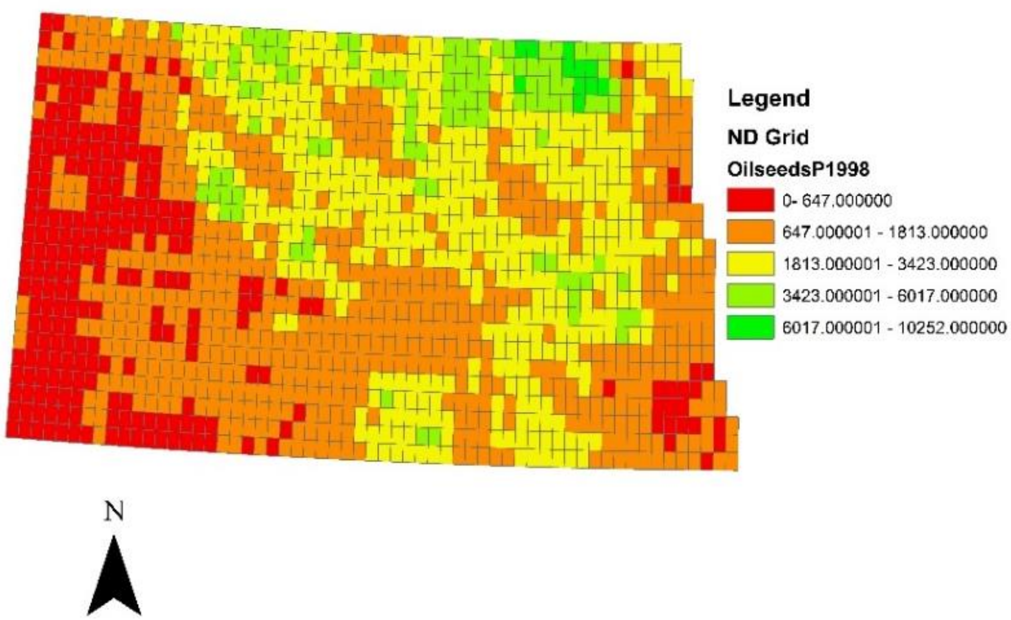


Figure 2.18. Predicted oilseeds acreage in year 1998

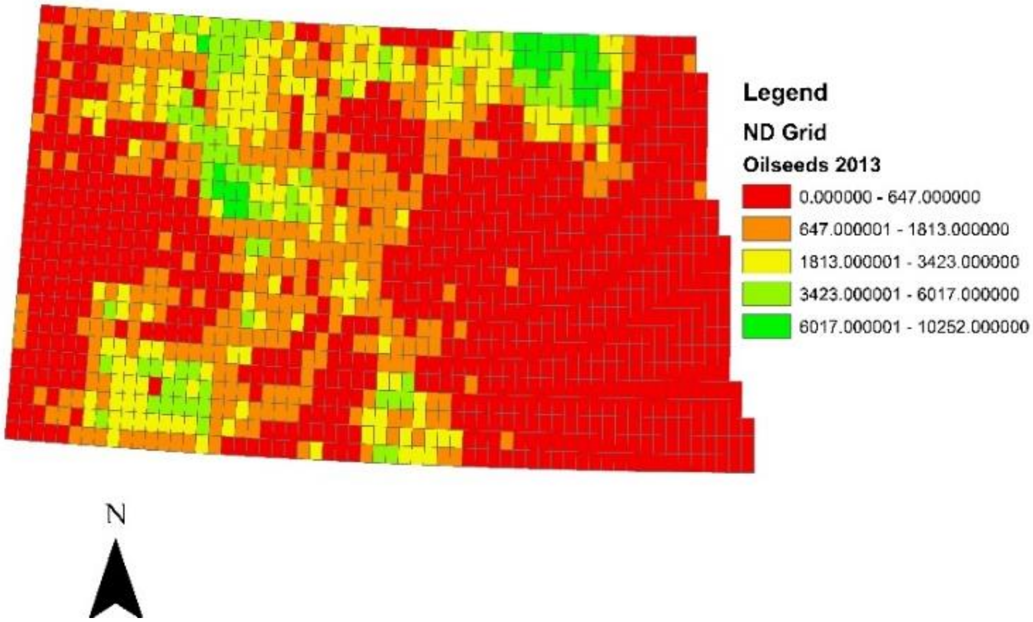


Figure 2.19. Actual oilseeds acreage in year 2013

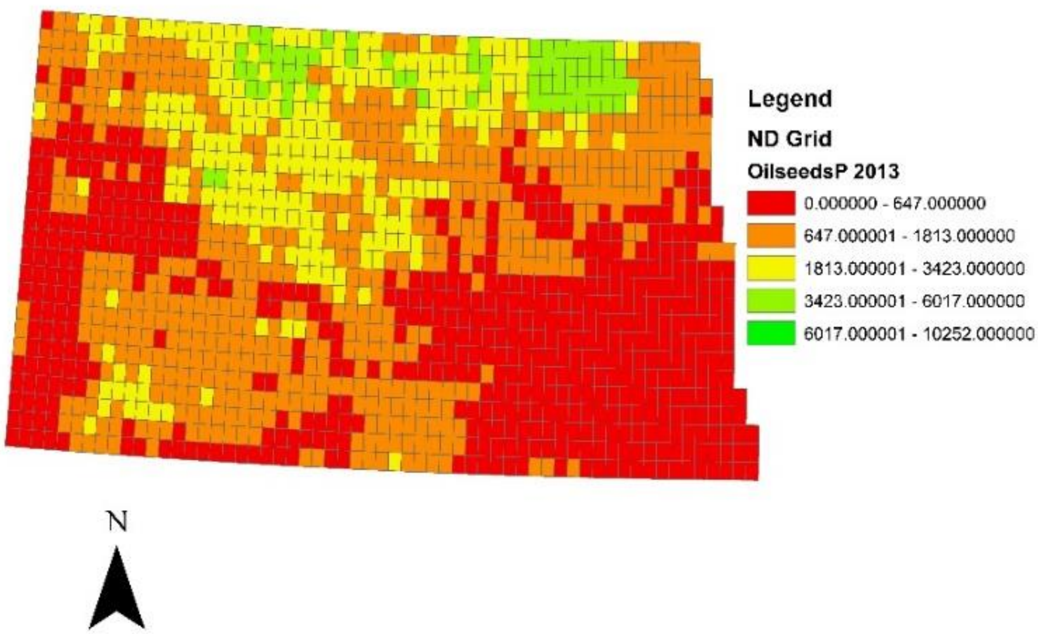


Figure 2.20. Predicted oilseeds acreage in year 2013

2.7.2. Model Predictions of Crop Acreages and Measures of Prediction Accuracy

Predicted values of each crop's acreage at each of the 1,355 locations were calculated each year based on the model parameter estimates. Based on the predicted acreages and the actual acreages of each crop, we calculated a forecast error—the difference between the actual acreage and the predicted value—for each crop at each location each year. With these forecast errors, measures of forecast accuracy were calculated, including bias (or average error), mean absolute deviation, and mean absolute percent deviation (presented in table 2.3). For our models, cumulative error and average error measures are all negative, which indicates that, on average, the predicted acreages are higher than the actual acreage values. This represents systemic prediction bias; model predictions average higher than actual values by about 140 acres for barley, 149 acres for corn, 214 acres for soybean, 78 acres for wheat, and 218 acres for oilseeds. However, this systemic bias is small relative to the size of each 50 mi.^{2} cross-sectional unit (32,000 acres). A major contributor to this systemic prediction bias is the formula for predicted values from Tobit regression, which does not allow for predicted acreage to be zero.

Table 2.4. Measures of acreage prediction accuracy

Name of equation	Prediction bias	Mean absolute deviation	Mean absolute percent deviation
Barley equation	-139.51	530.44	0.74
Corn equation	-148.71	501.90	0.42
Oilseeds equation	-218.28	994.98	0.65
Soybean equation	-213.57	815.57	0.34
Wheat equation	-77.71	1514.47	0.25

Thus, at every location where a crop was not grown the forecast error is negative, though typically small in magnitude. Though the predicted values are biased upward, the model parameter estimates are unbiased.

Mean absolute deviation indicates how far off target the model predicted acreages are on average, without any distinction between positive and negative prediction errors. The absolute value of the difference between the actual acreage and the predicted acreage averages 530 acres, 502 acres, 995 acres, 816 acres, and 1,514 acres for barley, corn, oilseeds, soybean, and wheat, respectively. These values are difficult to interpret, except in comparison with the magnitudes of the actual acreage values, which is why mean absolute percent deviation (MAPD) is also presented. The MAPD for the barley acreage predictions is 0.74, meaning the average absolute difference between the actual barley acreage and the predicted value is about 74% of the actual acreage. This indicates there are likely substantial opportunities to improve prediction accuracy. The predictor with the smallest MAPD is the wheat acreage response function, with prediction errors averaging only 25% of the actual wheat acreage values.

2.7.3. **Marginal Effects of Crops' Own Prices and Cross Prices on Crop Acreages**

Monte Carlo simulation was used to make random draws from the joint normal distribution of the parameter estimates from table 2.1. We made 1,000 random draws per site-year, such that we had 21,664,000 simulated vectors of parameter estimates (i.e. $\widehat{\boldsymbol{\beta}}$ vectors). Marginal effects of crop prices on crop acreages by applying equation 2.6 to each simulated $\widehat{\boldsymbol{\beta}}$ vector, plugging in the explanatory variable values, and then averaging the resulting numerical values of these simulated marginal effects by location over the entire study period.

Figure 2.21 contains two maps—one showing the estimated marginal effects of barley price on barley acreage during the study period, and a second showing the statistical significance of the estimate given for each location within the state. The estimates indicate that, on average, a one dollar increase in barley price resulted in barley acreage increases of between 50.4 and 240.96 acres per 50 mi.^{2} cross-section during the study period, depending on the location within the state. As indicated by the law of supply, the quantity of land planted (or supplied) for barley production has a positive relation to the price of the producers' output (commodity corn). The southwestern areas, southeastern areas, and the Red River Valley are the areas where barley acreage is least responsive to changes in barley price. Not surprisingly, these areas are portions of the state that typically have had lower levels of barley acreage, and are either dominated by row crops, as in the southeastern area and the Red River Valley, or areas that are dominated by other uses such as pasture and public lands in the southwestern portion of the state. Note also that the effects of changing the barley price on the barley acreage are not as statistically significant in the southeastern portion of the state. It should therefore be expected that the prices of crops that are production substitutes for barley should have prevalent effects on barley acreage in these areas. Figure 2.22 shows the marginal effects of corn price on barley acreages and indicates that barley acreage will increase by between 24.26 and 115.84 acres per 50 $mi.^2$ for a one dollar increase in corn price. The estimated marginal effects are smaller in magnitude and less statistically significant in southeastern and southwestern North Dakota, and larger in magnitude and more statistically significant in the north-central and northeastern portions of the state, where barley is most densely planted. These marginal effects indicate that corn prices have not been a primary driver of declining barley acreage but are directly correlated with barley acreage. This result is not very surprising, however, because real barley spot prices during the study period display no consistent trend *and* are highly correlated with real corn spot prices (see figure 1.3), which have a positive impact on barley acreage. Similarly, the effect of expected soybean prices on barley acreage, shown in figure 2.23, is positive, and ranges from 24.59 acres to 117.88 acres per cross-sectional unit for a one dollar increase in expected soybean price, with the lowest, least statistically significant estimates in the southeast and in the southwest portions of the state. These are portions of the state where increased soybean plantings have largely displaced wheat and barley as dominant crops (southeast) and where soybean is infrequently planted (southwest). The largest marginal effects of soybean price on barley acreage are in the north-central portion of the state where most barley acreage is located. Again, soybean price is highly correlated with barley price, so the finding of positive cross-price marginal effects is not surprising. Presented in figure 2.24, the marginal effect of expected sunflower price—a proxy for the price of oilseeds prices in general—on barley acreage is a decrease of between 5.42 acres and 28.81 acres per quadrangle for a one dollar increase in sunflower price, depending on the location within the state. The magnitudes of these estimates are largest and most significant in the locations where most of North Dakota's barley is planted, indicating that barley and sunflower (and perhaps oilseeds generally) are substitutes in production in the north central region of the state, since they appear to compete for the same spaces there. Figure 2.25 is a map of the marginal effects of wheat price on barley acreage throughout the state. Note that the estimated marginal effects are small (1.28 to 6.97 acres increase per one dollar increase in price) and are not statistically different from zero at any location with North Dakota.

Maps for own- and cross-price marginal effects on acreages for the other four crops are presented in Appendix B. Figures B.1 to B.5 illustrate the spatial distribution of the marginal effects of each expected crop price on corn acreage. The own-price marginal effects on corn acreage range from 27.51 to 572.22 acres per quadrangle for a one dollar increase in corn price. These positive relations comport with the law of supply. Cross-price marginal effects on corn acreage are positive for expected barley price, and most are statistically significant at $\alpha = 0.01$ (figure B.2). Corn acreage responds negatively to price expectations for the other crops—soybean, sunflower, wheat—though few of these are statistically significant (fig. B.3 to B.5).

These negative marginal effects, in the few cases of statistically significant estimates, indicate that soybean and wheat are production substitutes for corn in some portions of the state but have no statistical relation to corn acreage in others. Own and cross-price marginal effects on soybean are shown in figures B.6 through B.10. Interestingly, soybean acreage shows no statistically discernible response to the expected price of soybean anywhere in the state, and some of the estimated own-price marginal effects for soybean acreage are positive, while some are negative. On the other hand, estimated marginal effects of expected barley, corn, and wheat prices on soybean acreage are negative and most of these estimates are statistically significant. This result indicates that soybean production has a statistically detectable substitutionary relation with production of barley, corns, and wheat. On the other hand, sunflowers price has a positive marginal effect on soybeans acreage.

Figures B.11 through B.15 show the own- and cross-price marginal effects of the expected price of each crop on wheat acreage. Somewhat surprisingly, the marginal effects of expected wheat price on wheat acreage are negative throughout the state and are statistically significant everywhere except one quadrangle in the center of the Sheyenne National Grassland, indicating that farmers respond to increasing wheat prices by decreasing wheat acreage. The signs of these marginal effects to not comport with the law of supply, which states farmers ought to respond to higher expected wheat prices by producing more wheat on more acreage. Figure B.12 shows the marginal effects of expected barley price on wheat acreage are negative, but not statistically differ from zero, in the eastern North Dakota and positive and statistically significant in central and western parts of the state. This result is not completely surprising, as barley and wheat prices are highly correlated, and potentially cointegrated. In figure B.13 we present the estimated cross-price marginal effects of expected corn price on wheat acreage, which indicate that a one dollar increases in expected corn price leads to a decline of between 196.49 and 767.96 acres per quadrangle, with the largest decreases occurring in the Red River Valley, where corn and soybean cropping activities have made the biggest gains. However, increasing soybean prices appear to put upward pressure on wheat acreage—between 62.49 and 246.75 acres increase per one-dollar price increase (Fig. B.14), which may be because wheat is commonly planted in rotation with soybean, making the two crops complements in production in some cases and spaces. The estimated cross-price marginal effects of the expected sunflower price on wheat acreage (in Fig. B.15) are all negative: a one dollar increase in expected sunflower price causes a decrease of between 12.53 and 48.96 acres of wheat per quadrangle, depending on location within the state. In other words, high sunflower price expectations induce farmers to substitute sunflower production for wheat when the high sunflower prices are expected.

In figures B.16 to B.20 are the marginal effects of the crop prices on acreage of oilseeds. In accord with economic theory, the impact of increasing expected sunflower prices—our proxy for the price of oilseeds generally—on acreage of oilseeds is positive everywhere in North Dakota. The effect ranges from an increase in oilseeds acreage of 6.82 to 47.57 acres per quadrangle, with smaller effects in the south and larger ones in the north (Fig. B.16). As shown in figure B.17, barley price has no statistically discernible effects on acreage of oilseeds, though the estimates of the marginal effects are predominantly negative. Expected corn price has a negative effect on oilseeds acreage, implying farmers cut back on plantings of oilseeds so they can plant corn instead. Estimates range from a decrease of 151.04 to 1056.71 acres of oilseeds per one dollar increase in expected corn price (Fig. B.18). Expected soybean price appears to increase oilseeds acres by 53.92 to 415.52 acres per one-dollar price increase (Fig. B.19). These estimates are positive, perhaps because soybean oil, canola oil, and sunflower oil are substitutes in consumption, and are statistically significant at almost all locations. Finally, the marginal effects of expected wheat price are displayed in figure B.20. These estimates are all negative—indicating that wheat is generally a production substitute for oilseeds—and are statistically significant, except in Theodore Roosevelt National Park, Williston, and parts of the Red River Valley.

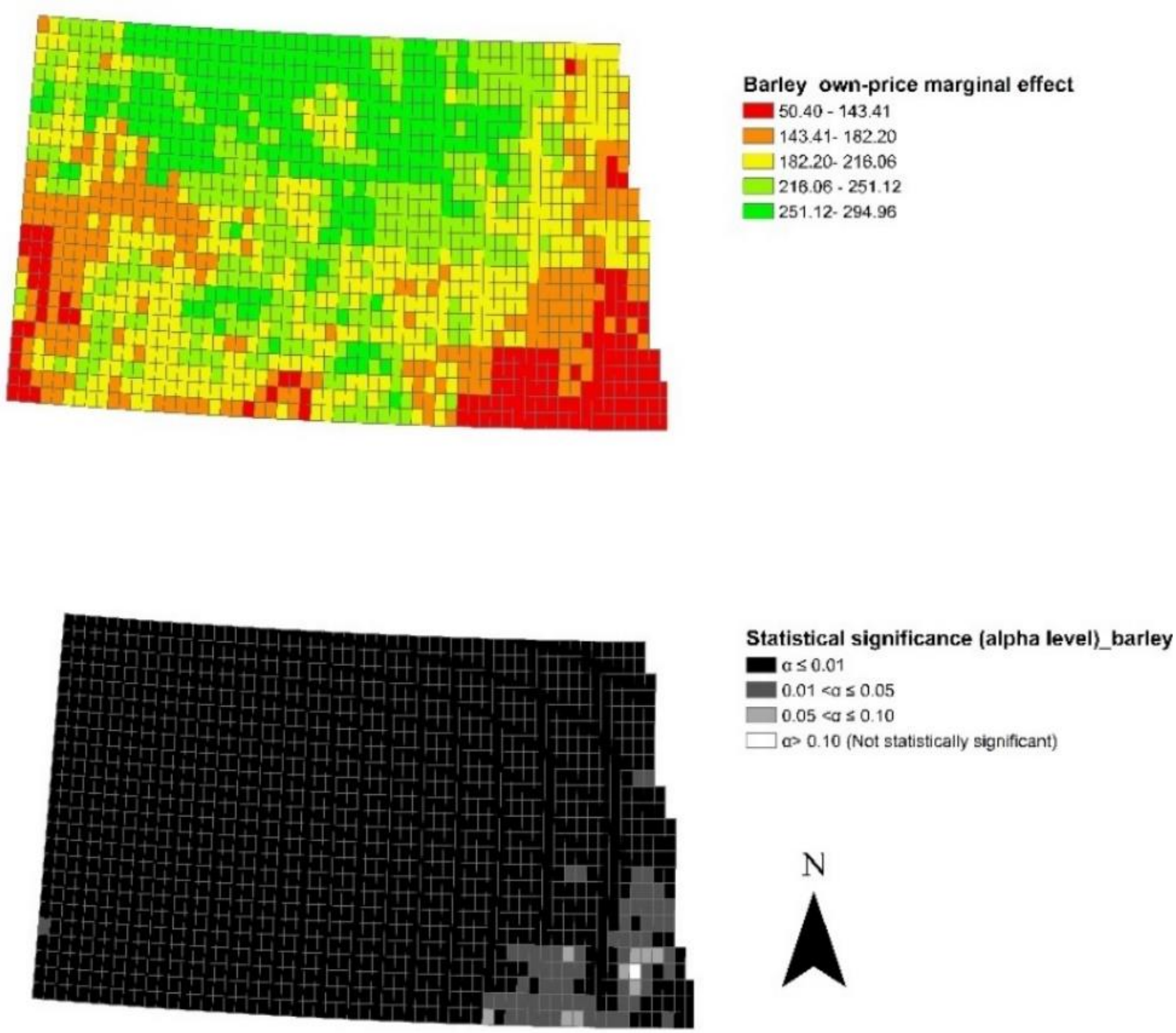
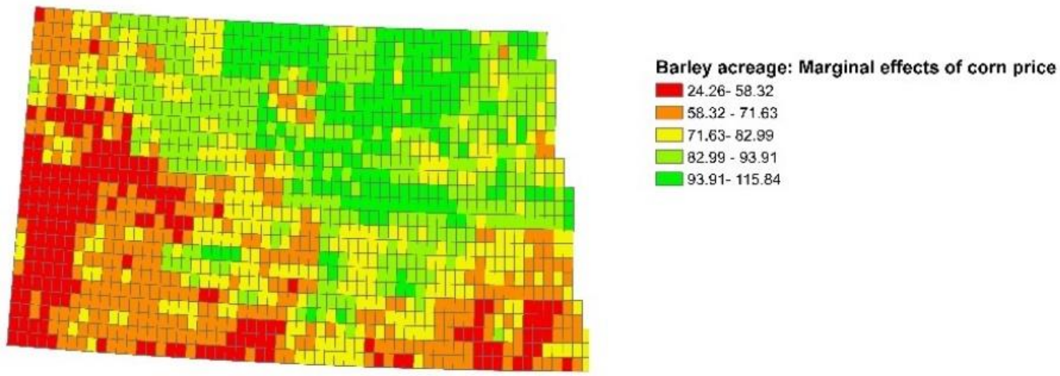


Figure 2.21. Estimated marginal effects of barley price on barley acreage with statistical significance levels



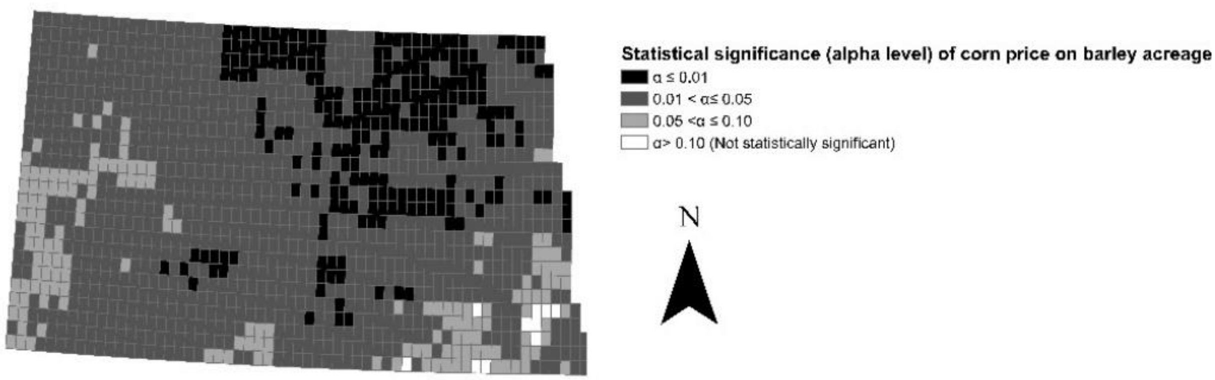


Figure 2.22. Estimated marginal effects of corn price on barley acreage with statistical significance levels

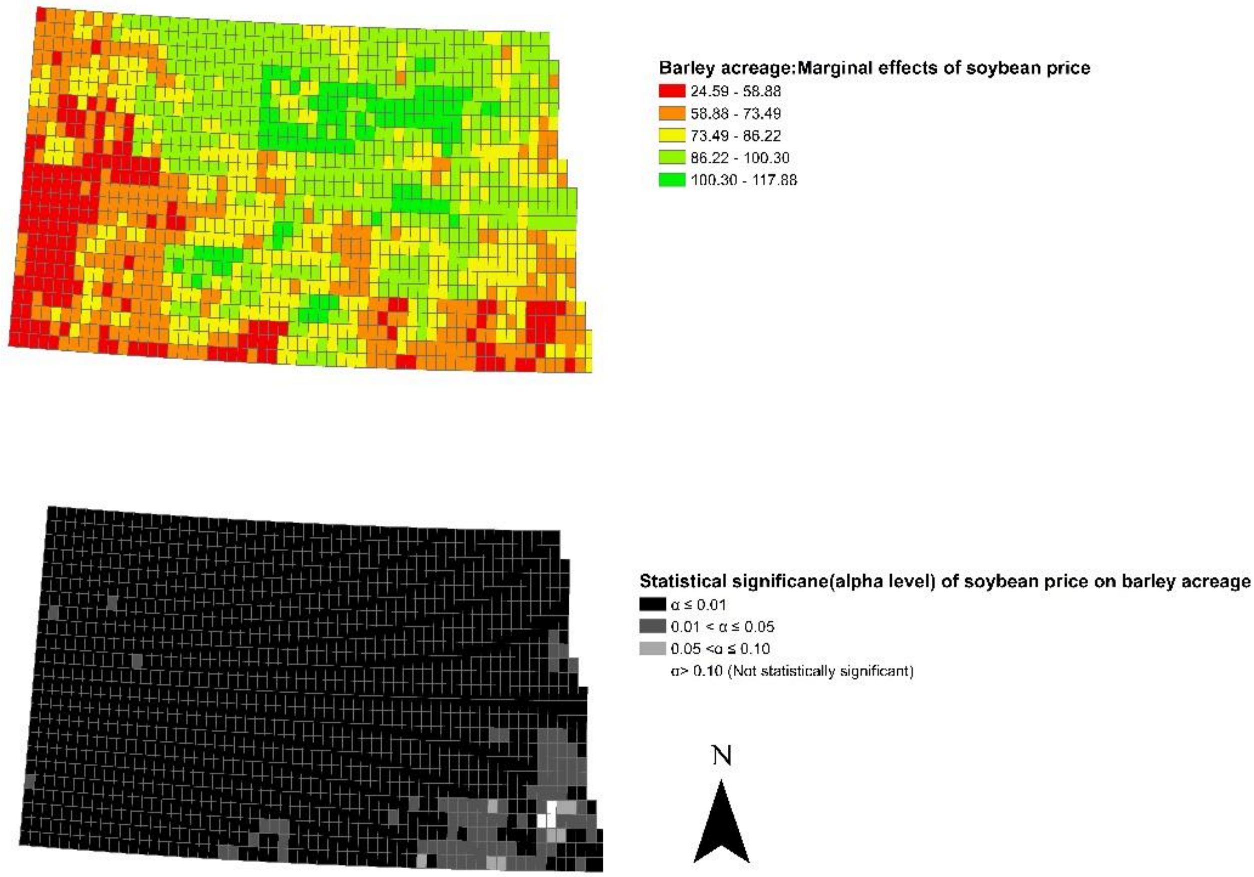
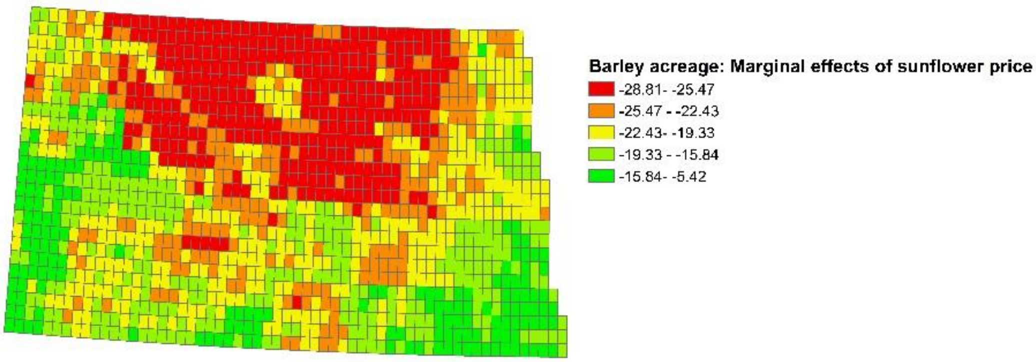


