MODELING THE IMPACTS OF CHANGING AGRICULTURAL PATTERNS ON RAINFALL AND TEMPERATURE IN NORTH DAKOTA

A Thesis
Submitted to the Graduate Faculty
of the
North Dakota State University
of Agriculture and Applied Science

By

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In Partial Fulfillment of the Requirements
for the Degree of
MASTER OF SCIENCE

Major Department:
Agribusiness and Applied Economics

June 2020

Fargo, North Dakota

North Dakota State University
Graduate School

Title

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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

MASTER OF SCIENCE

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ABSTRACT

Global climate change has been an issue of much concern for many years now with human activity being the main contributor to this phenomenon. However, some evidence in the United States Midwest suggests that there has been a decline in summer temperatures and a rise in summer rainfall as a result of increasing agricultural production in this region. This research applies a system of simultaneous equations more specifically a seemingly unrelated Tobit regression model to understand how land-use change and increasing crop production may be contributing to these changes in rainfall and temperature in the months of June, July, August and September in the state of North Dakota. The findings from the study indicate that corn production to some extent is contributing to increasing precipitation and declining temperatures in North Dakota.

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to the Almighty God for the strength to complete my study here in the Department of Agribusiness and Applied Economics. I would also like to thank my thesis advisor Dr. David C. Roberts, who provided me with the necessary guidance to enable me to complete my thesis and for the many things I learnt working as his research assistant. I am also very grateful to my committee members Dr. Robert Hearne and Dr. Xuefeng Chu for their tremendous support. I would like to give thanks for the necessary financial support provided by the National Science Foundation (NSF) and the North Dakota Established Program to Stimulate Competitive Research (ND EPSCoR) under Cooperative Agreement Award OIA-1355466 to the Center for Regional Climate Studies. Lastly, I would like to convey my appreciation to all members of the Department of Agribusiness and Applied Economics who have contributed to expanding my knowledge in the area of agribusiness and applied economics.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1. INTRODUCTION

Background

There has been significant agricultural development since the early 1900s (Pielke et al., 2011; Ramankutty and Foley, 1999). Before agricultural intensification in the mid-1900s, central North America was covered by 300 million hectares of grassland (Küchler, 1964; Sims and Risser 2000). Some studies indicate that there has been a rise in the conversion of grassland to cropland over the last twenty years (Faber et al., 2012; Lark et al., 2015; Wang et al. 2017). Many factors have led to increasing agricultural intensification, paramount among them being factors of food demand—e.g. rapid population growth and rising per capita incomes—and factors of supply, such as conversion of some prime agricultural land to non-agricultural uses (Tilman et al., 2011).

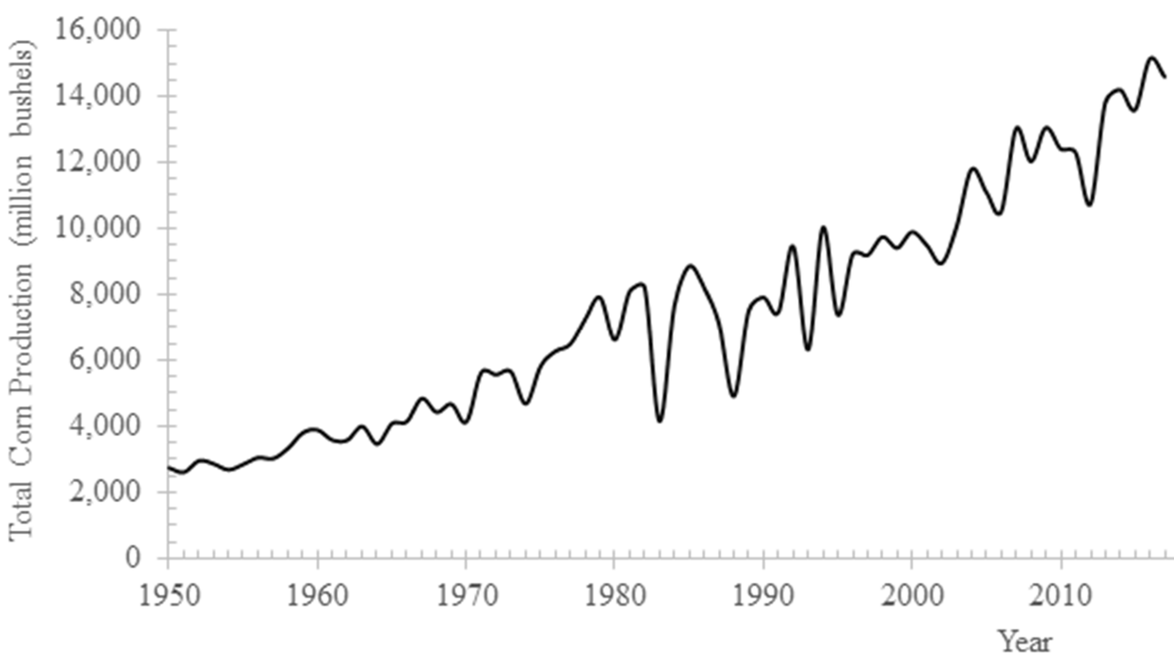

Figure 1. Total annual corn production in the U.S. Corn Belt, 1950-2018

Evidence of increased agricultural intensification can be found in the Corn Belt (includes Iowa, Indiana, Illinois, Kentucky, Kansas, Michigan, Ohio, Nebraska, Minnesota, Missouri, North Dakota, South Dakota and Wisconsin) of the United States, where total annual corn output has increased by 400%, from 2.7 billion bushels in 1950 to 14 billion bushels in 2018 (ERS, 2019). From 1950 to 2018 corn production in the U.S. has experienced an upward trend (Figure 1, USDA, ERS 2019). Even though planted acreage of corn has not seen much of an increase, corn production has seen an increase because of various advancements in technology and improved crop production practices.