Figure 2.23. Estimated marginal effects of soybean price on barley acreage with statistical significance levels



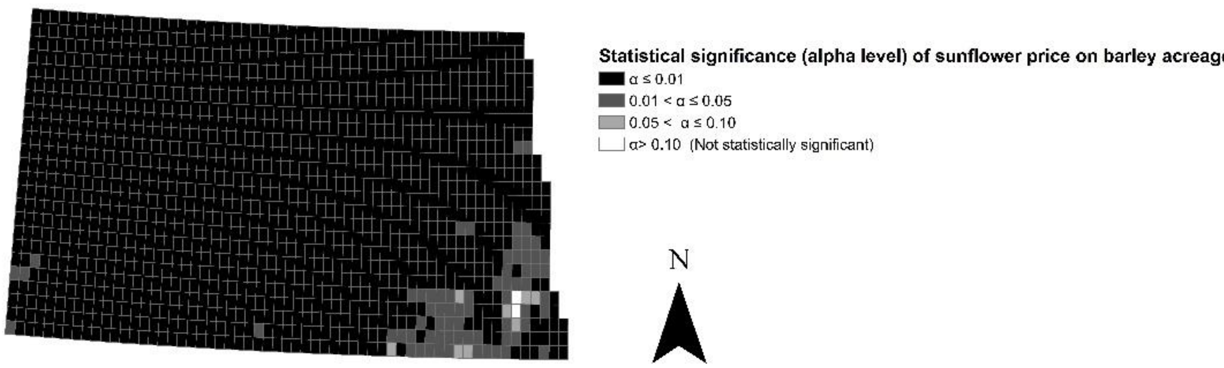


Figure 2.24. Estimated marginal effects of sunflower price on barley acreage with statistical significance levels

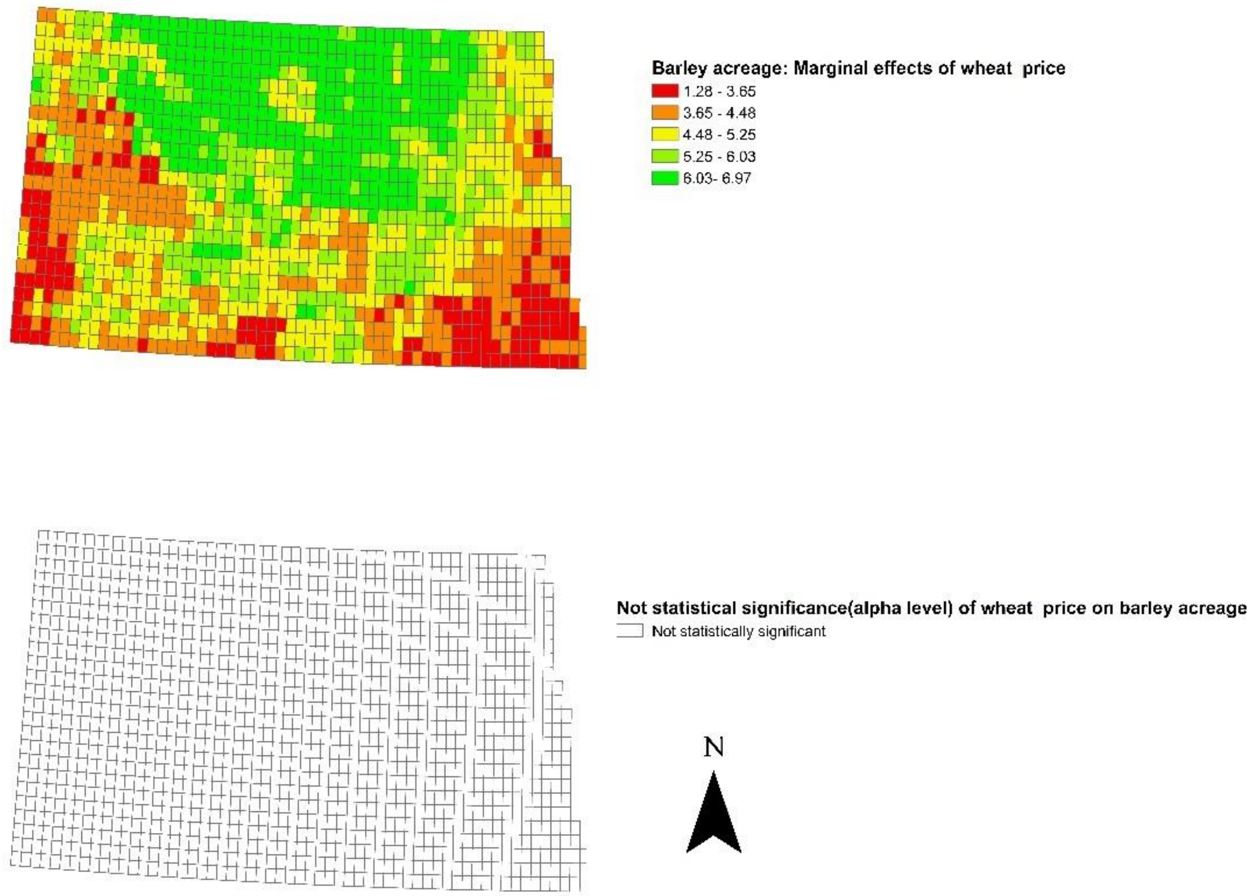


Figure 2.25. Estimated marginal effects of wheat price on barley acreage with statistical significance levels

2.7.4. Own and Cross-Price Elasticities of Crop Acreage Supply

The average own-price and cross-price elasticities during the study period are also calculated for each crop in each quadrangle based on the same Monte Carlo simulations of the $\widehat{\boldsymbol{\beta}}_{\mathbf{i}}$ vectors from equation 2.2 and applying equation 2.7 to these to simulate 1,000 own- and/or cross-price elasticities per site-year. The average barley acreage own-price elasticity throughout the state is 1.16, and ranges from 0.40 to 2.31 (see Fig. 2.26). Sixty-five percent of quadrangles have barley acreage own-price elasticity that is discernibly different from 0 at $\alpha \leq 0.10$. Cross-price elasticities of barley acreage and the four other crops are displayed in figures 2.26 to 2.30. Signs of cross-price elasticities vary. A negative cross-price elasticity indicates two crops are substitutes—replacing each other in rotations with other crops. Positive cross-price elasticities indicate two crops are complementary rotation crops. The expected corn price cross-elasticity of barley acreage supply (Fig. 2.27) is 0.52 for the average location—a 0.52% increase in barley acreage for a one percent increase in corn price—but estimates for individual quadrangles range from 0.16 to1.31, with about 37% of locations having statistically non-zero cross-price elasticity for $\alpha \leq 0.10$. The elasticities presented in figure 2.28 are the cross-price elasticities of barley acreage and expected soybean price. These elasticity estimates are all positive—ranging from 0.34% to 3.00% increase in barley acreage for a one percent increase in corn price, depending on location—and are statistically significant ($\alpha \leq 0.10$) for 70% of locations. The estimates of cross-price elasticity of barley acreage and wheat price shown in figure 2.29 range between 0.02 and 0.09, with an average of 0.05. None of these are statistically significant, from which we infer that barley acreage is unresponsive to wheat price expectations. The average cross-price elasticity of barley acreage and sunflower price across all quadrangles is -0.62, while estimates range from -1.31 to -0.24 depending on location and are statistically significant for 88% of locations in the state (Fig. 2.30). Thus, we infer sunflower—and perhaps also production of other oilseeds—is substitutable for barley in the farmers' production functions.

Own- and cross-price elasticities for all five crop acreage supply functions—barley, corn, oilseeds, soybean, wheat—are presented in tabular form in table 2.5. Figures A.1 through A.20 present all the own- and cross-price elasticities at all locations in graphic detail for each crop acreage supply function. Notably, the own-price elasticity of acres supplied is positive for all crops except wheat. The positive corn acreage barley price cross-elasticities of supply indicate statistically discernible complementary relation between corn and barley at every location. The average quadrangle has experienced a 1.01% increase in corn acreage for a one percent increase in barley price. The corn acreage own-price elasticity of supply for the average quadrangle indicates corn acreage increases by 1.23% for a one percent increase in corn price, with statistically significant, positive elasticity estimates in all but nine quadrangles. Negative corn acreage cross-price elasticities of supply for expected soybean, sunflower, and wheat indicate substitutionary relations between corn acreage and acreage of each of these three crops. However, these are only statistically discernible for expected soybean price in 251, zero locations for expected sunflower price, and 39 locations for expected wheat price. Acreage of oilseeds responds positively to expected prices of soybean and sunflower, likely because oils from soybean, sunflower, canola, and other oilseeds are substitutes in manufacturing of food products. The oilseeds acreage cross-price elasticities for corn and wheat prices are negative, indicating these crops are substitutable in farmers' multi-output production functions at 1,284 locations in the case of corn price and 751 for wheat price. Surprisingly, estimated soybean own-price elasticities of acreage supply are not statistically significant at any location; however, barley and corn price expectations have large, statistically discernible, negative influence on soybean acreage; one percent increase in barley price (corn price) causes 2.23% (3.72%) decrease in soybean acreage, suggesting these crops are highly substitutable for soybean. Contrary to the law of supply, the wheat acreage own-price elasticity is negative and statistically significant in 1,088 locations throughout the state; however, the estimated elasticities are small, averaging a 0.16% decrease in wheat acreage for a one percent increase in expected wheat price. Despite the sign conflicting with economic theory and the strong statistical significance at many locations, the small magnitude of these estimates is comforting. Based on own- and cross-price elasticities of wheat acreage supply, barley and soybean are complements to wheat in commodity production—i.e. they are produced together in the same quadrangles in some fairly constant proportion—while the negative cross-elasticities of wheat acreage and prices of corn and sunflower indicate corn and sunflower acres are generally substitutable for wheat acres throughout North Dakota, and that these substitutions have happened when justified by relative prices of the commodities.

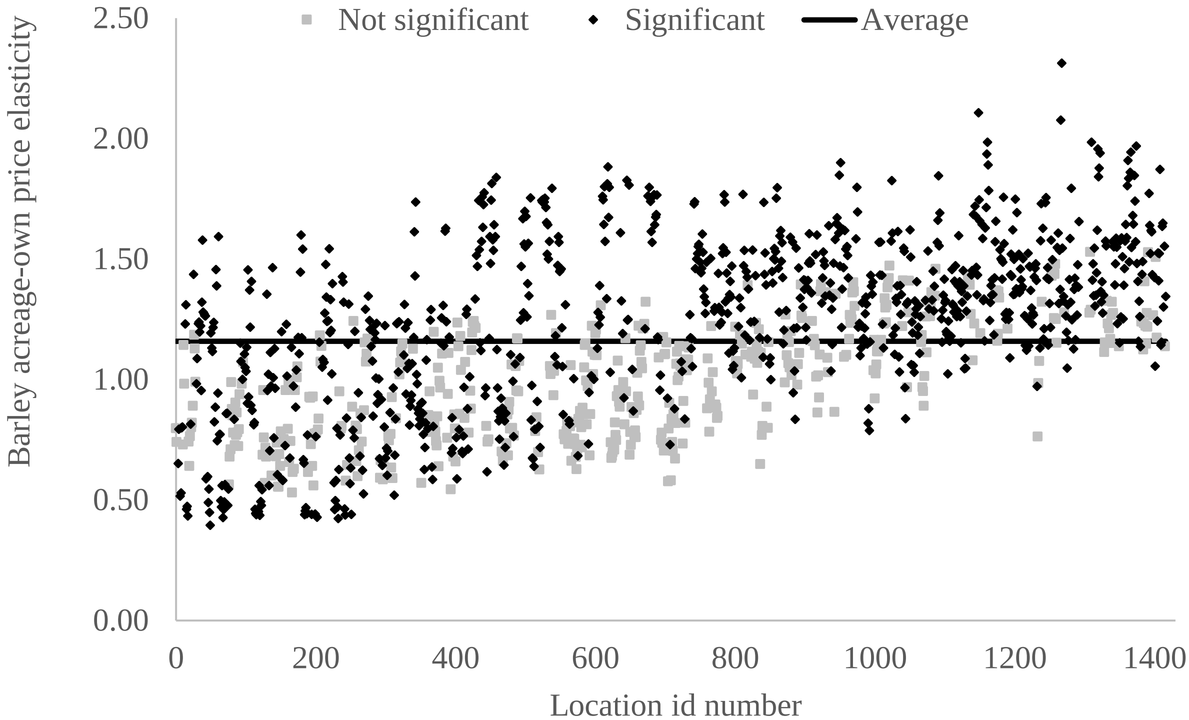


Figure 2.26. Own-price elasticity and significance level of barley acreage

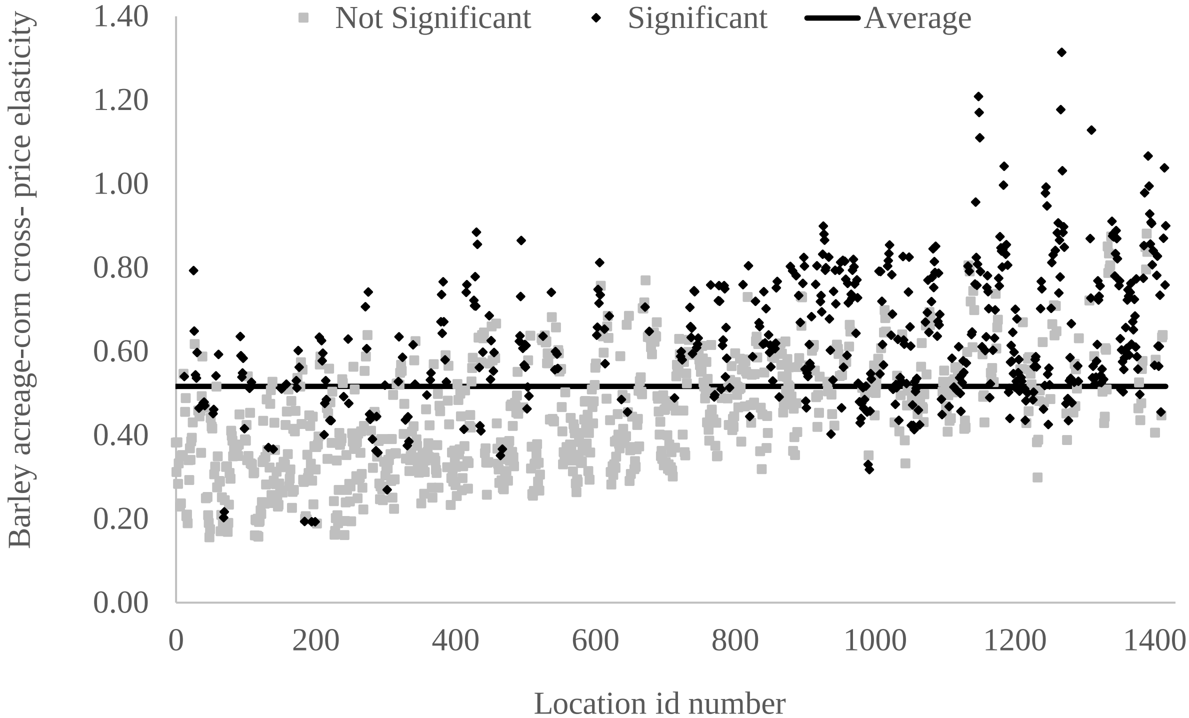


Figure 2.27. Cross-price elasticity and significance level of barley acreage and corn price

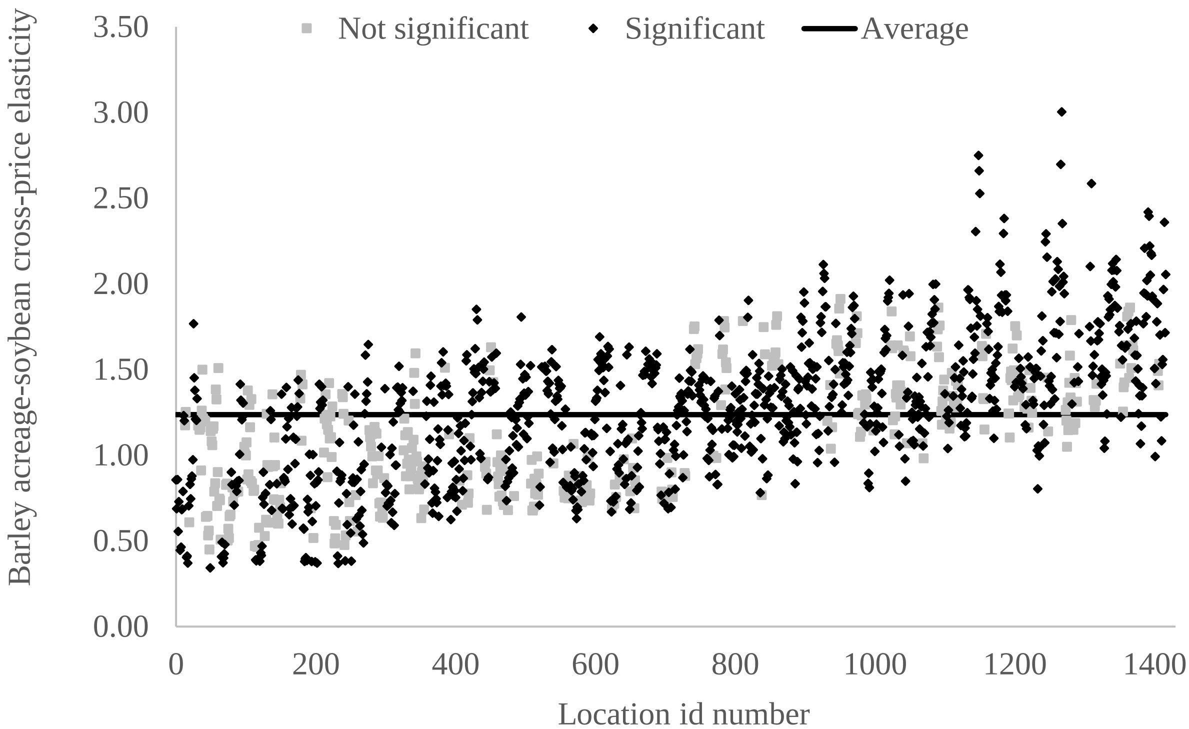


Figure 2.28. Cross-price elasticity and significance level of barley acreage and soybean price

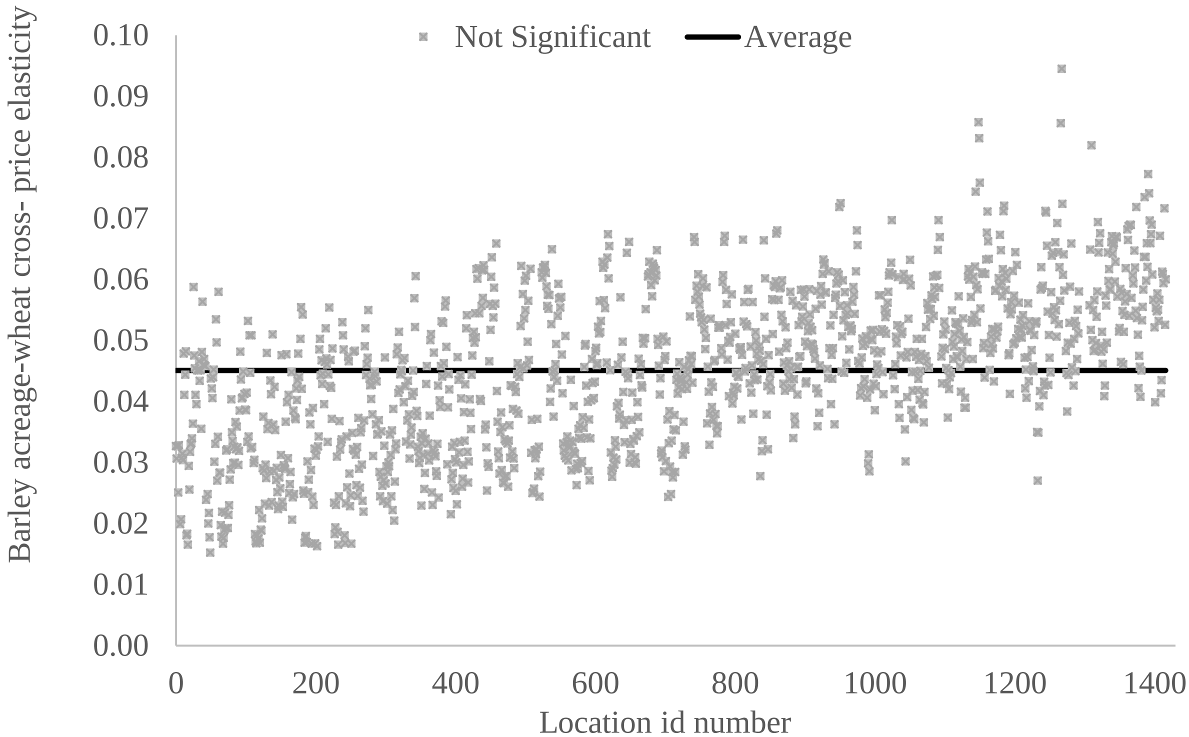


Figure 2.29. Cross-price elasticity and significance level of barley acreage and wheat price

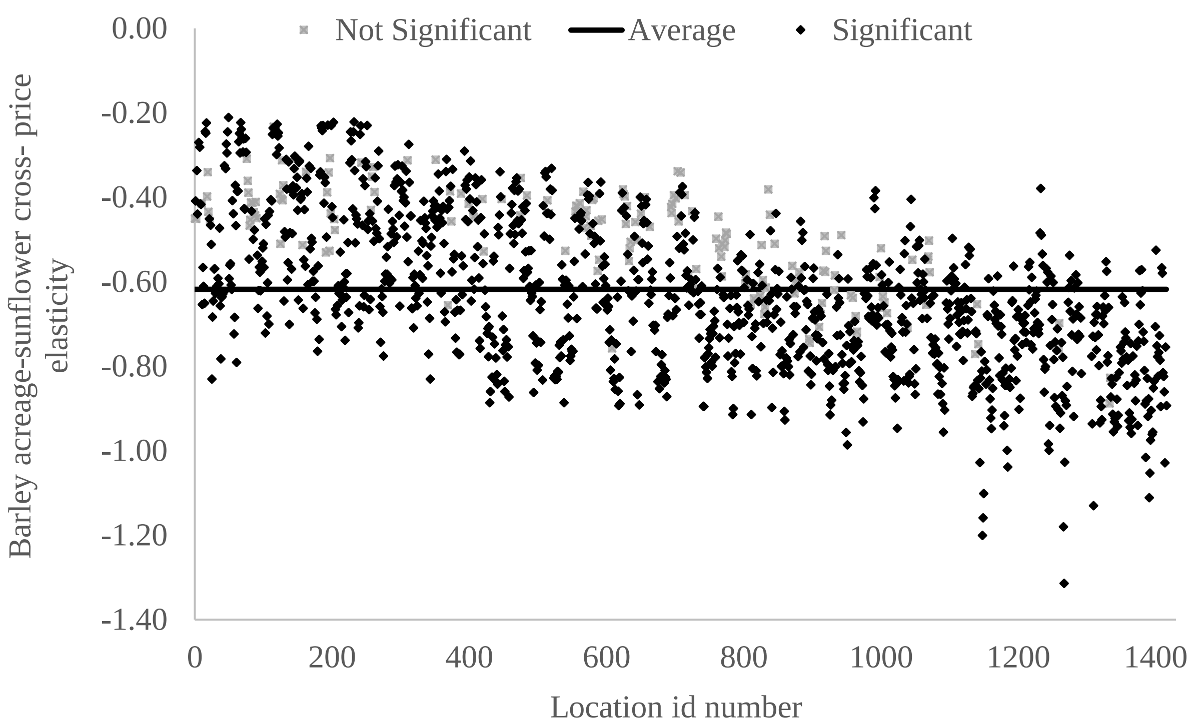


Figure 2.30. Cross-price elasticity and significance level of barley acres and sunflower price

Table 2.5. Statewide average own- and cross-price acreage supply elasticity point estimates with ranges and numbers of locations with statistically discernible estimates

Crop Acreage	Price Elasticity				
	Barley	**Corn**	**Soybean**	**Sunflower**	**Wheat**
Barley	1.16	0.52	1.24	-0.62	0.05
	[0.40, 2.31]	[0.16, 1.31]	[0.34, 3.00]	[-1.31, -0.21]	[0.02, 0.10]
	(886)	(501)	(950)	(1,187)	(0)
Corn	1.01	1.23	-0.31	-0.01	-0.10
	[0.09, 1.82]	[0.20, 3.09]	[-0.96, 0.08]	[-0.02, -0.00]	[-0.24, 0.01]
	(1,354)	(1,335)	(251)	(0)	(39)
Oilseeds	-0.05	-2.63	2.24	0.53	-0.20
	[-0.22, 0.10]	[-6.20, -0.74]	[0.61, 4.96]	[0.15, 1.22]	[-0.46, -0.05]
	(0)	(1,284)	(1,290)	(1,216)	(751)
Soybean	-2.23	-3.72	0.17	1.30	-0.33
	[-5.39, -0.22]	[-9.02, -0.34]	[-0.08, 0.53]	[0.12, 3.09]	[-.99, -0.05]
	(1,353)	(1,338)	(0)	(1,344)	(1,304)
Wheat	0.10	-0.66	0.42	-0.20	-0.16
	[-0.24, 0.45]	[-2.70, -0.17]	[0.10, 1.93]	[-0.77, -0.05]	[-0.74, -0.05]
	(447)	(1,153)	(793)	(1,070)	(1,088)

Notes: Numbers in brackets [ ] are the ranges of elasticity estimates across all locations. Numbers in parentheses ( ) indicate how many locations had statistically significant elasticity estimates.

2.8. Conclusion

The objective of this study was to estimate a system of crop acreage response functions to determine which factors influence farmers' decisions to supply (or allocate) land to various crops available to them. We find statistical evidence that farmers' land allocations decisions are influenced by crop price expectations and input price expectations, as well as temperatures, rainfall, soil moisture, and soil type. We have developed a system of equations that performs well in predicting corn, soybean, and wheat acreage based on these factors. However, the model performs quite poorly in predicting of acreages of barley and oilseeds. Two possible reasons for the poor predictive ability of the barley and oilseeds acreage supply functions are (1) the use of one-year price lags (as opposed to commodity futures market contract prices) as proxies for farmer price expectations for these two crops, (2) the fact that much of the barley grown in North Dakota is planted under contract, and (3) the fact that acreage of oilseeds is actually an aggregation of several different crops' acreages, including sunflower, canola, and a few other minor crops.

Our analysis indicates that marginal effects of crop prices on crop acreages mostly comport with economic theory—especially the own-price marginal effects and elasticities being positive for all crops apart from wheat, as predicted by the law of supply. The cross-price marginal effects and elasticities indicate substitutability (if negative) or complementarity (if positive) of each pair of crops. That is, they tell whether farmers replace one crop with the other in their rotations or whether farmers grow two crops in combination over time.

These models can be used to predict how the acreages of the five crops studied may change in the future in response to climate change and in response to structural changes in markets for agricultural commodities. For example, these estimates might be useful in predicting how farmers may adjust acreages of corn, soybean, and wheat in response to the drastic soybean price decline related to recent trade developments with China, a major destination for the US soybean crop. Trade policy analysts might, therefore, find the results and methods used herein to be valuable. Additionally, the possibility of forecasting how acreages of these crops may expand, decline, or shift to new locations could be of great benefit to farmers in planning on-farm infrastructure projects, such as new grain storage capacity. Large agribusinesses could also benefit from such forecasts in determining where rail cars will be needed and where new grain elevators will be needed to accommodate shifting grain production areas. Further effort should also be made to enhance predictive success of the barely and oilseeds acreage supply functions.

CHAPTER 3. MULTIPLE CROP ACREAGE RESPONSE DUE TO ECONOMIC FACTORS AND WEATHER: A CASE STUDY ON NORTH DAKOTA, SOUTH DAKOTA, AND MINNESOTA

3.1. Abstract

This paper applies supply theory and the concept of opportunity cost to model the impacts of expected crop prices and yields, input prices, and weather on producers' crop mix allocations, aggregated at the state level for North Dakota, South Dakota, and Minnesota from 1980 to 2013. We estimate acreage response functions for five crops—barley, corn, soybean, sunflower, and wheat—across the three-state region to quantify the market interactions that relate farmers' acreage allocations in each state to economic variables such as crop prices and yields, and input prices. Additional explanatory variables used in the acreage response functions are weather variables, including precipitation levels and average temperatures for the months of March and April each year. We produce a balanced panel dataset with annual observations of the planted acreages of each of the five crops in each of the three states, along with the relevant price and yield variables for each crop and pertinent precipitation and temperature variables for each year in each state. We apply the seemingly unrelated regressions approach developed by Zellner (1962) to jointly estimate the acreage supply curves for each of the five crops. We discover and discuss the implications of important economic, market, and weather variables for various situations.

3.2. Introduction

This research focus on three states North Dakota, South Dakota, and Minnesota crop acreage due to economic and weather factors. Climate has an influence on cropping area and cropping intensity (Toshichika and Ramankutty 2015). Magrini, Balié, and Opazo (2016) uses panel data to estimate price response with acreage, production, and yields in Sub-Saharan Africa. Key findings suggest that farmers more responsive supply staple crop production to price change (Magrini, Balié, and Opazo 2016). In addition, it also mentions in short run the elasticity of price to supply is positive and statistically significant (Magrini, Balié, and Opazo 2016). Elasticity of price to production, yield, and acreage are 0.59, 0.30, and 0.22, respectively (Magrini, Balié, and Opazo 2016). Elasticity of land supply to land price in the United States is 0.12 (Tabeau, Helming, and Philippidis 2017). Morzuch, Weaver, and Helmberger (1980) calculates elasticities of different wheat planted acreage to farm programs. Key findings suggested that, elasticities of wheat acreage planted in different states for spring wheat is 0.77, winter wheat is 0.45, and wheat is 0.52 (Morzuch, Weaver, and Helmberger 1980). It also suggests that, due to acreage allocation and quota intervention somewhat distorted effect of price effect on acreage allocation (Morzuch, Weaver, and Helmberger 1980). Output prices have an influence on farmers' decision-making process in allocating land and higher output prices related to price volatility (Gilbert and Morgan 2010). Crop acreage supply responsive more to price change whereas yields response to weather (Schlenker and Roberts 2006). Coyle 1993; Haile et al. (2014) studies use acreage for supply response function. They use acreage and yields to measure prices (Weersink et al. 2010; Yu et al. 2012). These studies also analyze supply function based on crops' caloric values (Roberts and Schlenker 2009, 2013). It indicates that if relative prices change, farmers and producers switch from low- to high-demand crops and increase acreage (Abbott et al. 2011; Goodwin et al. 2012). US acreage supply for corn and soybeans respond to prices through substitution (Hendricks et al. 2014). Developing countries supply response functions related to crop price changes (Peterson 1979).

Scott (2013) calculates yield-price elasticity incorporating fertilizer use elasticity to calculate indirect elasticity of yield and price. Scott's key findings are that elasticities of yield and price for US corn is 0.04, soybean is 0.11, and wheat is 0.13 (Scott 2013). In United States, elasticities of yield and price of major crops are greater than 0.1 (Berry and Schlenker 2011). Their findings show that the supply of rice, wheat, soybean, and corn are related to output price changes and price volatility. Producers' land allocation decisions are influenced by output price changes (Haile et al. 2015). Weather and crop yields are also related to each other. Due to changes in weather, yield varies from year to year. Changes in the spatial distribution of county-wide corn affect corn yields via spatial variations in climate (Leng and Huang 2017). Genetically modified corn crops also have an impact on corn price increases. Key findings of Ervin et al. (2010) suggest that corn price increases led to demand increases for GMO corn as well as yield increases (Ervin et al. 2010). Research by Hayami and Ruttan (1985) shows that increasing food prices led to the introduction of GMO crops. Houck and Gallgher (1976) show that corn yields from the period 1951 through 1971 had a yield own-price elasticity of between 0.25 and 0.75. Moreover, Goodwin et al. (2012) described presence of weather variation yield response to price increase in different way than price decrease. Agricultural output varies with weather changes calculated with crop yields, area of crops planted, and number of crops harvested in a year all have influence. Agricultural output changes by 70% in Brazil due to climate changes (Cohn et al. 2016). Besides, weather variation, economic variables such as lagged yields, lagged price, fertilizer price, and diesel price can influence farmers' crop planting decisions. Because some crops need less fertilizer than others, farmers can switch to closely related substitute crops (Haile et al. 2014). Moreover, farmers' and producers' land allocation decisions and land use patterns are influenced by crop prices, which are determined by the supply of crops like rice, wheat, soybeans, and corn (Haile et al. 2014). In addition, global crop acreage response is influenced by crop prices, price volatility, and input cost, which influence expected food supply (Haile et al. 2014). The results also show that due to crop price changes it causes a decline in crop acreage. Crop acreage elasticity helps with decision-making regarding farmers' expectation of demand for crops and inputs (Haile et al. 2014). Besides that, inelastic supply causes an increase in crop prices, which have an impact on crop demand as well (Haile et al. 2014). An increase of output prices acts as a signal for farmers to increase cropland acreage (Haile et al. 2014). Soybean crop acres planted vary more as compared with other crops. Moreover, global corn acreage planted increases in exchange with soybean acreage (Haile et al. 2014). Output price acts differently with national-level crop acreage decisions than that of global-level crop acreage decisions. National-level harvesting, and planting times are inelastic as compared with global harvesting and planting times throughout the year, which can adjust the supply of crops with changing prices (Haile et al. 2014). Changes in price and weather could lead to changes in allocation of cropland. Also, weather changes could have an impact on what kind of crops grow on the same land and national prices (Smithers and Smit 1997). Key findings of impact of weather, yields, and prices on farmers' planting decisions in Ontario that due to the increased length of the growing season, yields and crop acreage are increasing for corn, soybeans, and winter wheat (Weersink et al. 2010). Besides that, impact of weather changes can be minimized if farmers adopt crop rotation (Bryant et al. 2000). In addition, findings of this study, soybeans and wheat are complements, and corn and soybeans are substitutes in crop rotation (Weersink et al. 2010). Previous studies only focus on the impact of output prices on crop profits; whereas, this paper includes yields and expected prices as an important parameter for crop acreage allocation decisions (Weersink et al. 2010). Weersink et al. (2010) discusses crop acreage into price and yield elasticities, and their results show that yield elasticity is higher than price elasticity, which explains yield is an important parameter for changing area to acreage decisions. Zulauf (2016) explains yields and revenue per acre has a strong relationship. Key findings of this study, US yield decline per acre have not any impact of US decline of revenue per acre of corn, soybean, and wheat crop due to coverage of crop insurance (Zulauf 2016). Sub-Saharan African countries experienced agricultural production changes with producer price change (Bond 1983). Producer price act differently single to aggregate crop production (Bond 1983). In addition, acreage response positively related to single and aggregate crop production (Bond 1983). Besides that, price elasticities in the long run of single crop production is greater than short run (Bond 1983). It also mentions that, farmers decision influence with changes aggregate crop price for aggregate crop production (Bond 1983). Subsidized crop insurance program has greater influence on farmers' crop selection, crop production, price and rate of production return using simulation techniques (Young, Vandeveer, and Schnepf 2001). Key findings suggest that, due to crop subsidy programs, aggregate plantings shift little as well as wheat and cotton acreage increases in national level (Young, Vandeveer, and Schnepf 2001). Significant impact found in planted acreage increases at regional level (Young, Vandeveer, and Schnepf 2001). Due to inelastic demand of crops, farmers crop subsidy program benefits reduced though increased acreage of crop and increases production (Young, Vandeveer, and Schnepf 2001). In 2009, genetically modified corn acreage comprised almost 80% acreage in US corn belt (Just and Pope 2001). Genetically modified crop (GMO) corn and soybean crops were introduced in 1996 and 1994, (Monsanto 2017; Klümper and Qaim 2014) respectively. Introduction of genetically engineered (GE) crop enhance yields of crop due to incorporating insecticide and herbicides technology traits in plant itself. In addition, GMO corn, soybean, and cotton account almost 80% of acreage in US year 2009 (National research council 2010). GMO crop are environment-economic friendly and beneficial to farmers compare to traditional non-GMO crop (National research council 2010). In addition, GE herbicide resistant -crop helps environment by not using toxic chemicals that could pollute waterbodies and soil (National research council 2010). Moreover, farmers use GE herbicide resistant-crop follow conservation tillage to reduce top soil erosion and pollution of water quality through sediments (National research council 2010). From 1996 to 2008, increases GE herbicide resistant-soybean and corn crop planted acreage in US (National research council 2010). In addition, insect-resistant Bacillus thuringiensis (Bt)-corn crop acres planted also increases in acreage planted since 1996 as well as insecticide use also reduced (National research council 2010). Glyphosate-tolerant soybeans (GTS) is a weed control biotechnology variety of crop that help farmers increase yields without using any weed eradicating chemicals that could be detrimental to the environment (Padgette et al. 1995). From 1996 to 2011, 1.37 billion acres planted of herbicide resistant-soybean, corn, and cotton of which herbicide resistant-soybean crop constitute 60% of acres. Due to introduction of corn hybrid seed in the period of 1930 by University of Minnesota made drastic change in per acre yields of corn increased from 40 bu/acre in 1940 to 50 bu/acre after World War II (Hart 1986).

The research questions in this study are how economic variables, like input prices, output prices, and yield and weather variables, like precipitation, and minimum and maximum temperature, have an impact on crop acreage in North Dakota, South Dakota, and Minnesota. Five crops: corn, barley, soybeans, wheat, and sunflowers are considered.

3.3. Study Area

North Dakota, South Dakota, and Minnesota fall into the Northern Great Plains and Midwest regions. South Dakota, in the Midwest region, comprises the east, west, and the Black

Hills. Corn is a major crop harvested in South Dakota with the largest portion of acreage, followed by soybeans, hay, and wheat, according to the 2013 edition of South Dakota Agriculture, the common thread. South Dakota's fertile soil is conducive to growing different crops. Southeast and east of the Missouri River is mainly good for growing corn and soybeans, whereas the north central is good for growing wheat (SD Conservation Districts n.d.). From the period 1970s to 2000s in SD state, corn yields rose on average by 89.64 bu/acre to 140.67 bu/acre; soybeans yield rose by 28.06 bu/acre to 39.16 bu/acre; and wheat yields rose by 31.37 bu/acre to 42.74 bu/acres at the same period (SD Agriculture, the common thread 2014).

Minnesota is in the midwestern and northern regions. Minnesota agricultural regions are in the south-central where corn and soybeans are produced; the west-central region, which is mainly concentrated on wheat, corn, and soybeans; the northwest region, which is mainly concentrated on wheat, sugar beets, and potatoes; and the northeast region, composed mainly of urban and forest areas (Schreinemachers et al. 1999). The eastern and western Minnesota soils are fertile. The southern part of Minnesota is good for growing corn and soybeans because of fertile lands. In the Red River Valley, small grains like barley and wheat are predominant (Gustafson and Adams n.d.). Until 1900, wheat became the major crop produced about half of Minnesota state acreage, but it started to decline in acreages after the period 1910 (Historic Context Study of Minnesota Farms (1820-1960) (n.d.). After the period 1900, corn start to grow mostly in southern side of Minnesota (Historic Context Study of Minnesota Farms (1820-1960) (n.d.). Due to development of new varieties of corn in 1930s, corn planted in northern side with rotation of three-year other crops such as barley or oats and hay (Historic Context Study of Minnesota Farms (1820-1960) (n.d.).

Eastern North Dakota falls in the Red River Valley, which is rich in fertile soil suitable for a variety of crops such as soybeans, winter wheat, sugar beets, and corn as a grain (Bertone 2016). The Drift Prairie region of North Dakota is good for growing all types of crops, including spring wheat, soybeans, corn, barley, and canola. North Dakota consider number one in production of canola, honey, and spring wheat. This region's soil consists of clay, gravel, and sand (Bertone 2016). The Missouri Coteau starts from east of the Missouri River to Drift Prairie, and durum wheat, oats, and other varieties of crops are predominant in this region (Bertone, 2016). Sunflower and alfalfa production also predominate the Missouri Slope and Badlands areas. This area's soil falls mainly in the clay category (Bertone 2016).

3.4. Conceptual Framework

The premise of this work is that farmers are individual agents attempting to maximize profit (or minimize losses) by planting the right crops in the right places at the right times. It is therefore assumed that a farmer plants each field to the crop expected to bring the highest net return. Effectively, the expected net return for a crop the farmer does *not* choose is the expected opportunity cost of the crop that *is* selected. Myriad factors affect the expected net returns from commodity production—for example, farmers' expectations about prices, yields, and production and marketing costs for each crop considered. Thus, *ceteris paribus,* the likelihood that a farmer will allocate any field to corn should increase along with the farmer's expectations on corn price and/or corn yield and should decrease in response increasing expectations on prices and yields of other crops. Thus, any system of crop acreage response models should include crop prices, crop yields, and costs of inputs used in crop production.

Additionally, the current year's crop selection may also be constrained by crop selection in previous years. For example, fall-seeded crops like hard red winter wheat typically cannot be planted in rotation with corn because fall-seeded crops must be planted before the corn harvest is complete. Additionally, crop rotations are used to decrease disease risk. Durum wheat, for instance, should not be planted into corn residue or near corn because doing so increases the risk of *fusarium* head blight, which drastically reduces the monetary value of the durum crop. Variables such as lagged acreages of each crop must also be included in the models to account for potential rotational constraints that affect farmers' present choices.

Additionally, site-specific variables such as expected precipitation, and expected temperature are likely to influence farmers' crop selections, partly because these factors influence yields and revenues but also partly because these factors can sometimes preclude planting some crops. For example, areas that regularly experience high early-season rainfall or snowmelt are sometimes so saturated they cannot be planted to spring wheat early enough to qualify for crop insurance coverage.

Conceptually, then, our crop acreage response functions, like equation (2.1), are supply curves for acreages of each of five crops—barley, corn, sunflower, soybean, and wheat—where the acreage allocated to each crop is a function of the crop's own price, the prices of competing crops, and any constraints imposed by weather, soil characteristics, or rotational considerations.

3.5. Data Collection

Statewide price received in marketing year, yields, and acreages of barley, corn, soybean, sunflower, and wheat for North Dakota, South Dakota, and Minnesota were collected from the USDA-NASS Quick Stats 2.0 Database from 1980 through 2013. Lagged statewide yields of barley, corn, soybean, sunflower, and wheat were used as proxies for farmers' expected yields. Prices were inflation-adjusted to 2012 US dollars using the Implicit GDP Price Deflator. We take marketing year price received of crops as lagged crop prices used as proxies for producers' crop price expectations.

Nitrogen fertilizer also accounts for a large proportion of the cost of crop production, so average United States farm prices of ammonium nitrate fertilizer for April from 1998 through 2013 were acquired from the United States Department of Agriculture, Economic Research Service, Fertilizer Use and Price 2017. We also collected regional farm level diesel prices from the United States Department of Agriculture Agricultural Price Report for April from 1980 through 2013. These prices were also inflation adjusted and are given in 2012 US dollars. Dummy variables were used to indicate periods before and after the introduction of the first transgenic corn—introduced in 1996 by Monsanto (2017) and soybean (introduced 1994) varieties (Klümper and Qaim 2014). Weather variables—total monthly precipitation, monthly average daily high and low temperatures—were obtained for each state each year for the March and April from 1980 to 2013 (National Centers for Environmental Information, Climate Data Online: Dataset Discovery 2017).

3.6. Methodology

A system of five seemingly unrelated regressions was estimated using maximum likelihood estimation, in which the five dependent variables are the proportion of the state covered by barley, corn, soybean, sunflower, and wheat. The seemingly unrelated regressions model was proposed by Arnold Zellner in 1962. We estimated the parameters using the SUREG procedure in SAS. Error terms are assumed to be correlated across equations but to exhibit no serial correlation within equations (Davidson and MacKinnon 1993).

The system of equations can be written as follows:

$$y_{ijt} = x'_{jt}\beta_i + u_{ijt} \tag{3.1}$$

where y_{ijt} is the proportion of state *j* planted to crop *i* in year *t*; x'_{jt} are the values of the exogenous variables (e.g. prices, weather, etc.); β_i is the vector of parameter estimates relating crop *i*'s planted area to the explanatory variables; and u_{ijt} is an unexplained disturbance with mean zero and variance σ_i^2. We assume no serial correlation of the error terms, such that $corr(u_{ijt}, u_{ij(t-1)}) = 0$. Cross-equation error correlation is allowed, however, such that $corr(u_{corn,jt}, u_{wheat,jt}) \neq 0$.

The dependent variables consist of the percentages of each state's total land area planted to each of the five crops each year. Independent variables include lagged yields, lagged crop prices, and early-season prices of ammonium nitrate fertilizer and farm diesel. Total monthly precipitation, monthly average daily high and low temperatures—were obtained for each state each year for March and April from 1980 to 2013. Indicator variables represent the introduction of two genetically modified (GM) crops—soybean and corn—introduced for commercial use in 1994 and 1996, respectively (Monsanto 2017; Klümper and Qaim 2014). We also consider revenues and lagged acreages of corn, barley, wheat, soybean, and sunflowers. Table 3.1 lists each of the numerical variables in y_{ijt} and x'_{jt} with its mean and standard deviation, by state. Variables included in the model but not in the table are indicator variables for two of the three states—North Dakota and South Dakota—and indicator variables for the introduction of transgenic corn (after 1996) and soybean varieties (after 1994).

Table 3.1. Means and standard deviations for model variables

Variable	Minnesota	North Dakota	South Dakota
	State		
Percentage planted to . . .			
Barley	0.969	4.545	0.617
	(0.751)	(1.821)	(0.586)
Corn	12.798	2.976	8.135
	(1.462)	(1.814)	(1.746)
Soybean	11.042	4.162	5.961
	(1.877)	(3.347)	(2.637)
Sunflower	0.329	3.208	1.161
	(0.298)	(1.411)	(0.394)
Wheat	4.064	21.211	7.036
	(1.013)	(3.417)	(1.067)
Expected price			
Barley ($/bu.)	3.538	3.509	3.495
	(1.228)	(1.211)	(1.136)
Corn ($/bu.)	3.776	3.722	3.692
	(1.332)	(1.327)	(1.368)
Soybean ($/bu.)	9.563	9.229	9.282
	(2.840)	(2.722)	(2.826)
Sunflower ($/cwt.)	19.353	17.920	16.694
	(5.301)	(4.933)	(5.210)
Wheat ($/bu.)	5.669	6.246	5.583
	(1.632)	(2.261)	(1.647)
Fertilizer ($/short ton)	345.243	345.243	345.243
	(85.956)	(85.956)	(85.956)
Diesel ($/gal)	1.861	1.785	1.785
	(0.826)	(0.859)	(0.859)
Expected yield			
Barley (bu.)	56.318	51.409	42.879
	(9.349)	(9.434)	(8.598)
Corn (bu.)	132.545	94.364	95.545
	(28.010)	(23.490)	(26.311)
Soybean (bu.)	37.273	28.591	31.788
	(5.639)	(5.369)	(5.151)
Sunflower (cwt)	12.202	11.320	11.789
	(2.067)	(1.938)	(2.419
Wheat (bu.)	42.573	31.939	34.112
	(9.232)	(6.603)	(8.189)

Notes: Numbers in parentheses are standard deviations. N = 33.

Table 3.1. Means and Standard Deviations of Model Variables (continued)

	State		
Variable	**Minnesota**	**North Dakota**	**South Dakota**
Expected Revenue			
Barley ($/ac.)	197.537	177.336	144.042
	(69.278)	(65.225)	(34.727)
Corn ($/ac.)	492.466	342.134	342.761
	(197.844)	(139.817)	(152.638)
Soybean ($/ac.)	351.847	258.099	290.852
	(102.638)	(75.778)	(86.985)
Sunflower ($/ac.)	235.780	201.825	194.767
	(78.776)	(66.374)	(72.383)
Wheat ($/ac.)	240.987	195.738	187.845
	(87.925)	(74.900)	(69.976)
Temperatures (°F)			
March Daily High	37.818	37.218	44.358
	(5.267)	(6.617)	(6.224)
March Daily Low	18.094	17.394	22.073
	(5.124)	(5.521)	(4.376)
April Daily High	54.145	54.412	57.815
	(4.808)	(5.305)	(4.747)
April Daily Low	31.218	29.758	32.491
	(3.097)	(3.180)	(2.935)
Precipitation			
March Average	1.368	0.832	1.182
	(0.504)	(0.403)	(0.562)
April Average	2.294	1.260	2.115
	(1.026)	(0.753)	(1.030)

Notes: Numbers in parentheses are standard deviations. N = 33.

Table 3.2. Seemingly unrelated regression results relating coverage of each crop to the market and the weather

	Dependent variables: annual percentages of state planted to . . .				
Variable	**Barley**	**Corn**	**Soybean**	**Wheat**	**Sunflower**
Crop and Input Prices					
Corn	0.25^{**}	0.66^{***}	-0.37^{**}	-0.27	-0.12
	(0.12)	(0.18)	(0.15)	(0.34)	(0.12)
Soybean	-0.17^{***}	-0.20^{**}	0.13^{*}	-0.12	0.01
	(0.06)	(0.08)	(0.08)	(0.18)	(0.06)
Wheat	0.07	-0.20	0.06	0.38^{***}	0.21^{**}
	(0.05)	(0.15)	(0.07)	(0.14)	(0.10)
Barley	-0.01	-0.03	-0.42	0.50^{*}	-0.25^{***}
	(0.10)	(0.15)	(0.28)	(0.26)	(0.09)
Sunflower	0.03^{a}	0.07^{*}	0.08^{***}	0.02	0.11^{***}
	(0.02)	(0.04)	(0.03)	(0.07)	(0.02)
Diesel	-	0.04	-0.51^{***}	0.82^{*}	-0.20^{*}
		(0.18)	(0.15)	(0.47)	(0.11)
Ammonium nitrate	-0.05^{a}	-	-	-0.20^{a}	
	$(0.10)^{a}$			$(0.50)^{a}$	
Lagged crop yield					
Corn	-	-0.02^{**}	-	-	-
		(0.01)			
Soybean	-	0.04	0.08^{***}	-	-
		(0.03)	(0.02)		
Barley	-	-0.02^{*}	-0.04^{**}	-	-0.80^{a}
		(0.01)	(0.02)		$(0.80)^{a}$
Wheat	-	-0.01	-	-	0.04^{**}
		(0.03)			(0.02)
Sunflower	-0.04	-	-	-	0.04
	(0.03)				(0.03)

Notes: The symbols ***, **, and * indicate statistical significance at $\alpha = 0.01$, $\alpha = 0.05$, and $\alpha = 0.10$, respectively. Numbers in parentheses are standard errors. The symbol ^{a} indicates the estimate has been multiplied by 100. N = 99.

Table 3.2. Seemingly unrelated regression results relating coverage of each crop to the market and the weather (continued)

	Dependent variables: annual percentages of state planted to . . .				
Variable	**Barley**	**Corn**	**Soybean**	**Wheat**	Sunflower
Revenue					
Soybean	0.10^{a}	-	-	-0.50^{a}	0.10^{a}
	(0.10)^{a}			(0.40)^{a}	(0.10)^{a}
Barley	-0.08^{a}	-	0.01*	-	-
	(0.10)^{a}		(0.50)^{a}		
Wheat	-	0.20^{a}	-	-	-0.70^{**a}
		(0.40)^{a}			(0.30)^{a}
Sunflower	-	0.30^{a}	-	-0.50^{a}	-
		(0.20)^{a}		(0.40)^{a}	
Average minimum daily temperature					
March	-	-	0.06*	-	-
			(0.03)		
April	-0.06**	-0.14***	-0.14***	-	-0.11***
	(0.03)	(0.05)	(0.04)		(0.03)
Average maximum daily temperature					
March	-	-	-0.06**	0.05**	-0.01*
			(0.03)	(0.02)	(0.90)^{a}
April	0.05***	0.12***	0.10***	-0.08**	0.08***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)
Average precipitation					
March	-	-	-0.67***	-0.37	-
			(0.14)	(0.23)	
April	0.13**	0.15*	0.17**	-	0.19***
	(0.05)	(0.09)	(0.08)		(0.05)

Notes: The symbols ***, **, and * indicate statistical significance at $\alpha = 0.01$, $\alpha = 0.05$, and $\alpha = 0.10$, respectively. Numbers in parentheses are standard errors. The symbol ^{a} indicates the estimate has been multiplied by 100. N = 99.

Table 3.2. Seemingly unrelated regression results relating coverage of each crop to the market and the weather (continued)

	Dependent variables: annual percentages of state planted to . . .				
Variable	**Barley**	**Corn**	**Soybean**	**Wheat**	**Sunflower**
Lagged acreage					
Corn	-	0.18^{**}	-	-0.54^{***}	-
		(0.09)		(0.13)	
Barley	0.69^{***}	-	-0.39^{***}	0.83^{***}	-0.11^{*}
	(0.06)		(0.08)	(0.17)	(0.06)
Soybean	-0.04	0.51^{***}	0.86^{***}	-	-
	(0.04)	(0.06)	(0.05)		
Wheat	-0.01	0.07	-	0.52^{***}	0.09^{***}
	(0.03)	(0.04)		(0.07)	(0.02)
Sunflower	0.20^{***}	-	-	-0.40^{***}	0.82^{***}
	(0.05)			(0.14)	(0.05)
State dummy					
North Dakota	0.43	-5.80^{***}	0.96^{**}	-0.11	-0.51
	(0.44)	(1.03)	(0.42)	(1.70)	(0.44)
South Dakota	-0.52^{**}	-1.89^{***}	-0.38	-1.03	0.08
	(0.24)	(0.41)	(0.33)	(0.73)	(0.17)
Genetically modified crop dummy					
Soybean	-0.41^{**}	-	0.02	-	-
	(0.16)		(0.21)		
Corn	-	-	-	0.81^{**}	-
				(0.41)	
Constant	0.52	2.23	0.72	10.83^{***}	-3.45^{***}
	(0.83)	(2.05)	(1.68)	(2.54)	(0.86)
R^2	0.97	0.98	0.98	0.98	0.93

Notes: The symbols ***, **, and * indicate statistical significance at $\alpha = 0.01$, $\alpha = 0.05$, and $\alpha = 0.10$, respectively. Numbers in parentheses are standard errors. The symbol [a] indicates the estimate has been multiplied by 100. N = 99.

3.7. Results and Discussion

We estimated the system of seemingly unrelated regressions based on the balanced panel dataset we created using the SUREG procedure in SAS 9.4. Table 3.2 displays the parameters estimates of for each crop's acreage supply function along with each equation's R-square. Some explanatory variables were dropped from each equation—specifically, those that had low explanatory power but high collinearity with other independent variables. Notably, the R-square for each equation is at least 0.93, indicating that the selected independent variables collectively have extremely high explanatory power. Notably, the lagged barley price, which is our proxy for expected barley price, has no statistically discernible effect on the acreage planted to barley. Corn and soybean prices appear to be the primary economic drivers of changing barley acreage throughout the three states. April temperatures and precipitation also seem to have a considerable influence on the amount of barley planted. That is, within the three-state region, years and locations with high total precipitation and high average daily maximum temperatures in April tend to have higher barley acreage, ceteris paribus. On the other hand, places and years with high average minimum daily temperatures in April tend to have lower barley acreage. Other important variables with statistically discernible relations to planted barley acreage include the values of two lagged dependent variables—acreages of barley and sunflower planted in the state during the preceding production year. Both variables have positive effects on barley acreage planted, likely indicating that barley production has a synergistic—potentially complementary—relation to sunflower production due to rotational considerations. The introduction of transgenic soybean varieties also is highly correlated with declining barley acreage in the region. Interestingly, the previous year's barley price has a negative sign, but no statistically discernible impact on total acreage planted to barley. This result probably indicates that farmers' expectations of barley price are not informed by the previous year's barley price. Since most barley is grown under contract, this should be no surprise—the terms of the grower contracts stipulate price, quantity, and quality. Many crop prices have statistically apparent effects on the acreage responses for corn, soybean, wheat, and sunflower. High diesel prices appear to instigate reductions of soybean and sunflower acreage but cause increases of wheat acreage—potentially because wheat requires less diesel fuel than soybean or sunflower. Ammonium nitrate prices, however, have no statistically evident effect on farmers' aggregate multi-crop acreage allocations.

Nineteen of the parameters estimates in Table 3.2 represent statistical relations between each crop's planted acreage and each of several weather variables—statewide monthly averages of daily maximum temperatures and of daily minimum temperatures as well as monthly statewide precipitation levels for March and April each year. Eighteen of these are statistically different from zero at the 90% confidence level or higher. For example, higher daily maximum temperatures in April will tend to increase plantings of barley, corn, soybean, and sunflower, while apparently depressing plantings of wheat. Higher daily minimum temperatures in April, on the other hand, will tend to depress plantings of barley, corn, soybean, and sunflower.

Each crop's acreage is strongly correlated with not only its own time-lagged acreage but also with the time-lagged acreages of other crops typically grown with it in rotation. Each crop's geographic extent in a state is positively correlated to its own extent in the same state in the previous year, which indicates farmers in each state tend to plant a somewhat stable mix of crops over time.

3.7.1. Own and Cross-Price Elasticity of Crop Acreage by State

Own- and cross-price elasticities of acreage supply were obtained for each crop by partially differentiating each of the five-acreage response function with respect to each commodity price and multiplying each of these by the quotient of price and quantity. We used Monte Carlo Simulation to simulate 90% confidence intervals for each of these elasticities by creating 99,000 simulated sets of parameter estimates drawn randomly from the distribution of acreage response parameter estimates. Simulated elasticities were derived from the simulated acreage response functions, and these elasticities were then evaluated at the values of the variables observed in the dataset.

Table 3.3 contains the elasticity estimates, along with the upper and lower bounds of their confidence intervals. The own-price elasticity estimates for corn, soybean, wheat, and sunflower are all positive in each state, and are statistically significant at $\alpha \leq 0.05$. Despite the estimated elasticities being statistically significant, however, most of elasticity estimates indicate statewide crop plantings are own-price inelastic. Sunflower own-price elasticities in Minnesota and South Dakota were both positive and greater than one. In fact, estimates indicate that a one percent increase in the expected sunflower price will result in an 11.337% increase in Minnesota sunflower acres and a 1.723% increase in South Dakota’s sunflower acreage. The own-price elasticity estimates for barley acreage response are negative, counter to theory-based expectations—but are not statistically significant in any of the three states.

Table 3.3. Own and cross-price elasticity to crop acreage and confidence interval in states from 1980 through 2013

	Price elasticity in Minnesota				
Crop acreage	**Barley**	**Corn**	**Soybean**	**Wheat**	**Sunflower**
Barley	-0.506	-0.009	0.020	0.471**	-4.918***
	[-3.272, 0.818]	[-0.082, 0.062]	[-0.074, 0.119]	[0.063, 1.172]	[-16.054, -0.675]
Corn	2.362**	0.197***	-0.131***	-0.270	-2.474
	[0.188, 9.463]	[0.084, 0.361]	[-0.289, -0.031]	[-0.944,0.263]	[-9.710, 1.144]
Soybean	-2.925**	-0.152***	0.116**	-0.782**	3.553
	[-10.915, -0.315]	[-0.300, -0.043]	[0.001, 0.279]	[-1.819, -0.111]	[-1.015, 13.282]
Wheat	0.998*	-0.051	0.032	0.566***	-3.168
	[-0.091, 4.236]	[-0.139, 0.027]	[-0.026, 0.102]	[0.188, 1.237]	[-14.626, 0.913]
Sunflower	0.012	0.165***	0.151***	-0.237	11.337***
	[-2.343, 2.402]	[0.073, 0.281]	[0.053, 0.286]	[-0.844, 0.217]	[2.142, 7.838]

	Price elasticity in North Dakota				
Crop acreage	**Barley**	**Corn**	**Soybean**	**Wheat**	**Sunflower**
Barley	-0.054	-0.042	-0.044	0.087**	-0.340***
	[-0.288, 0.092]	[-0.439, 0.329]	[-0.759, 0.496]	[0.012, 0.203]	[-0.905, -0.090]
Corn	0.275**	1.018***	-0.742***	-0.050	-0.168
	[0.043, 0.885]	[0.321, 2.199]	[-2.286, -0.067]	[-0.178,0.049]	[-0.547,0.088]
Soybean	-0.369***	-0.773***	0.639**	-0.120**	0.192
	[-1.092, -0.089]	[-1.745, -0.163]	[0.003,2.051]	[-0.286, -0.004]	[-0.108,0.621]
Wheat	0.128*	-0.362*	0.193	0.116***	-0.048
	[-0.019, 0.434]	[-0.972, 0.011]	[-0.139, 0.796]	[0.036, 0.250]	[-0.446, 0.231]
Sunflower	0.002	0.766***	0.758***	-0.036	0.720***
	[-0.179, 0.190]	[0.266, 1.475]	[0.105, 2.128]	[-0.131, 0.042]	[0.316, 1.977]

Notes: The symbols ***, **, and * indicate statistical significance from one-tailed tests at $\alpha = 0.01$, $\alpha = 0.05$, and $\alpha = 0.10$, respectively. Numbers in brackets are the bounds of 90% confidence intervals.

Table 3.3. Own and cross-price elasticity to crop acreage and confidence interval in states from 1980 through 2013 (continued)

	Price elasticity in South Dakota				
Crop acreage	**Barley**	**Corn**	**Soybean**	**Wheat**	**Sunflower**
Barley	-0.739	-0.013	-0.061	0.257**	-0.859***
	[-5.186, 1.978]	[-0.131, 0.100]	[-0.396, 0.137]	[0.034, 0.577]	[-1.910, -0.229]
Corn	4.973**	0.312***	-0.333***	-0.145	-0.433
	[0.278, 22.319]	[0.121, 0.635]	[-1.128, -0.050]	[-0.510, 0.150]	[-1.404, 0.241]
Soybean	-6.272***	-0.239***	0.290**	-0.380**	0.532
	[-25.992, -0.538]	[-0.510, -0.063]	[0.001, 1.013]	[-0.869, -0.029]	[-0.280, 1.659]
Wheat	2.045*	-0.097*	0.081	0.309***	-0.072
	[-0.164, 9.208]	[-0.246, 0.011]	[-0.052, 0.340]	[0.107, 0.619]	[0.609, 3.243]
Sunflower	0.008	0.227***	0.329***	-0.107	1.723***
	[-4.040, 4.057]	[0.092, 0.413]	[0.067, 1.051]	[-0.373, 0.112]	[-0.846, 0.834]

Notes: The symbols ***, **, and * indicate statistical significance from one-tailed tests at $\alpha = 0.01$, $\alpha = 0.05$, and $\alpha = 0.10$, respectively. Numbers in brackets are the bounds of 90% confidence intervals.

Price elasticities in the second column of table 3.3 indicate that a one percent increase in expected barley price will lead to no statistically discernible change in barley plantings in any state, but to increased corn acreage in Minnesota (2.362% increase), North Dakota (0.275% increase), and South Dakota (4.973% increase) and to decreased soybean acreage in Minnesota (2.925% decrease), North Dakota (0.369% decrease), and South Dakota (6.272% decrease). These results signify that high barley price expectations precede the replacement of some soybean acreage by corn. Additionally, a one percent increase in expected barley price leads to statistically significant increases in wheat acreage in all three states—increases of 0.998%, 0.128%, and 2.045% in Minnesota, North Dakota, and South Dakota, respectively. Elasticities in the third column table 3.3 attest that increases in farmers' corn price expectations tend to have discernible, though inelastic, effects on corn acreage supply (0.197%), soybean acres (-0.152%) and sunflower acreage planted (0.165%) in Minnesota. On the other hand, the corn price elasticity estimates for North Dakota indicate that a one percent increase in expected corn price leads to a 1.018% increase in corn acreage, concurrent with decreased soybean and wheat acreage (-0.773% and -0.362%, respectively) and to a 0.766% increase in sunflower acreage.

Per column four of table 3.3, a one percent hike is expected soybean price tends to induce statistically significant, though relatively small, increases in soybean and sunflower acres in each of the states, along with a small statistically evidenced decrease in corn acreage. Own-price elasticity estimates for wheat price are positive and statistically significant in all three states but fall in the inelastic range. Soybean acreage has a negative, inelastic response to wheat price, regardless of state. Elasticities of barley acreage with respect to wheat price are discernibly positive but are very small in magnitude. Changes in expected sunflower price have statistically significant relations only with barley acreage and sunflower acreage. Barley acreage decreases

4.918% in Minnesota, 0.390% in North Dakota, and 0.859% in South Dakota in response to a one percent increase in the expected sunflower price. Sunflower acreage is particularly highly responsive to its own price in Minnesota—an 11.337% in acreage per one percent increase in expected price. The response of sunflower acreage to sunflower price in South Dakota also falls into the elastic range, at 1.723%. However, sunflower acreage in North Dakota is not very responsive, though the elasticity estimates of 0.720% is statistically significant.

A positive cross-price elasticity should be understood to indicate that a pair of crops is complementary in production, at least in the sense that the two crops are grown in close association. For example, the positive cross-price elasticities of the wheat acreage responses to barley price—$0.128\% < \eta_{w,b} \leq 2.045\%$ and statistically non-zero in each state—and the acreage responses of barley acreages to wheat price—$0.087\% < \eta_{b,w} \leq 0.471\%$ and statistically significant in all states—indicate that wheat and barley are often grown in close areas to each other in a proportion that is somewhat stable over time, such that their acreages increase and decrease together. Negative estimates of the elasticity of corn acreage response to soybean price ($-0.742\% < \eta_{c,so} \leq -0.131\%$, depending which state) and of the elasticity of soybean acreage response to corn price ($-0.773\% < \eta_{so,c} \leq -0.152\%$, depending which state) indicate that at the margin corn and soybean act as substitutes in production, perhaps because farmers are willing to plant corn (or soybean) in the same field two years in a row if corn (or soybean) prices are expected to be high enough to justify temporarily altering their corn-to-soybean rotations. Ultimately, what is clear is that several complex statistical relations have been detected between the crop planting levels and the prices of complementary and competing commodities, and that these relationships comport with microeconomic supply theory.

3.8. Conclusion

This three states paper use seemingly unrelated uncensored regression technique to analyses crop acreage response due to economic factors and weather factor. Farmers choose alternative crops depending on the crop prices, yields, revenue, input price (diesel and ammonium nitrate price), last year acreage of each crop, precipitation during March and April, and minimum and maximum temperature during March and April. All these factors influence farmers decisions to choose alternative crops and different crop rotation at different states. Key findings suggest that, price is the most driving factor influence farmers decision to acreage allocation among different crop alternative. Soybean prices increases, corn acreage decreases and statistically significant. It indicates that, corn and soybean substitute in production. So, farmers can choose depending on this price factors. Last year barley yield is negatively and statistically significant impact on soybean acreage this year. Revenue of wheat is negatively and statistically significant impact on sunflower acreage. Last year wheat acreage is negatively and statistically significant impact on soybean acreage this year. In Midwest states, corn-soybean-wheat crop rotation is practiced. So, our result indicates that as soybean and wheat can be allocating that way which beneficial for farmers. Last year soybean acreage positive and statistically significant impact of corn acreage this year which shows complement in production relation. Input price (diesel price) is negatively relate soybean acreage and statistically significant. As production cost decreases, farmers rate of return will increase. Ammonium nitrate price negatively and diesel price positively related to wheat acreage which define combinedly lower production cost and statistically significant only diesel price.

Maximum temperature during April positively related whereas April minimum temperature negatively and statistically significant impact on barley, corn, soybean, and sunflower acreage. Precipitation during March negatively and statistically significant impact on soybean acreage. Our results support literature says.

GMO crop (corn and soybean) dummy is an important component in our acreage analysis because it increases yield and increase acreage allocation. GMO soybean crop positive and statistically significant impact on soybean acreage.

Monte Carlo Simulation technique used to calculate elasticity of own and cross-price to acreage in North Dakota, South Dakota and Minnesota help farmers to choose between alternative crops and allocate acreage. Own-price elasticity of MN state barley, corn, soybean, wheat, and sunflower to their own acreage are -0.506%, 0.197%, 0.116%, 0.566 %, and 11.34%, respectively; in ND state are -0.054%, 1.018%, 0.639%, 0.116%, and 0.720%, respectively; in SD state are -0.739%, 0.312%, 0.290%, 0.309%, and 1.72%, respectively and statistically significant except barley crop elasticity.

These models can be used for predicting acreage of corn, barley, wheat, soybean, and sunflower acreage changes due to weather in the future across state of ND, SD, and MN. In addition, it also helps predicting how farmers crop acreage decision adjusted with crop price changes across states.

CHAPTER 4. GENERAL CONCLUSIONS AND FUTURE RESEARCH IMPLICATION

4.1. General Conclusions and Future Research Implication

This dissertation comprised of two papers crop acreage ND and multiple crop acreage response in states of ND, SD, and MN. In North Dakota paper, we use seemingly unrelated tobit censored regression to analyze crop acreage allocation changes overtime and Monte Carlo simulation technique to calculate marginal effects and elasticity issues. Key findings suggest that, statistically significant effect of crop's own price positively influences crop acreage, whereas cross-crop prices negatively influence it. Statistically significant impact of crop's own yields is positively influenced, whereas yields of closely substituted crop are negatively related to crop acreage. Input price (farm-level diesel oil and ammonium nitrate prices) is inversely related to crop acreage. But we do not get always the exact relationship as we expected. A crop's own revenue is positively related, whereas revenues of substitute crops are negatively related to crop acreage. A crop's own lagged acreage is positively related, whereas lagged acreage of substitute crops is inversely related to crop acreage. Maximum and minimum temperatures during March and April are good for small grains like barley and winter wheat, whereas maximum and minimum temperatures during May and June are good for warms crop like corn and soybeans. Precipitation increases during March and April could decrease crop yields, whereas growing season precipitation increases during May and June could increase crop yields. Latitude (north or south) and longitude (east or west) are important factors to define specific crop acreage variation locations. As move north or south in North Dakota, barley acreages increase and east or west, corn and soybean acreages increase. As demand for biofuel use decreased or increased after 2005 and 2007, crop acreages increased or decreased as land competed for two reasons. Soil texture is also an important component for crop yields. Marginal effect and elasticity of price own and cross with respect to crop acreage gives location-specific crop acreage response as well as which crop rotation maximize rate of return in North Dakota. Key findings suggest that, marginal effects of crop price increase by $1 to own acreage of barley, corn, soybean, wheat, and oilseeds ranges between 50 to 295 acres, 28 to 572 acres, -24 to 45 acres, -198 to-39 acres, and 7 to 48 acres throughout ND and statistically significant except soybean. Elasticity of barley price, corn, soybean, wheat, and oilseeds cross-price to barley acreage are 1.16%, 0.52%,1.24%,0.05% and -0.62%, respectively, and statistically significant except wheat. It also says that, cross-price of corn, soybean, wheat to barley acreage shows complement in production relation whereas with oilseeds acreage shows substitute relation. Elasticity of own-price to acreage of corn, soybean, wheat, and oilseeds are 1.23%, 0.17%, -0.16%, and 0.53%, respectively, and statistically significant except soybean.

ND research paper's key findings can use for broader spectrum considering all factors that influence crop acreage allocation decisions in other states as well as whole USA. Future direction can be used the same methodology to look for regional changes in crop acreage over long period of time and make comparison with different regions crop acreage allocation response. We find agricultural land allocation decision not only influenced by economic factors but also climate factors and soil quality. This research findings will help forecast future agricultural land use trends & crop area response. Our research combines economic and climate factors of agricultural land conversion which help crop choice decision of producers, farmers, and landowner's.

Three states paper combine ND, SD, and MN states to see the crops acreage response changes due to economic factors as well as weather factors. We are using seemingly unrelated uncensored regression technique for our analysis. Key findings of this research tell that, last year price of crop, last year crop yield, revenue, and input price (diesel price and ammonium nitrate price) have profound impact on acreage response across states. Price of soybean statistically significant and negative effect on corn acreage which shows substitute in production relation. Last year yield of corn is negative and statistically significant impact on corn acreage this year. Last year wheat and barley acreage have statistically significant effect on wheat acreage this year. In addition, weather factor like April maximum temperature statistically significant positive impact on barley, corn, soybean, and sunflower acreage. Precipitation of March statistically significant negative impact on soybean acreage. GMO corn and soybean crop acreage allocations also compete with allocations of other crop acreages. Monte Carlo Simulation technique used to calculate elasticity of own price to acreage response among crops give us idea how price responsive of each crop across states. Own-price elasticity of MN state barley, corn, soybean, wheat, and sunflower to their own acreage are -0.506%, 0.197%, 0.116%, 0.566 %, and 11.34%, respectively; in ND state are -0.054%, 1.018%, 0.639%, 0.116%, and 0.720%, respectively; in SD state are -0.739%, 0.312%, 0.290%, 0.309%, and 1.72%, respectively and statistically significant except barley crop elasticity.

This research findings can be used to look at the trend of multiple crop acreage allocation acreage states of South Dakota, North Dakota, and Minnesota. In addition, this research also incorporates weather variable as well as economic variables to forecast more better and prudent decision regarding crop acreage response modeling. Besides that, the same methodology can be used for short-run to compare regional crop acreage response.

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APPENDIX A. GRAPHICAL EXPOSITION OF OWN AND CROSS-PRICE ELASTICITY AND SIGNIFICANCE LEVEL OF CROP ACREAGE

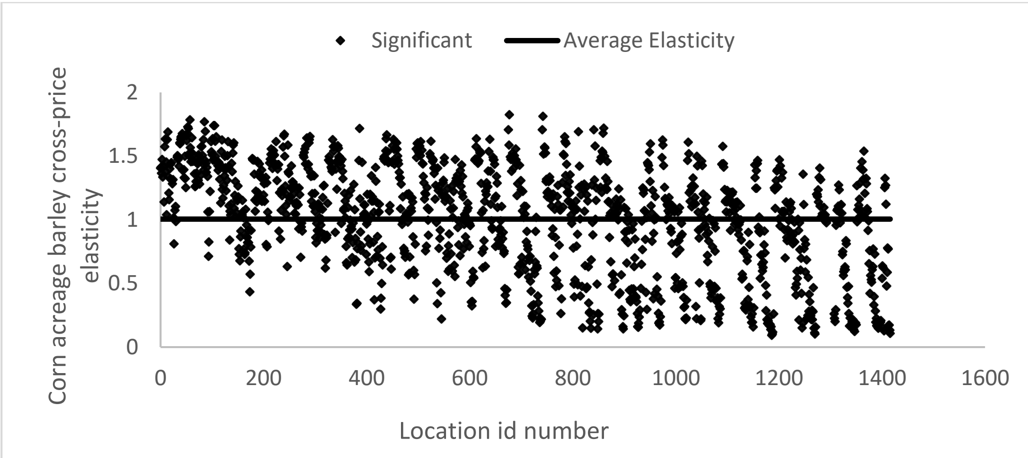


Figure A.1. Cross-price elasticity and significance level of corn acreage and barley price

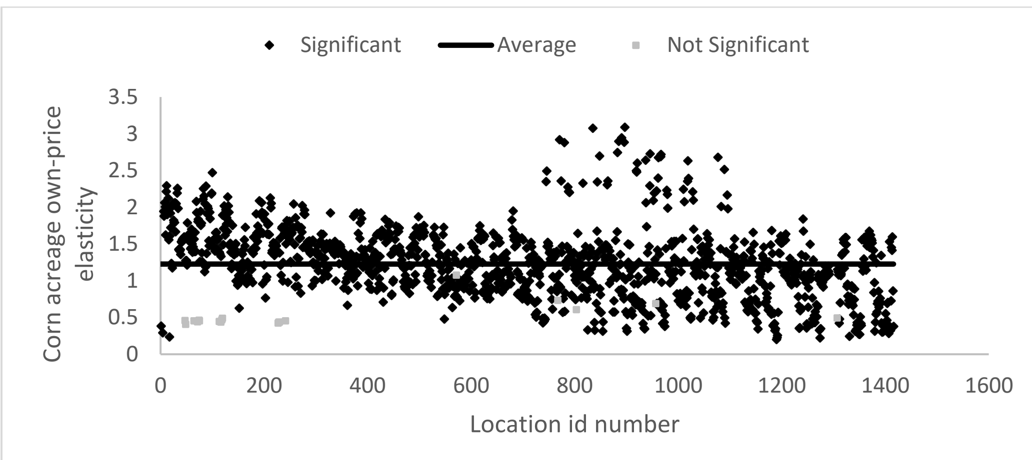


Figure A.2. Own-price elasticity and significance level of corn acreage

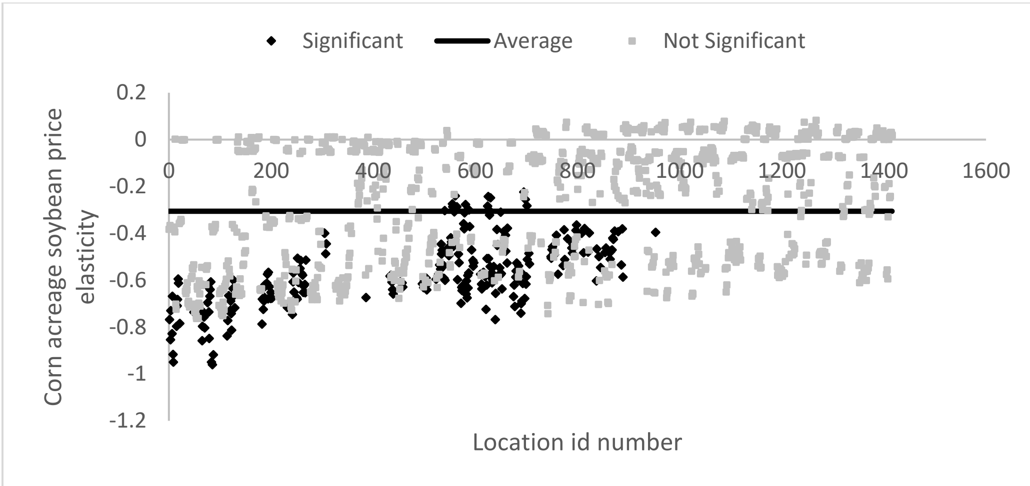


Figure A.3. Cross-price elasticity and significance level of corn acreage and soybean price

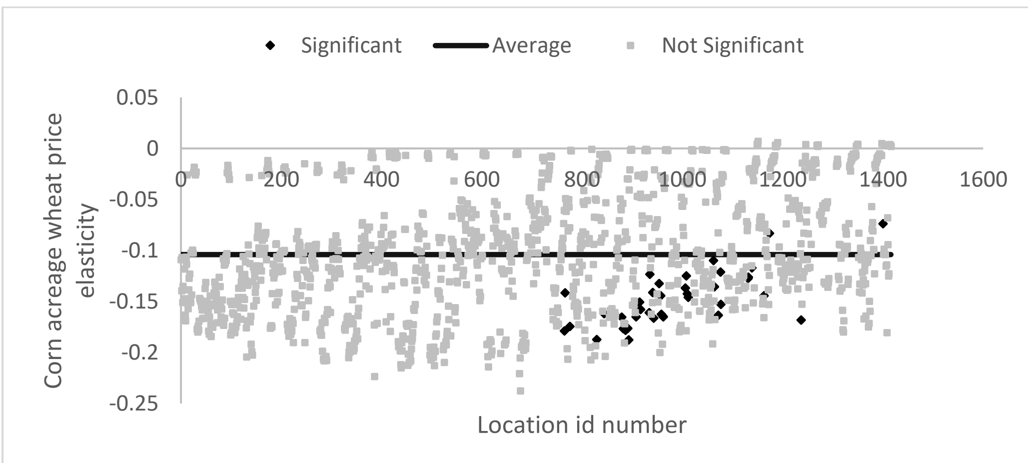


Figure A.4. Cross-price elasticity and significance level of corn acreage and wheat price

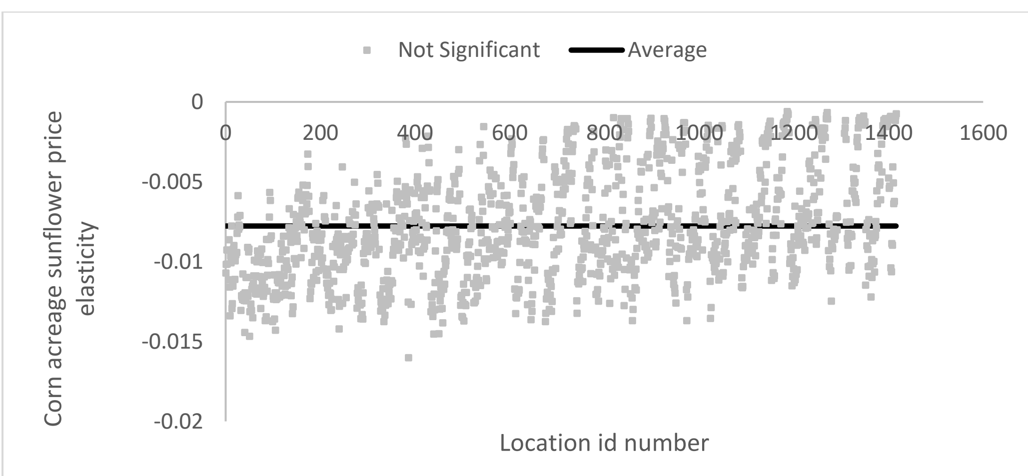


Figure A.5. Cross-price elasticity and significance level of corn acreage and sunflower price

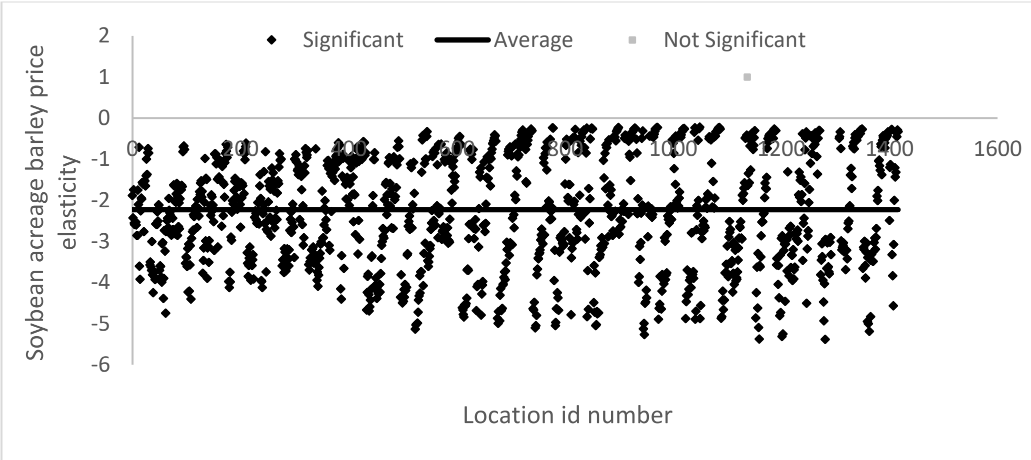


Figure A.6. Cross-price elasticity and significance level of soybean acreage and barley price

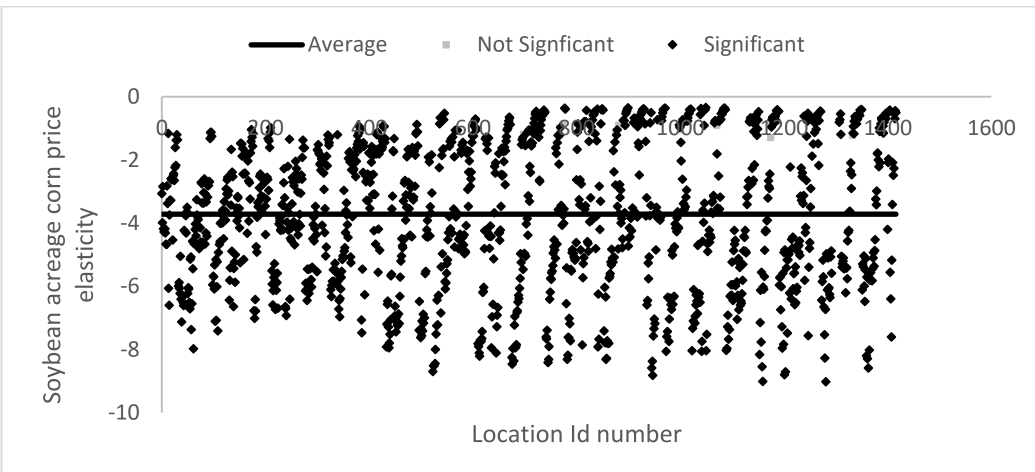


Figure A.7. Cross-price elasticity and significance level of soybean acreage and corn price

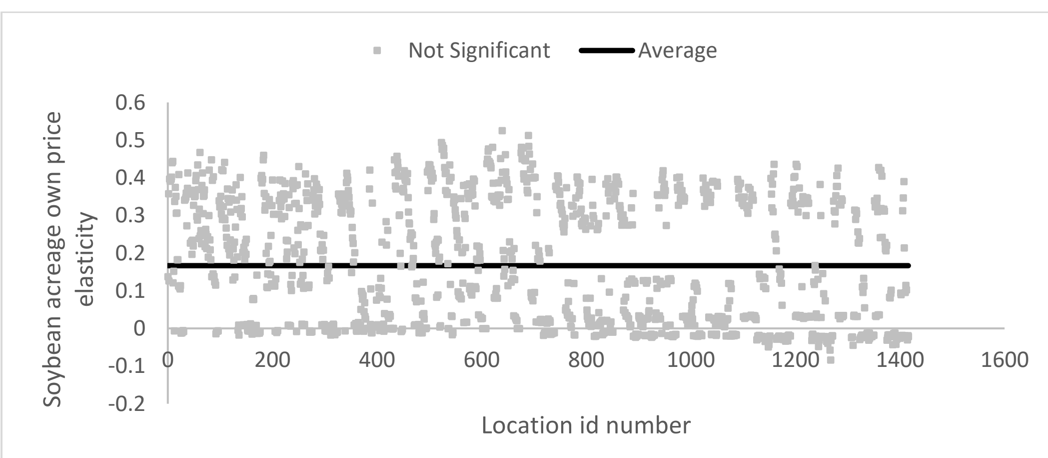


Figure A.8. Own-price elasticity and significance level of soybean acreage

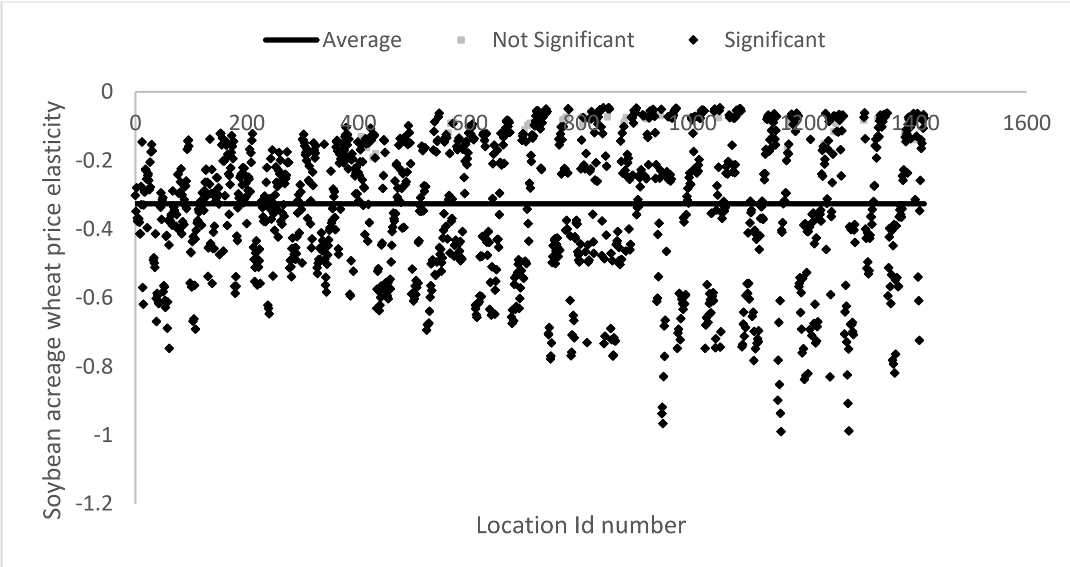


Figure A.9. Cross-price elasticity and significance level of soybean acreage and wheat price

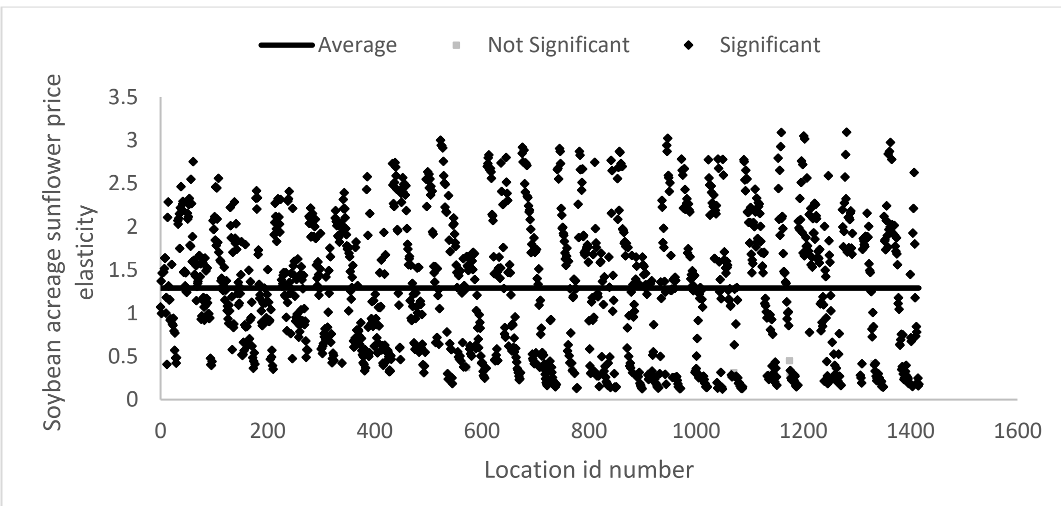


Figure A.10. Cross-price elasticity and significance level of soybean acreage and sunflower price

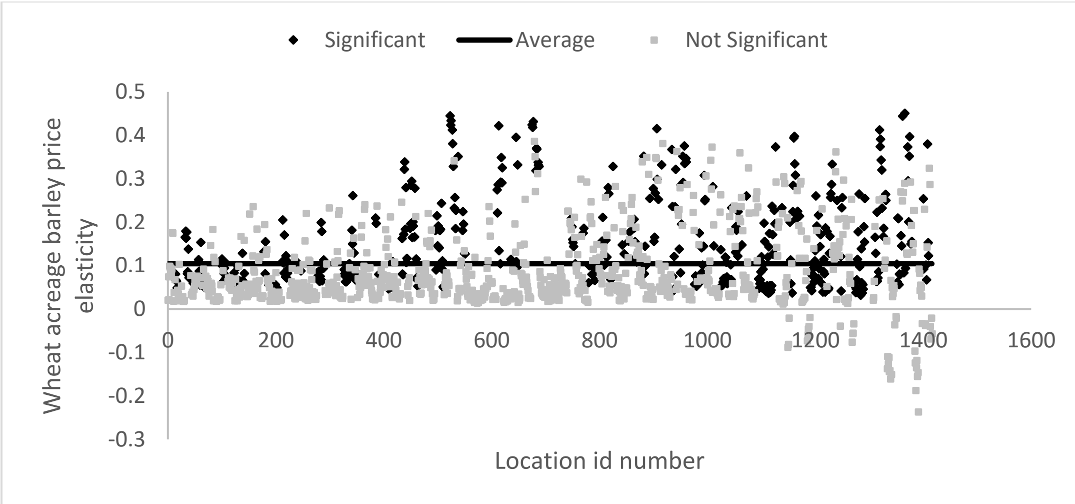


Figure A.11. Cross-price elasticity and significance level of wheat acreage and barley price

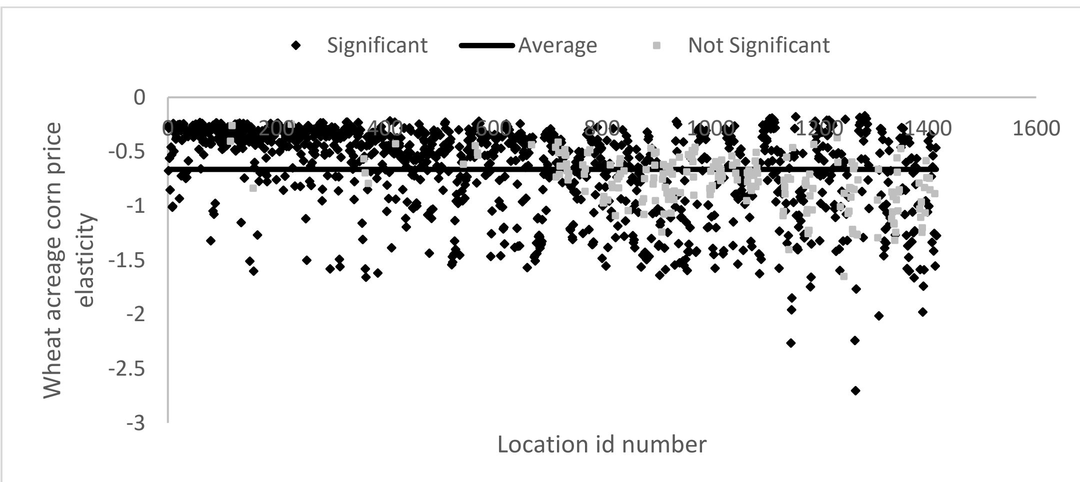


Figure A.12. Cross-price elasticity and significance level of wheat acreage and corn price

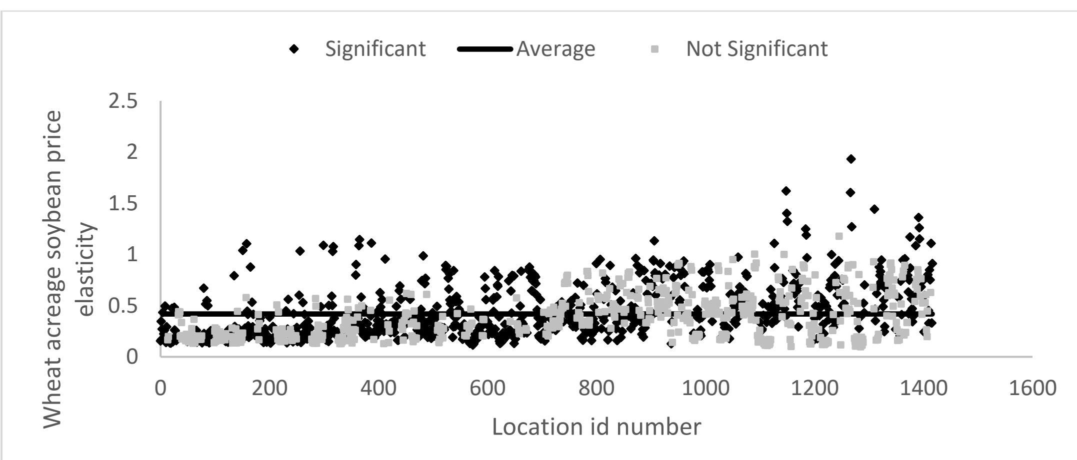


Figure A.13. Cross-price elasticity and significance level of wheat acreage and soybean price

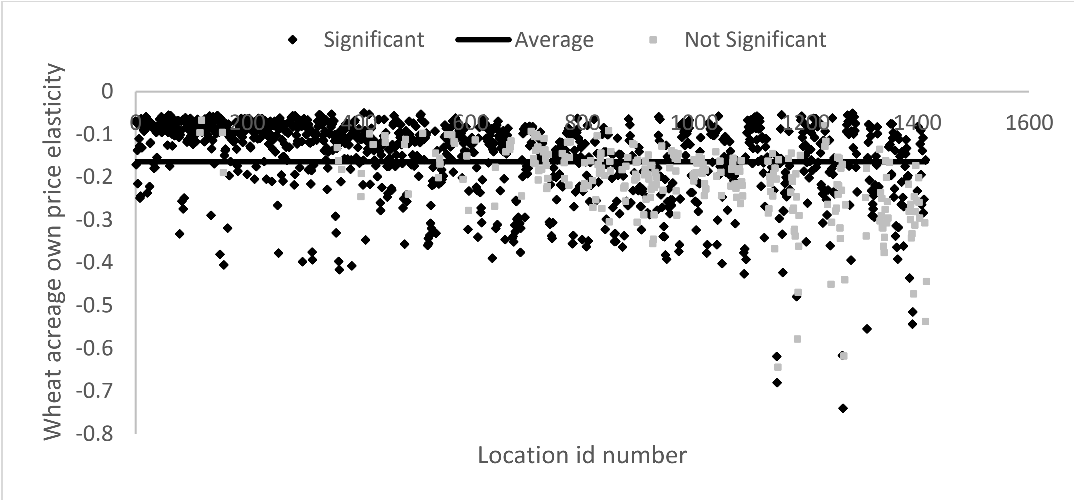


Figure A.14. Own-price elasticity and significance level of wheat acreage

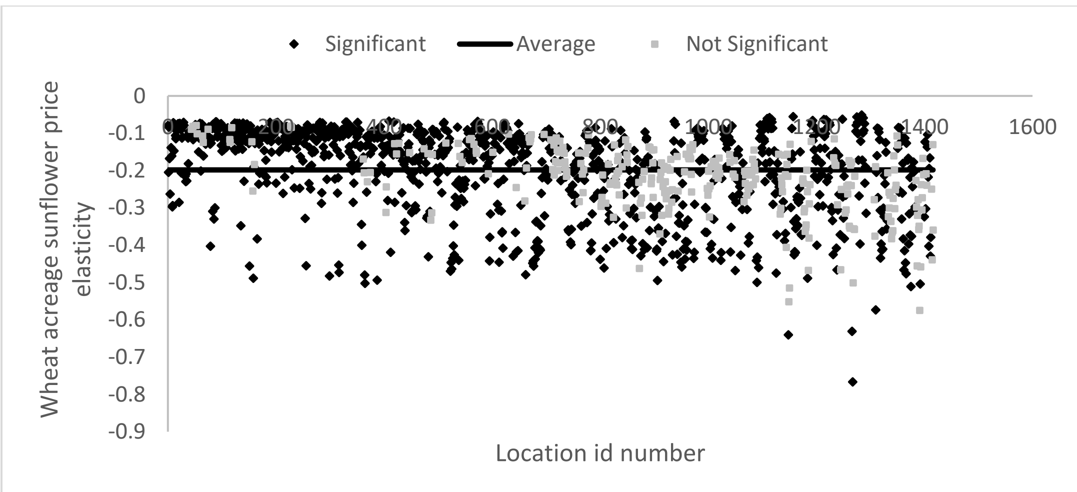


Figure A.15. Cross-price elasticity and significance level of wheat acreage and sunflower price

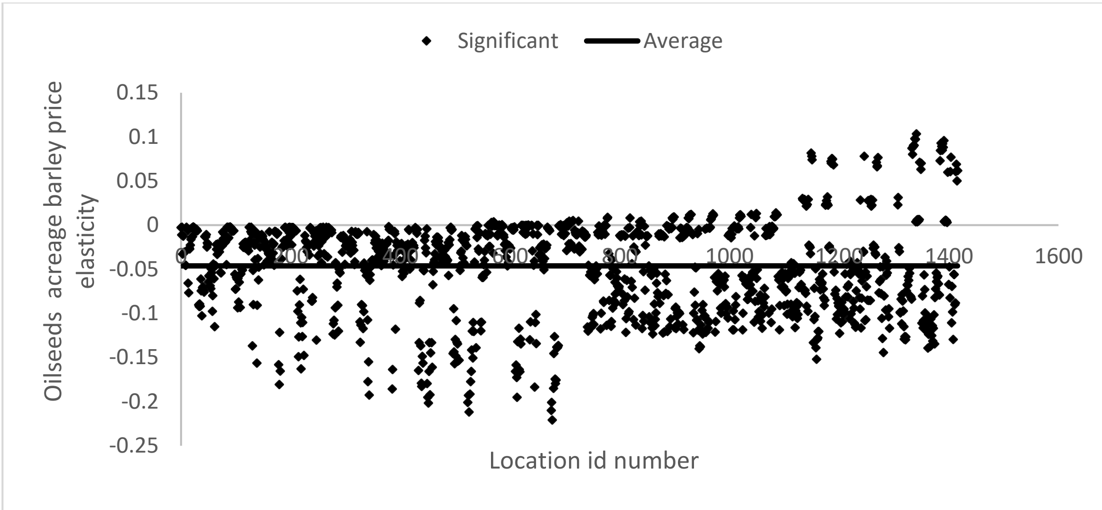


Figure A.16. Cross-price elasticity and significance level of oilseeds acreage and barley price

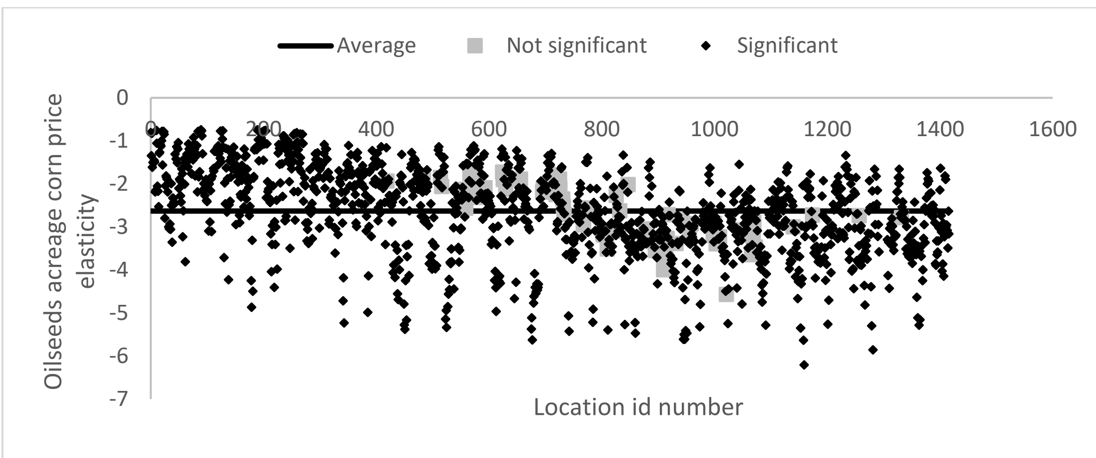


Figure A.17. Cross-price elasticity and significance level of oilseeds acreage and corn price

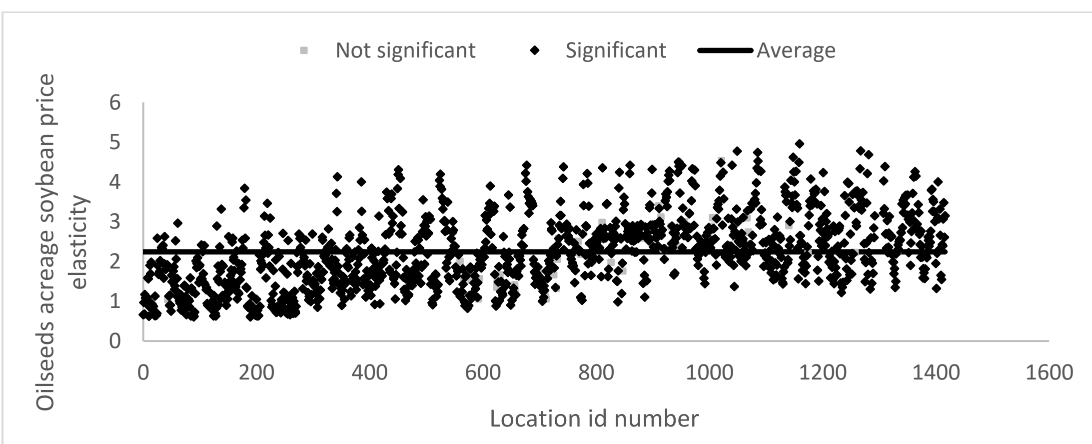


Figure A.18. Cross-price elasticity and significance level of oilseeds acreage and soybean price

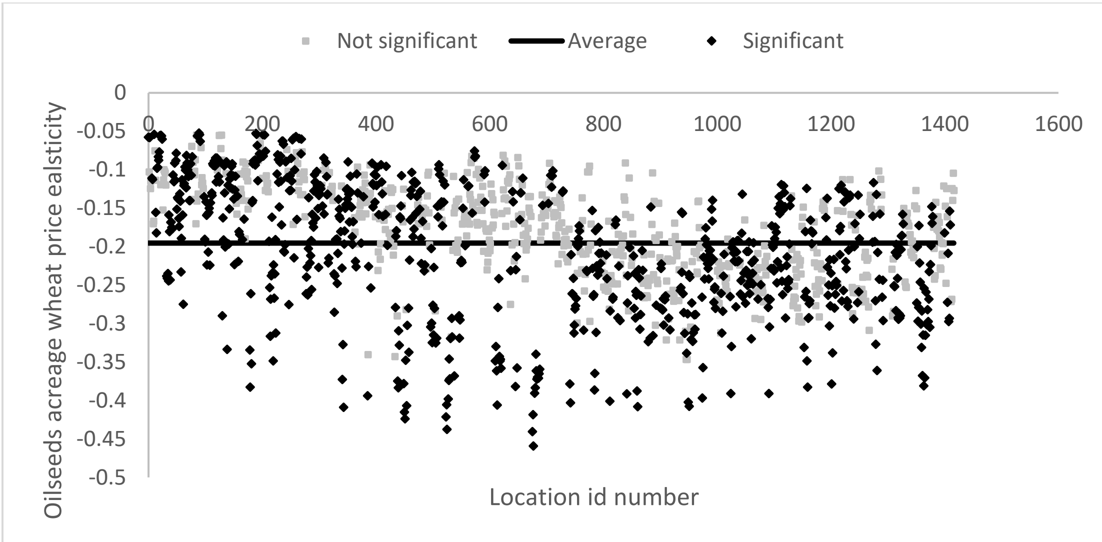


Figure A.19. Cross-price elasticity and significance level of oilseeds acreage and wheat price

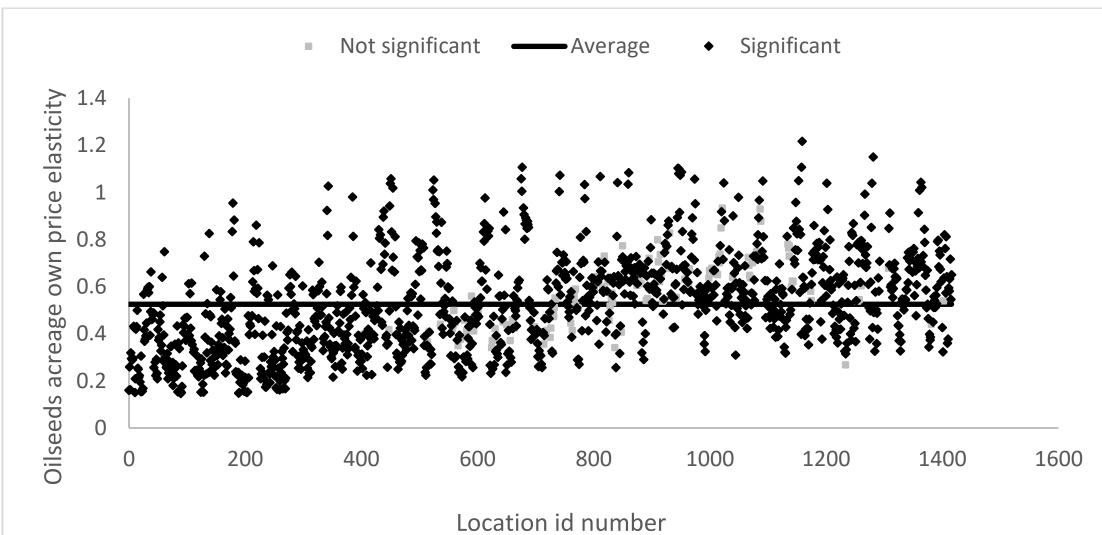


Figure A.20. Own-price elasticity and significance level of oilseeds acreage

APPENDIX B. SPATIAL DISTRIBUTION OF ESTIMATED MARGINAL EFFECTS OF OWN AND CROSS-PRICE AND ACREAGE AMONG CROPS AND THEIR STATISTICAL SIGNIFICANCE LEVELS

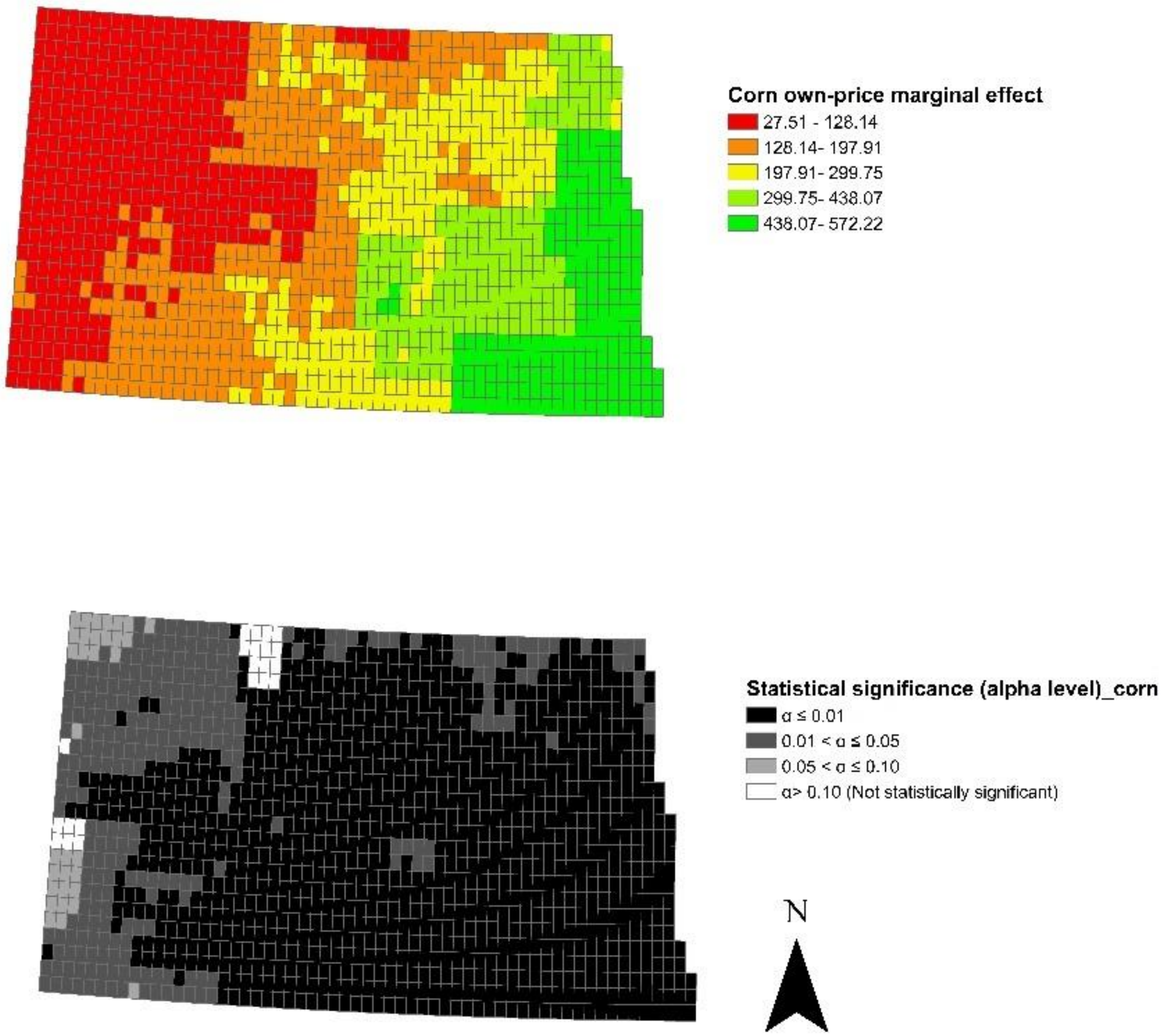


Figure B.1. Estimated marginal effects of corn price on corn acreage with statistical significance levels

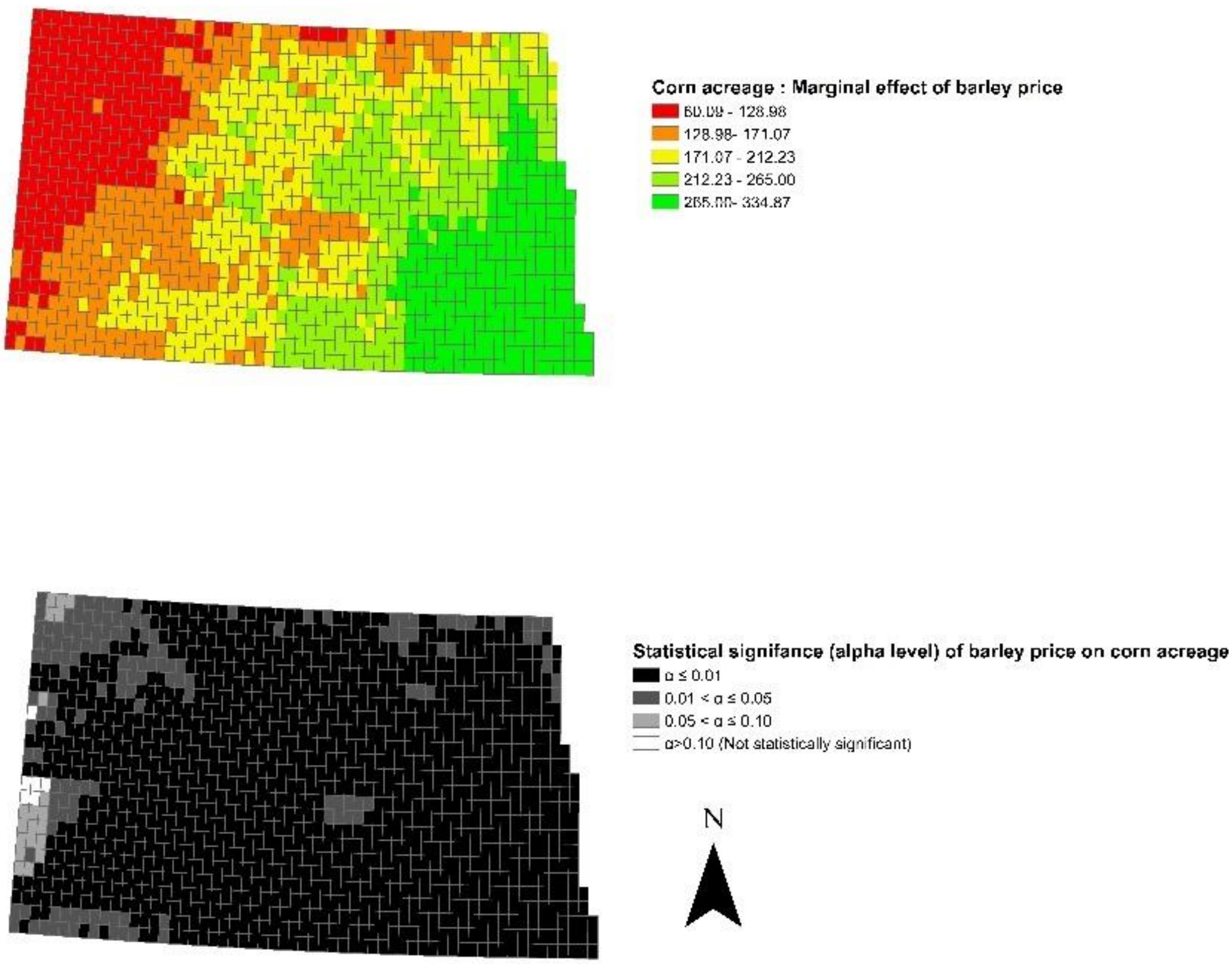


Figure B.2. Estimated marginal effects of barley price on corn acreage with statistical significance levels

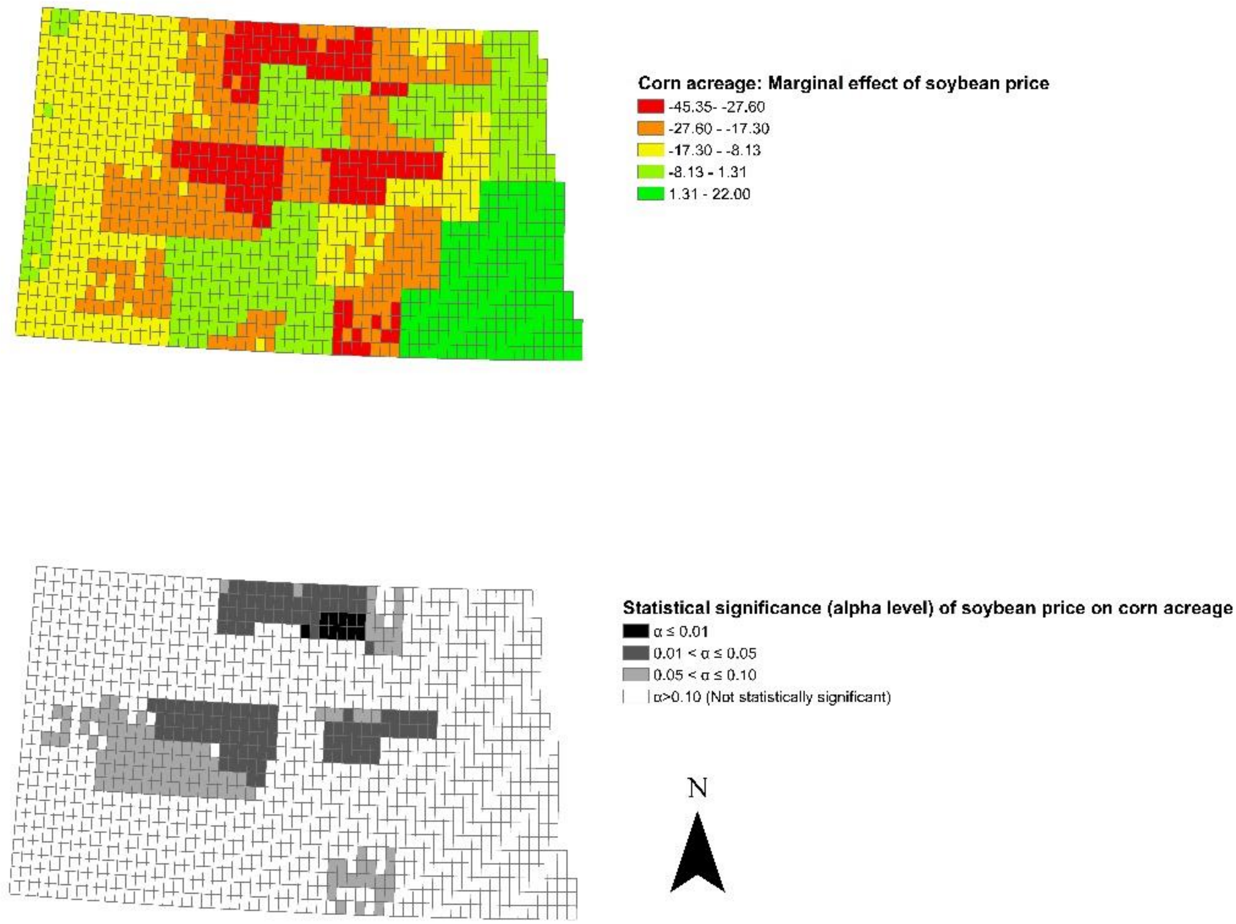


Figure B.3. Estimated marginal effects of soybean price on corn acreage with statistical significance levels

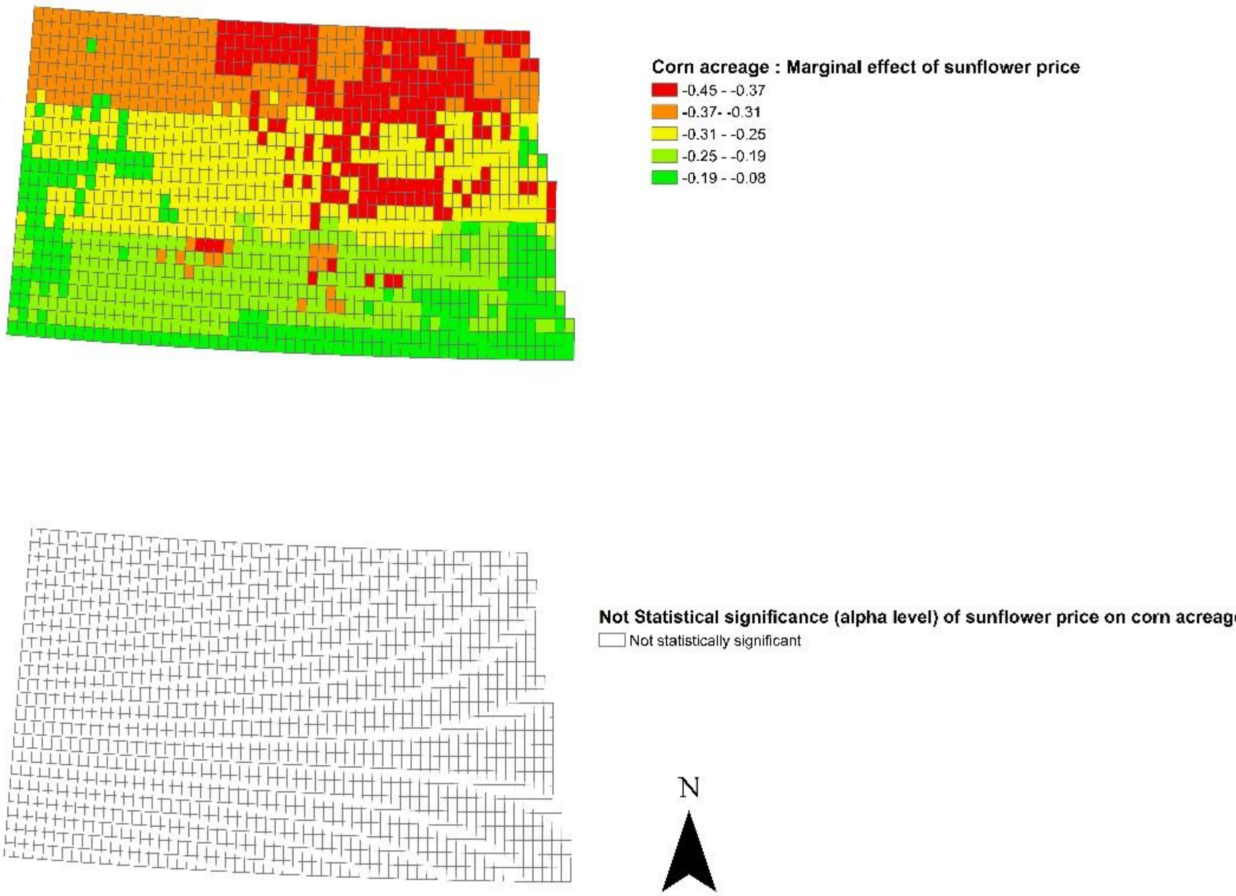


Figure B.4. Estimated marginal effects of sunflower price on corn acreage with statistical significance levels

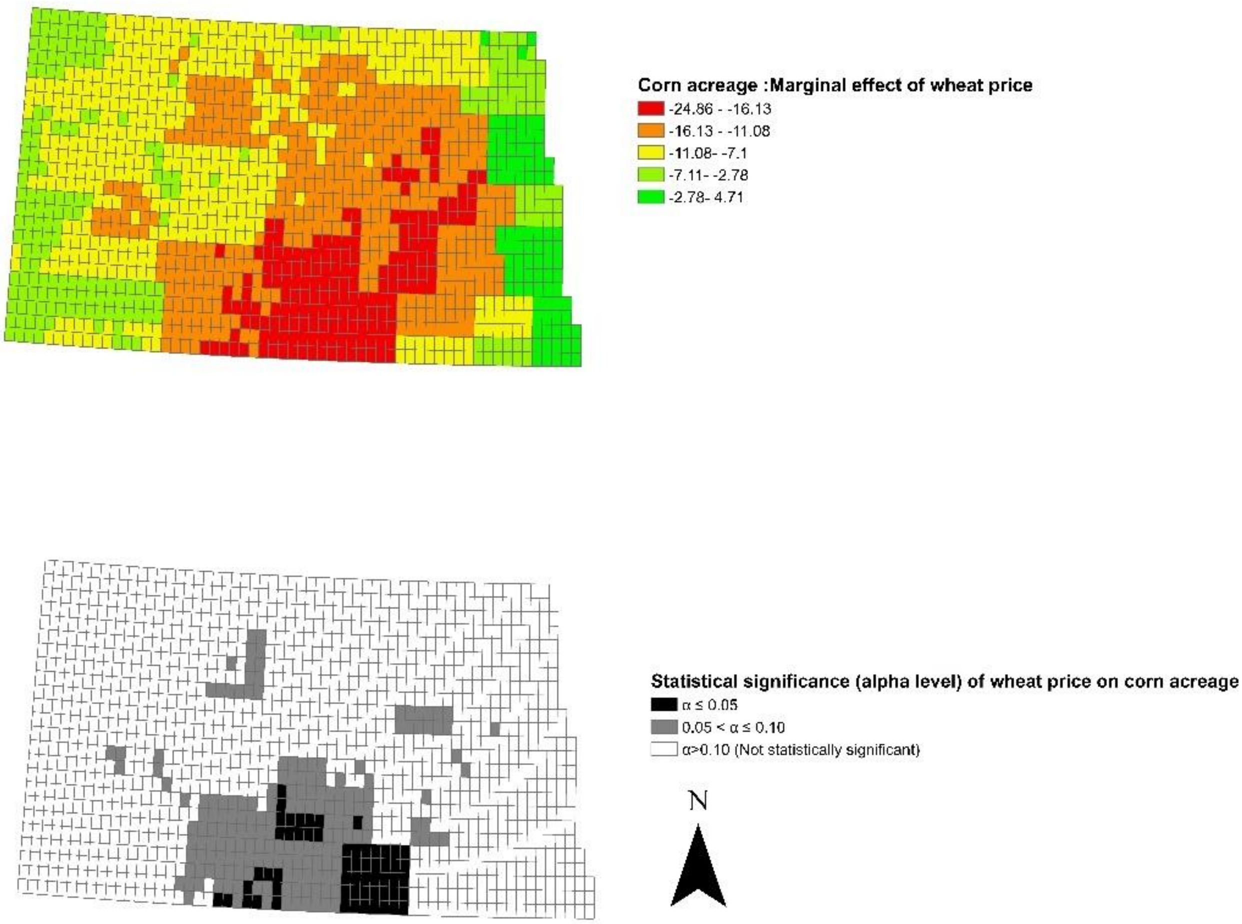


Figure B.5. Estimated marginal effects of wheat price on corn acreage with statistical significance levels

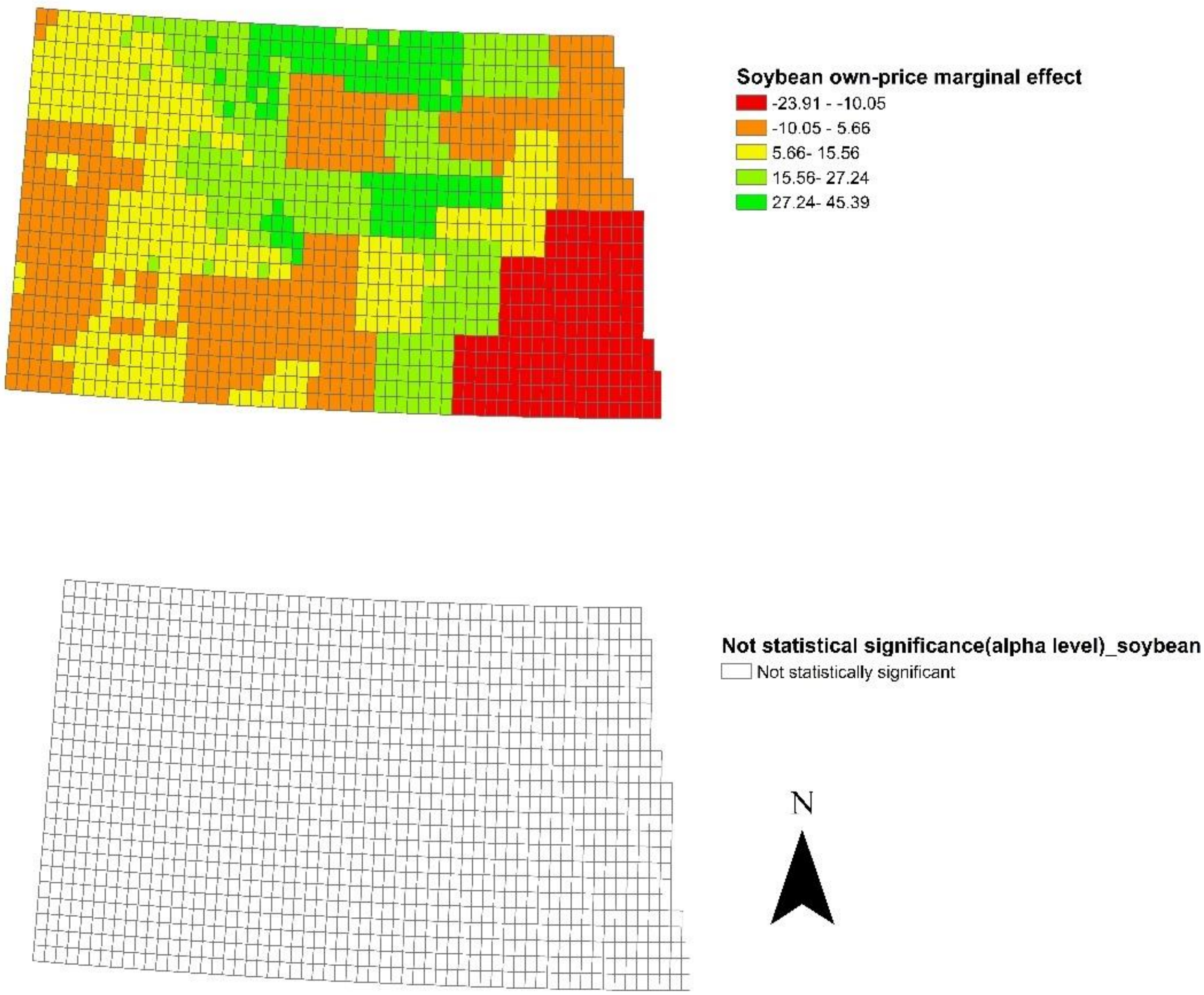


Figure B.6. Estimated marginal effects of soybean own-price on acreage with statistical significance levels

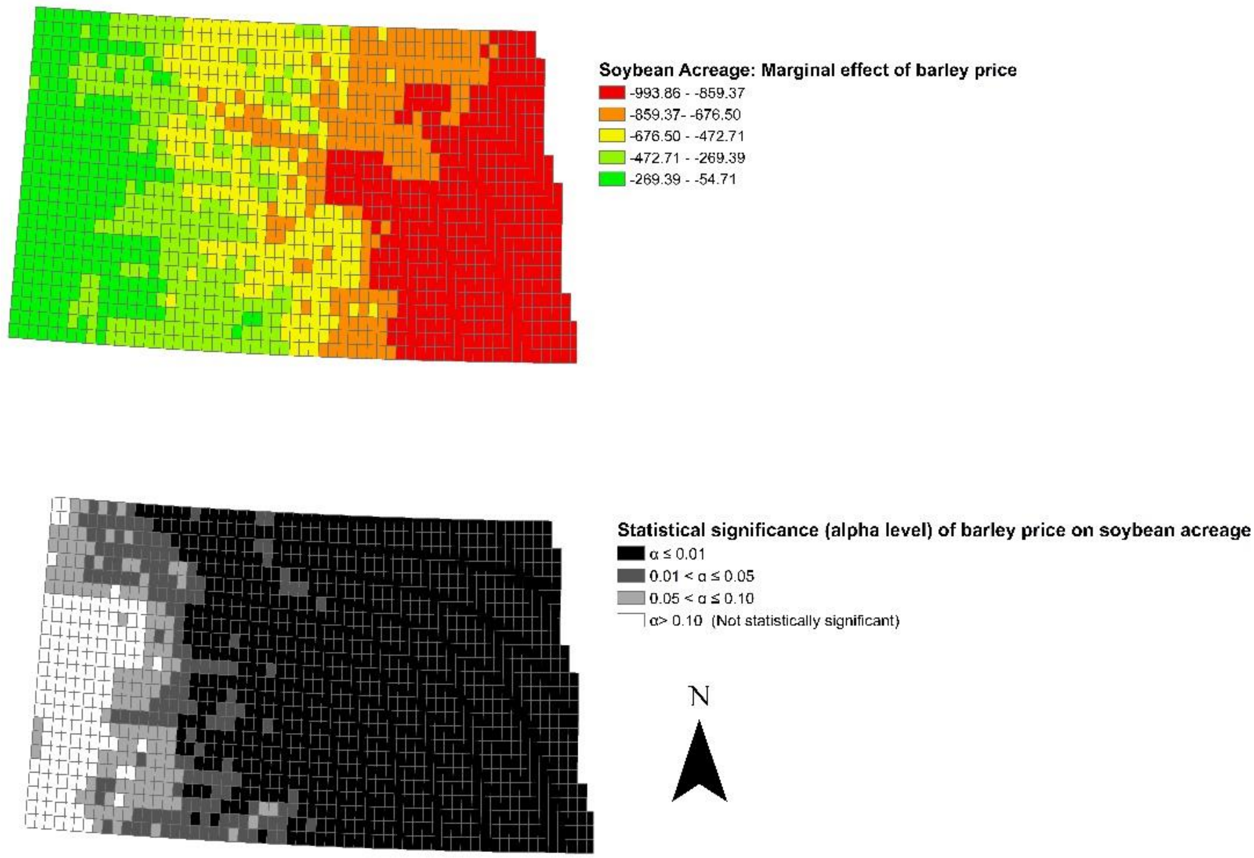


Figure B.7. Estimated marginal effects of barley price on soybean acreage with statistical significance levels

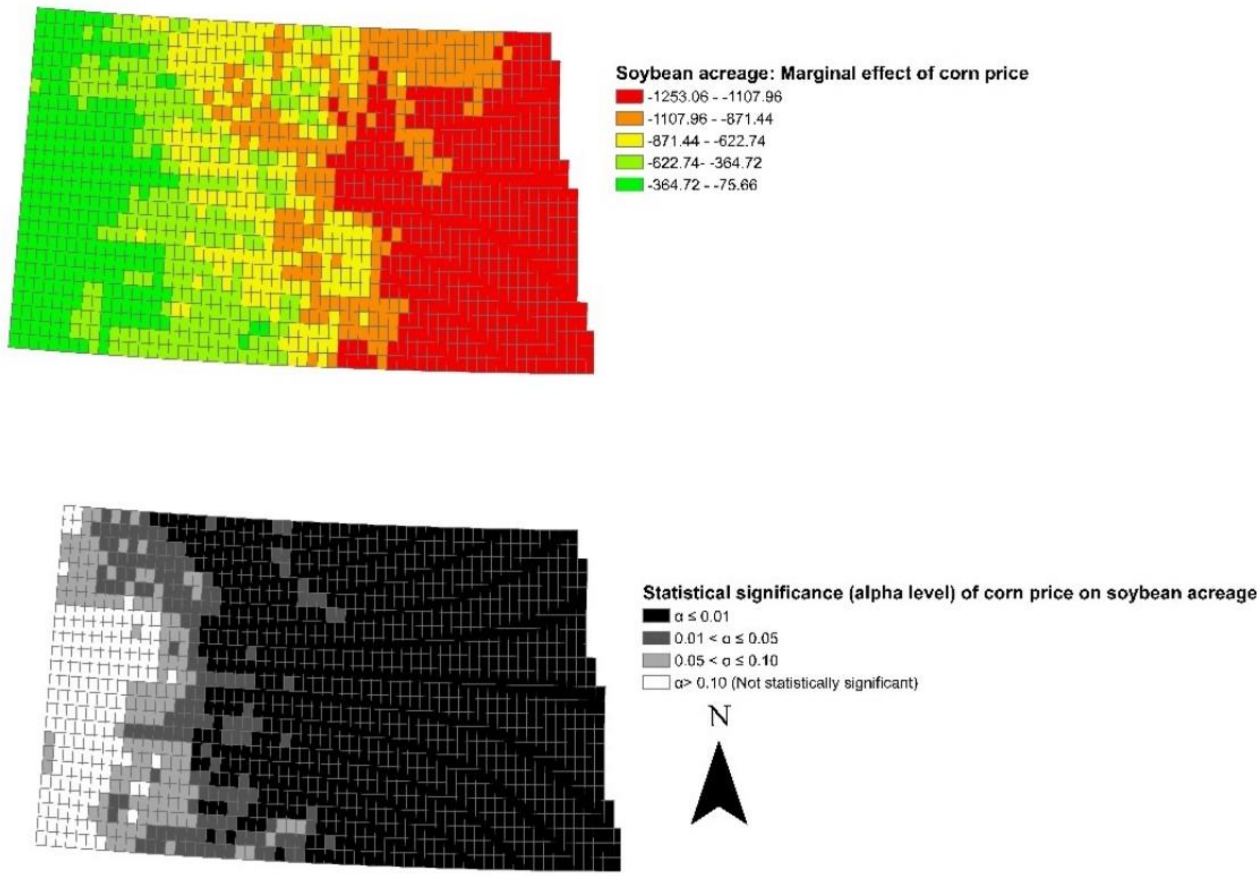


Figure B.8. Estimated marginal effects of corn price on soybean acreage with statistical significance levels

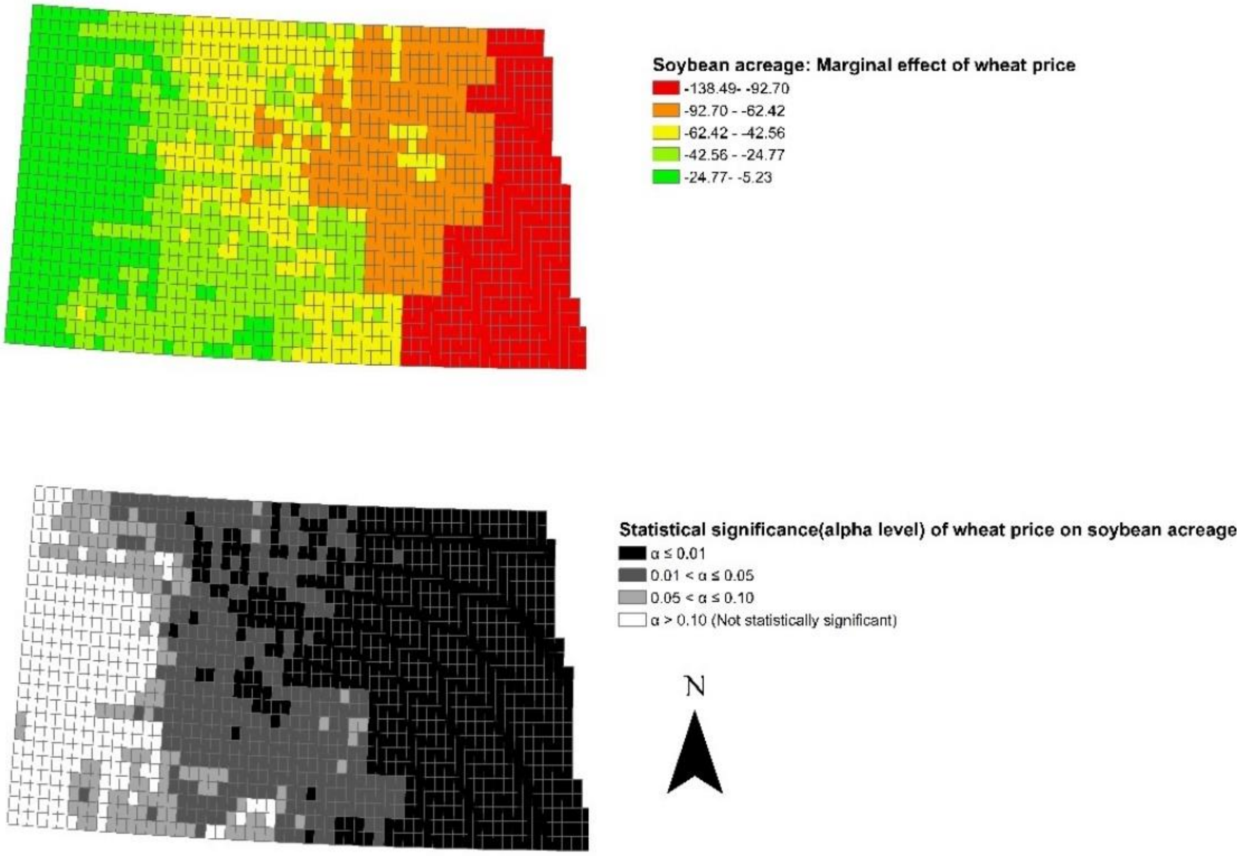


Figure B.9. Estimated marginal effects of wheat price on soybean acreage with statistical significance levels

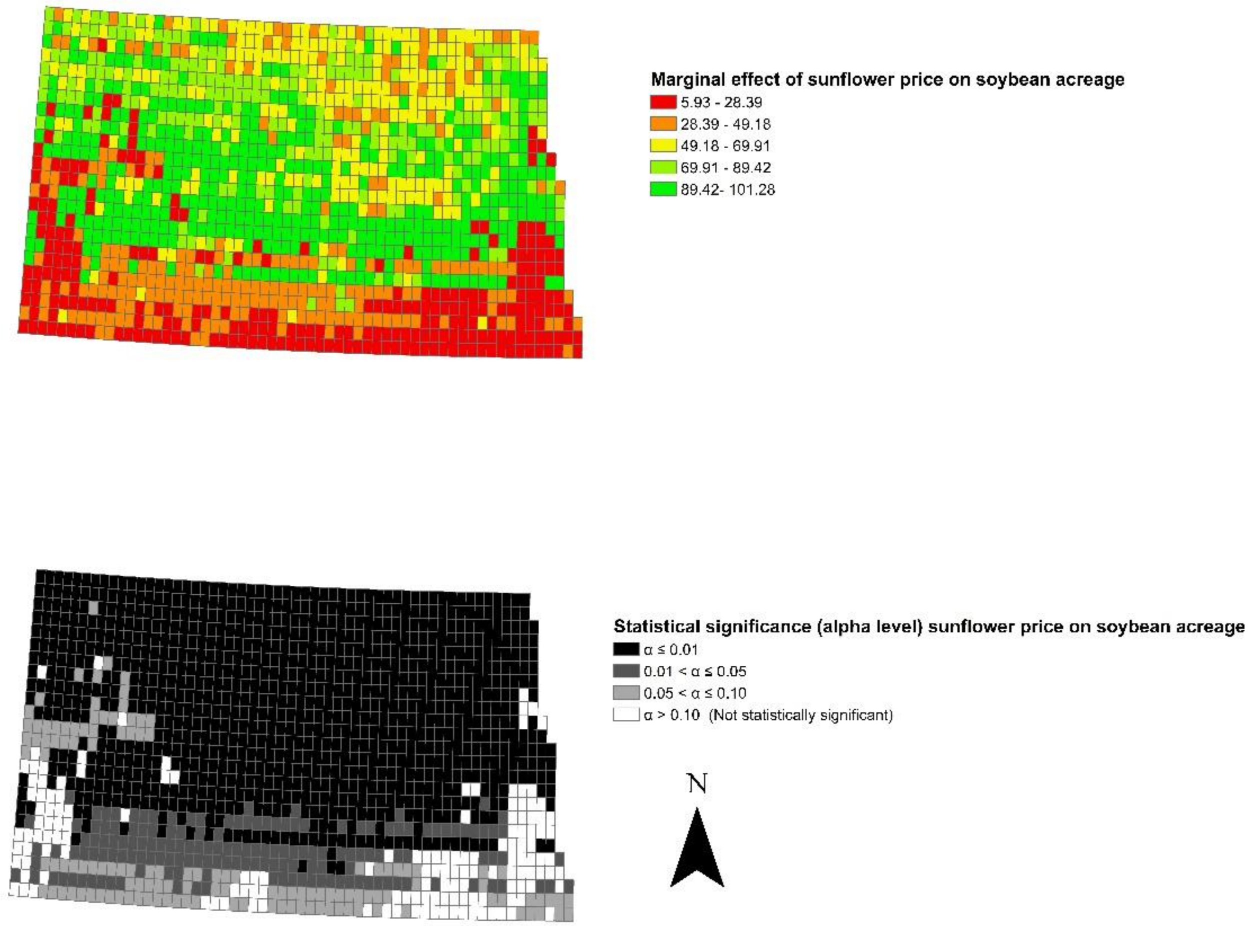


Figure B.10. Estimated marginal effects of sunflower price on soybean acreage with statistical significance levels

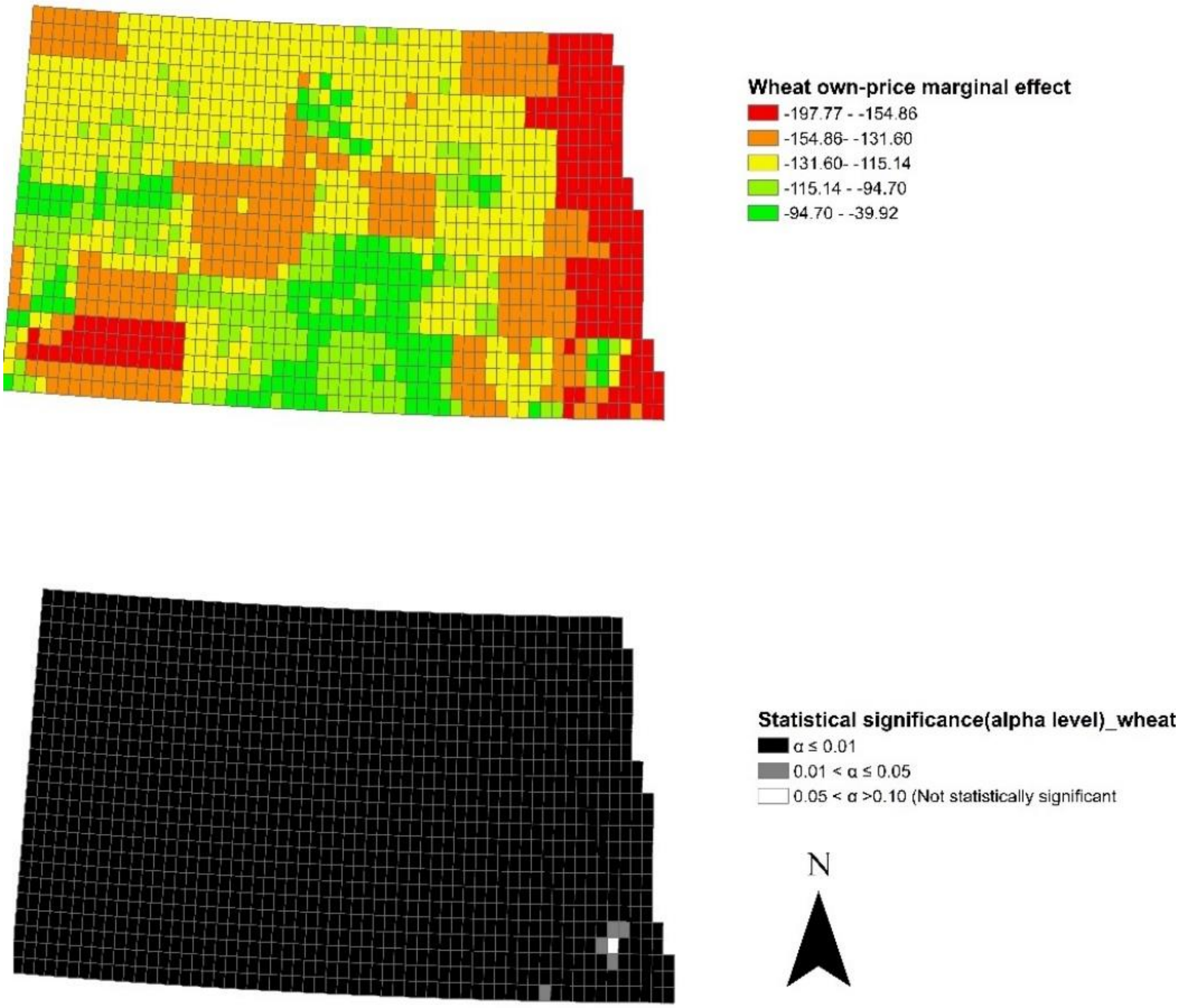


Figure B.11. Estimated marginal effects of wheat price on wheat acreage with statistical significance levels

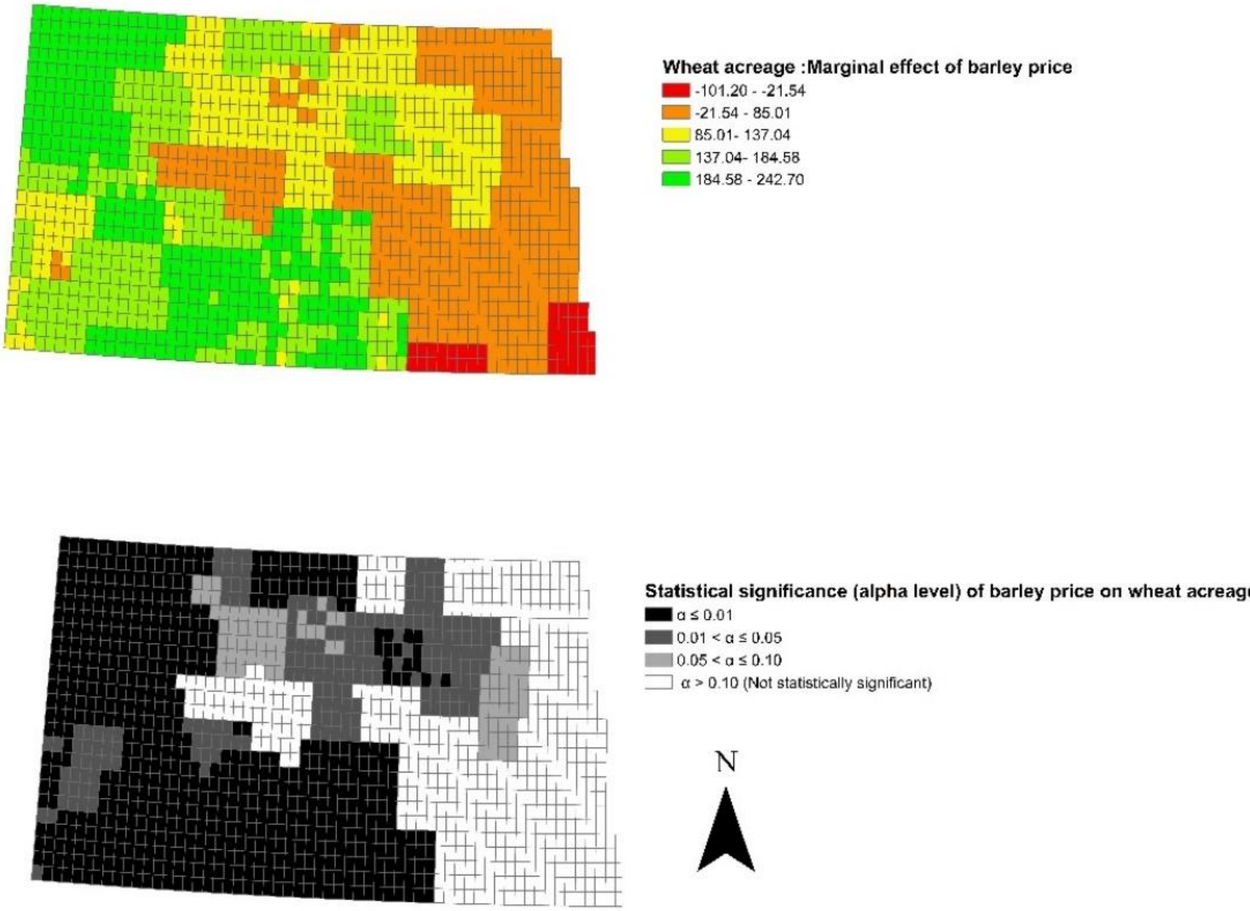
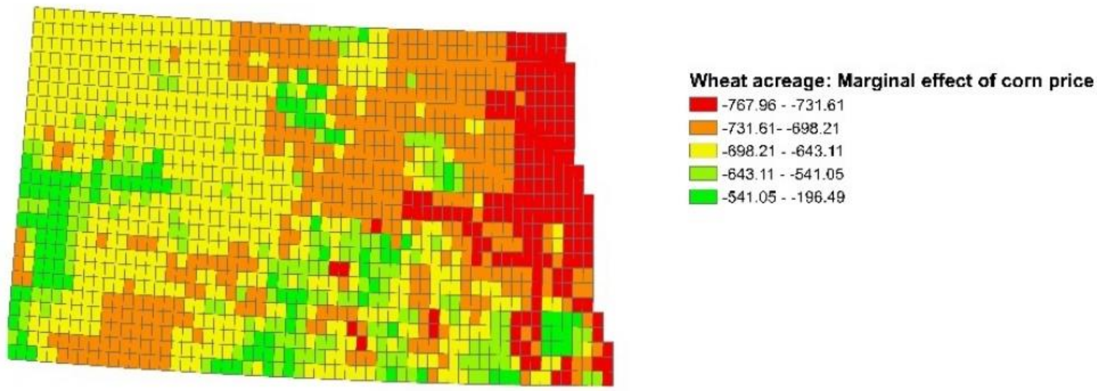


Figure B.12. Estimated marginal effects of barley price on wheat acreage with statistical significance levels



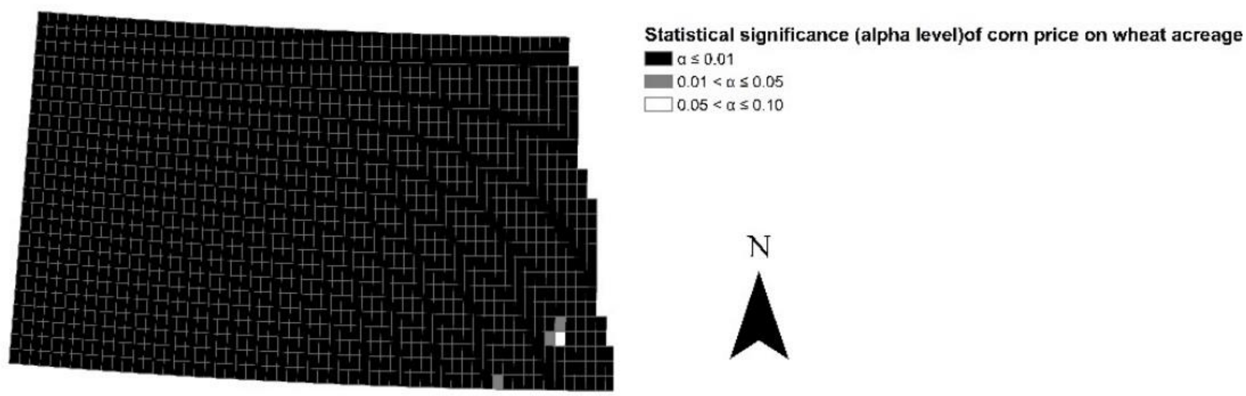


Figure B.13. Estimated marginal effects of corn price on wheat acreage and their statistical significance levels

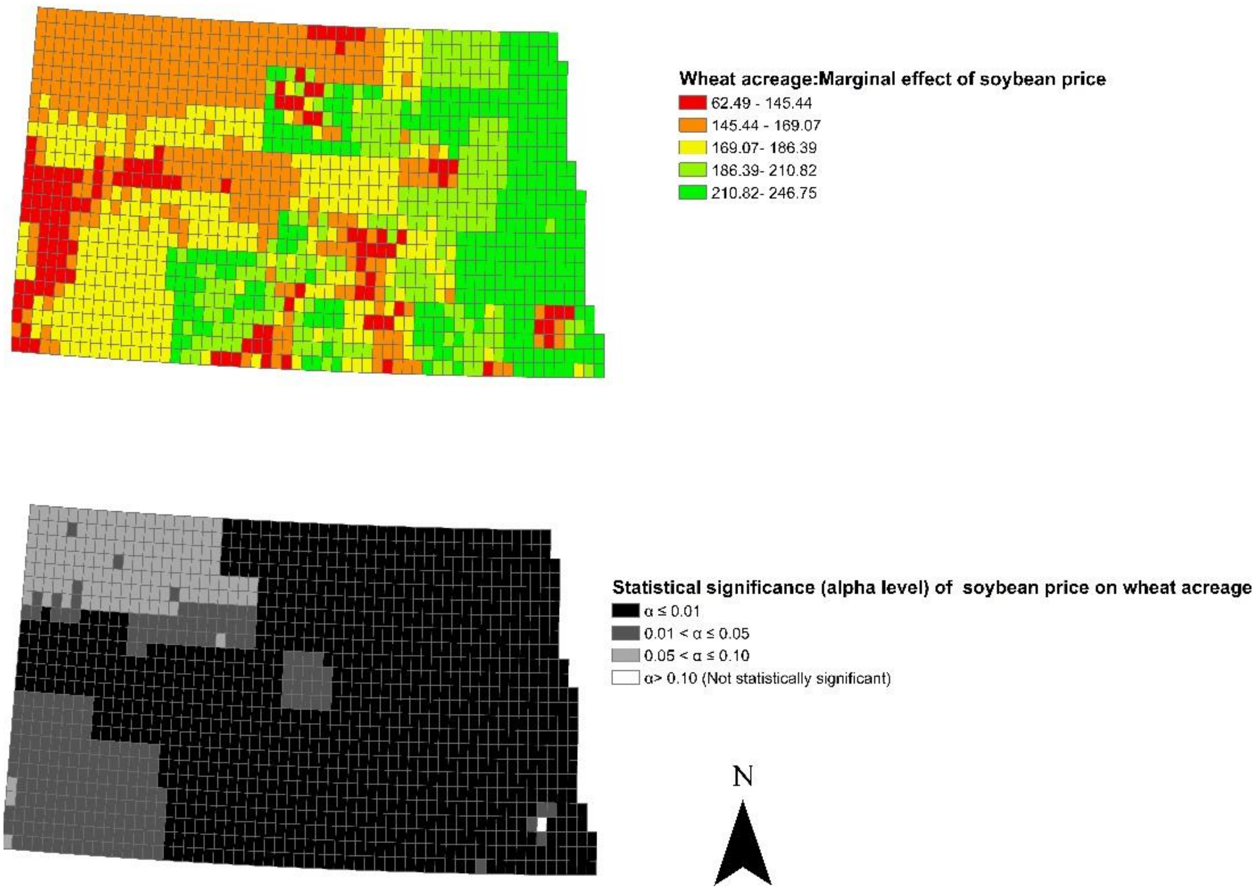


Figure B.14. Estimated marginal effects of soybean price on wheat acreage with statistical significance levels

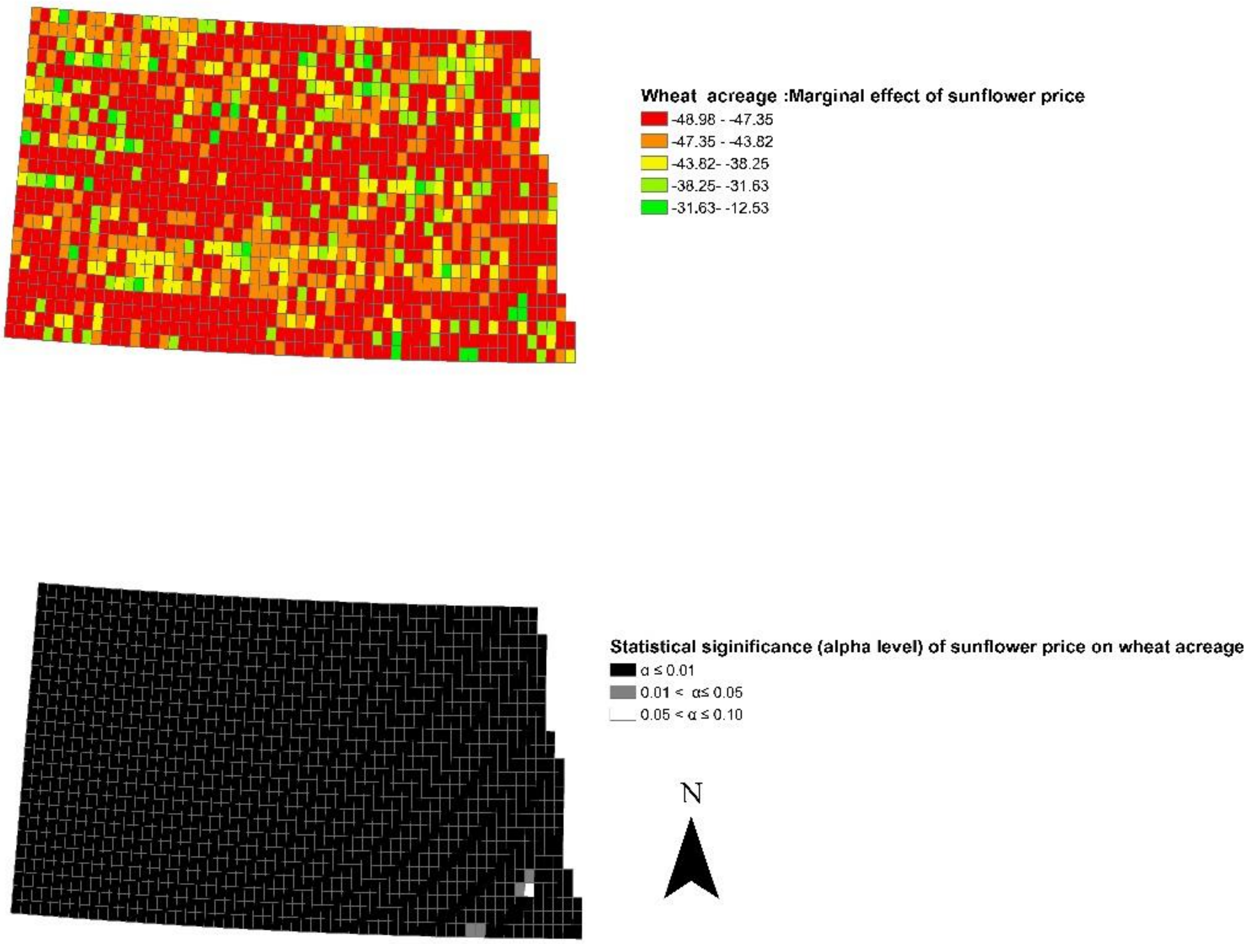
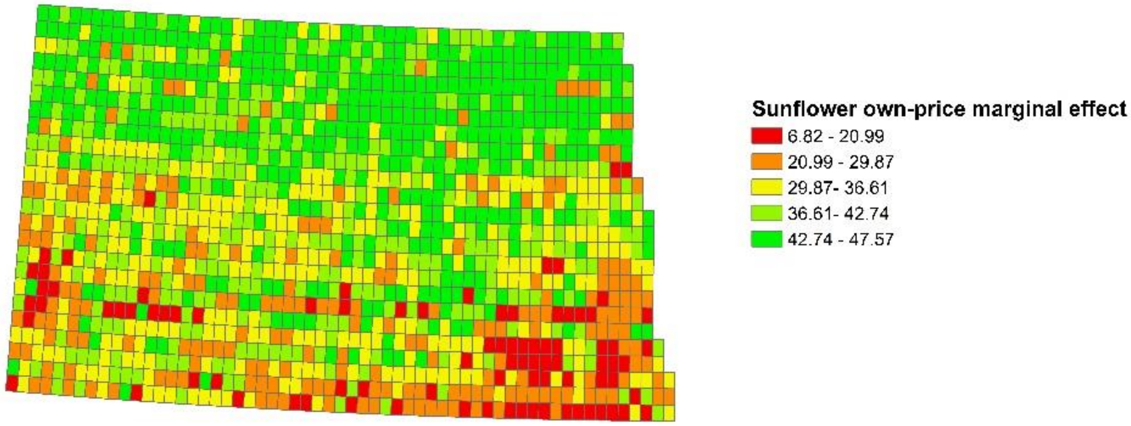


Figure B.15. Estimated marginal effects of sunflower price on wheat acreage with statistical significance levels



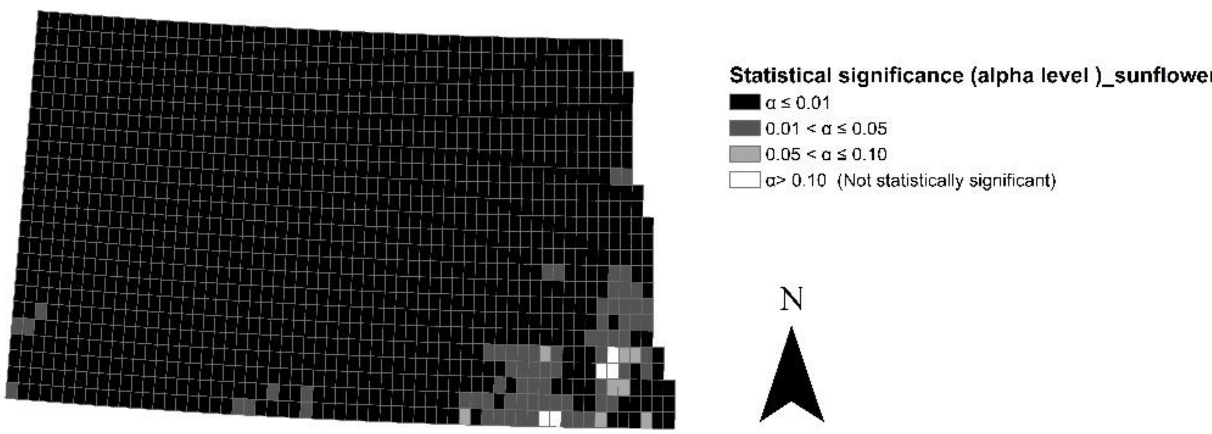


Figure B.16. Estimated marginal effects of sunflower price on oilseeds acreage with statistical significance levels

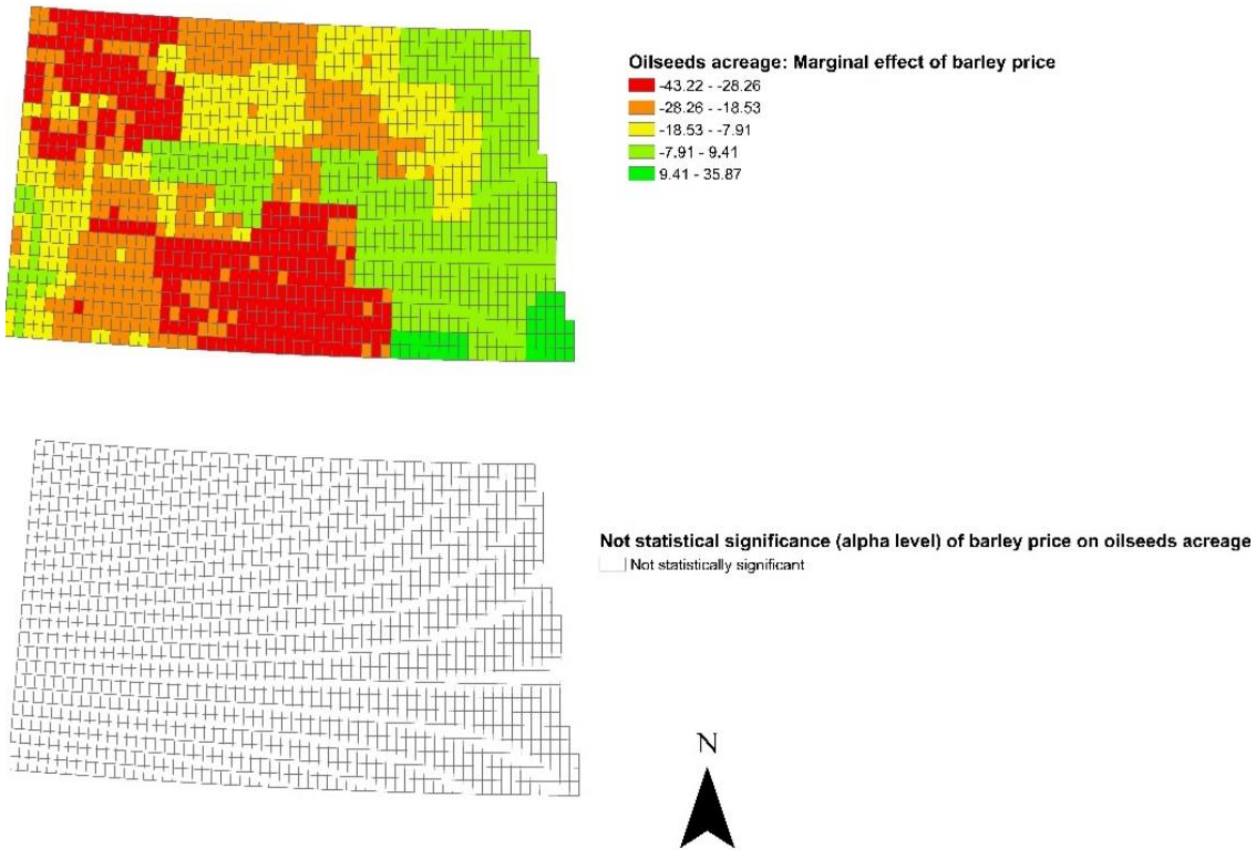


Figure B.17. Estimated marginal effects of barley price on oilseeds acreage with statistical significance levels

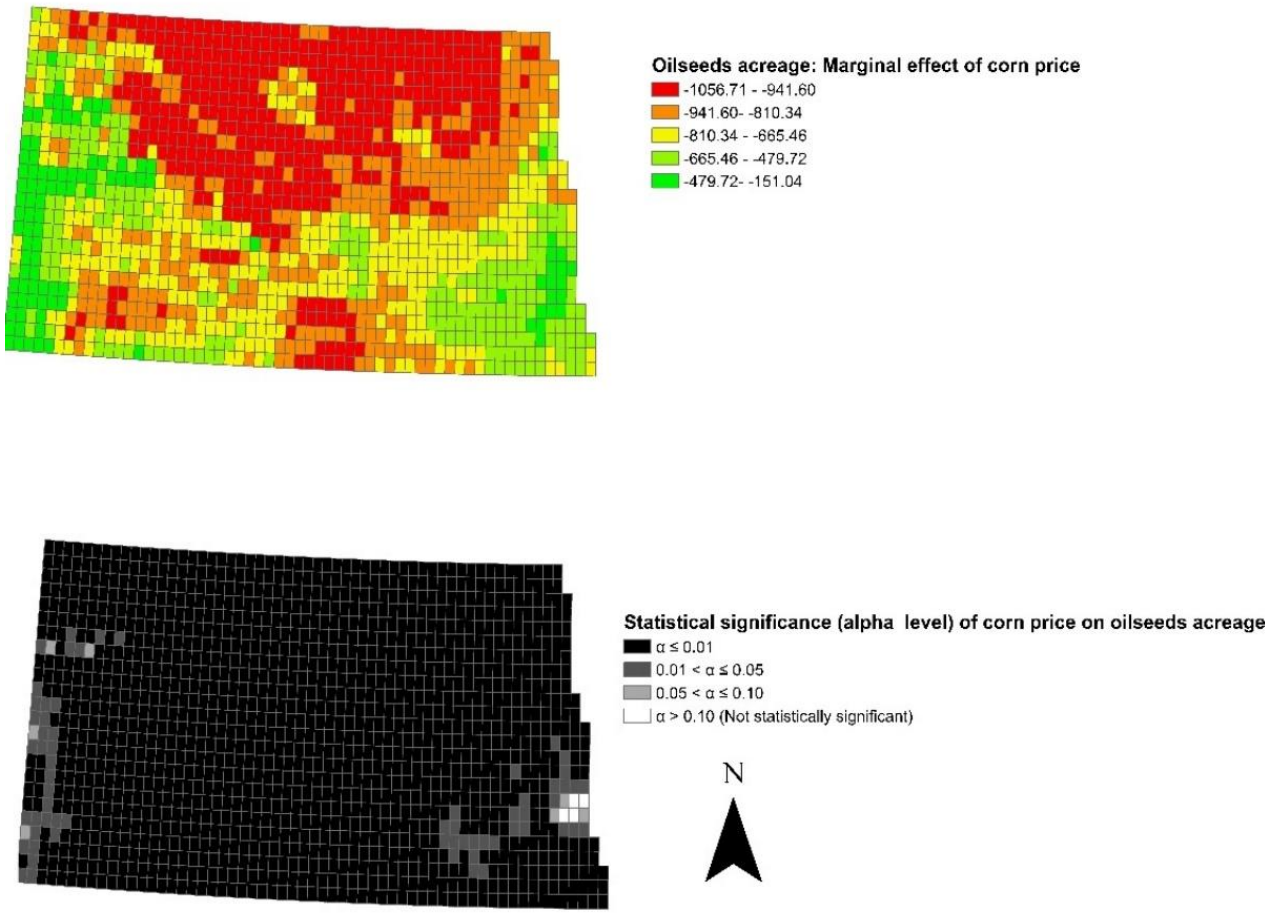


Figure B.18. Estimated marginal effects of corn price on oilseeds acreage with statistical significance levels

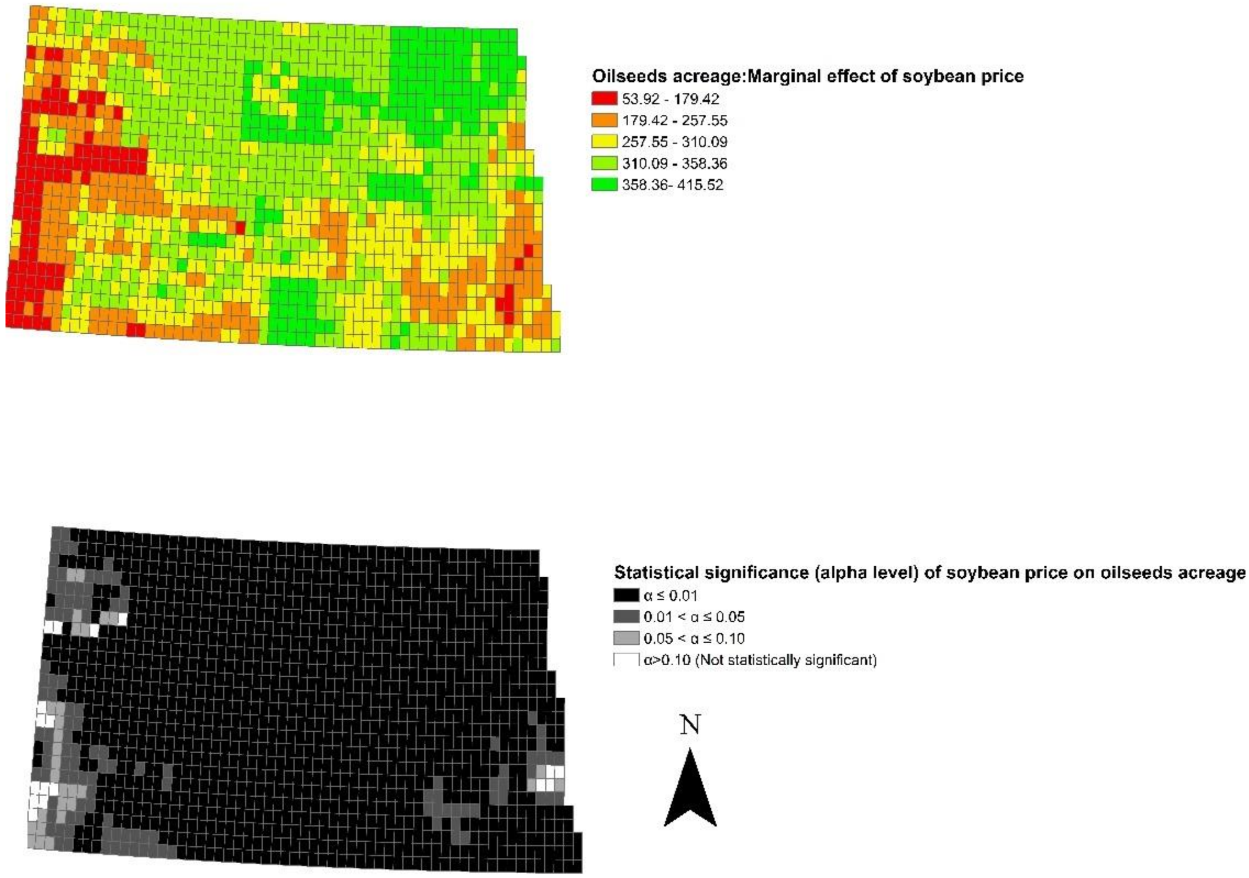
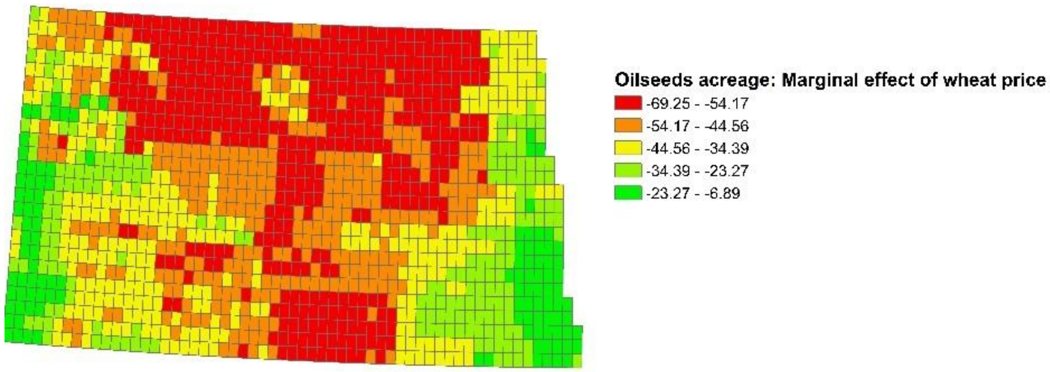


Figure B.19. Estimated marginal effects of soybean price on oilseeds acreage with statistical significance levels



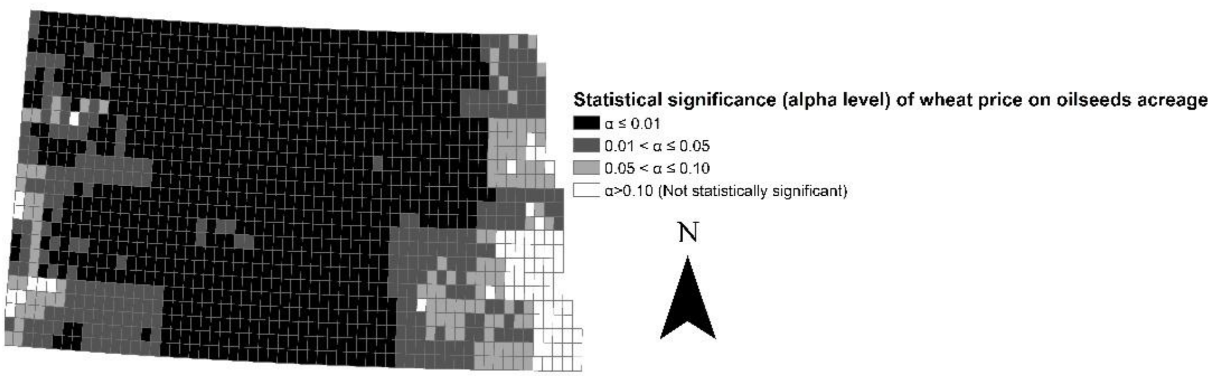


Figure B.20. Estimated marginal effects of wheat price on oilseeds acreage with statistical significance levels