Many economic factors influence landowners' decisions about land use—decisions such as whether to convert grassland to cropland or which crop to plant in a field. Input prices, output prices, soil productivity, agricultural policy, environmental policy, and weather (or climate) all affect a farmer's decision to go into the production of a crop and crop acreage. According to NASS (2019), while acreage of crops such as corn and soybean has been rising steadily, other crops such as barley, oats and wheat are experiencing a decline in share of agricultural land. Corn acreage harvested has steadily risen over the years, potentially due to some agricultural and environmental policies that have increased demand for corn. The Energy Independence and Security Act of 2007 (EISA 2007), through the Renewable Fuel Standard (RFS), has greatly increased the demand for corn as an ethanol feedstock. Rising ethanol demand has contributed to increasing corn prices, leading to an increase in corn acreage. Also, government payments such as crop insurance, disaster aid and others have enhanced the production of corn in the United States. From 1995 to 2018 acres harvested for corn and soybean have generally been on the rise (Figure 2.). Wheat, oats and barley however have experienced a decline in acres harvested over the same period (Figure 2.)

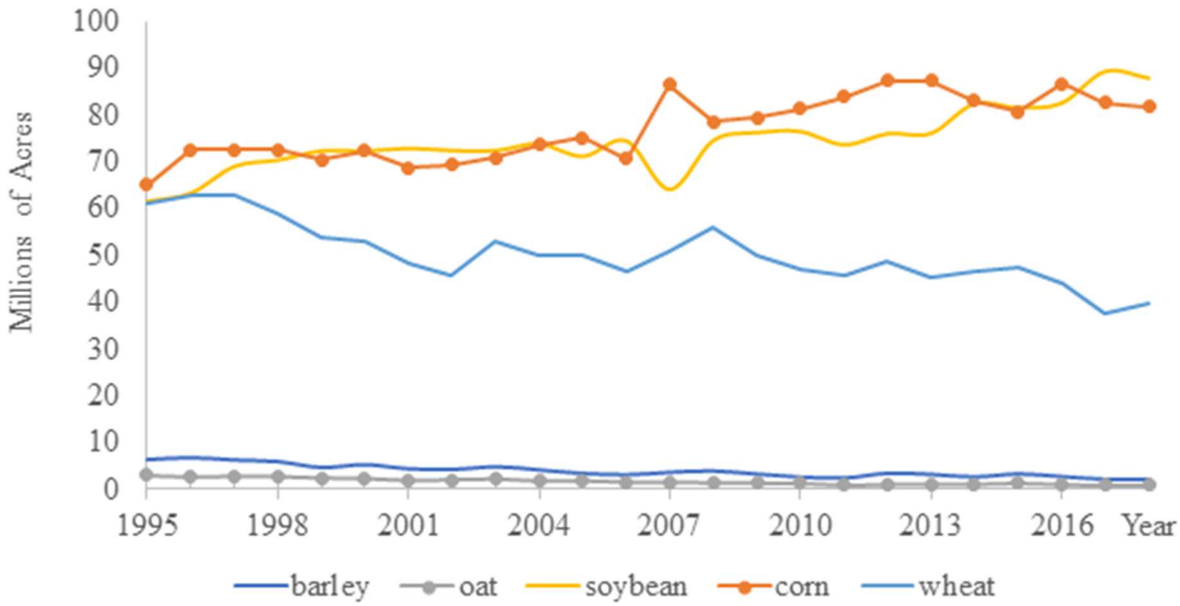

Figure 2. U.S. acreage of barley, oat, wheat, soybean, and corn harvested, 1995-2018

It is well known that elements of climate such as rainfall, temperature, seasonal water balance and length of growing seasons are important to crop production (Prentice et al., 1992; Woodward et al., 1995). The importance of climate in crop production cannot be overemphasized because many physiological processes in crops depend on rainfall and temperature. However, recent evidence suggests that some areas in the United States specifically the Corn Belt have experienced significant changes in climate because of crop intensification. Alter et al. (2018) indicates that intense crop production may have impacted regional climate due to changes in atmospheric processes. Bounoua et al. (2002) suggest that converting natural vegetation to agricultural land can increase or decrease temperature and humidity depending on the geographical zone, type of natural vegetation destroyed, and the type of crops established. As suggested by previous studies the midwestern United States has experienced some notable increases in precipitation (Groisman et al. 2012; Karl et al. 1996; Melillo et al. 2014). This rise in precipitation is believed to be as a result of the conversion of grassland and forests to cropland, increased crop production and irrigation (Barnston and Schickedanz, 1984; Baidya Roy et al 2003; DeAngelis et al. 2010; Groisman et al., 2012). Muller et al. (2015) indicate that temperature in the United States over the last hundred years has been increasing; however, in the Midwestern U.S., peak temperatures experienced during the growing season have been decreasing, leading to an overall seasonal cooling effect in this region.

Problem statement

Alter et al. (2018) show that significant changes in regional climate occurred simultaneously with increasing crop production in the Corn Belt over the last century. They find evidence that crop intensification in the Midwestern U.S. has increased rainfall by 35 percent and has decreased summertime temperatures by 1ºC. This implies that the factors that influence corn production in the U.S.—including energy policy, agricultural policy, and international trade policy—may be contributing to the observed changes in regional climate.

This study investigates potential climate impacts of cropping intensification in North Dakota. Though the state is not part of the traditional U.S. Corn Belt, it has experienced major changes in agricultural cropping densities over the last two decades. Over the past 24 years, evolving land use patterns in North Dakota have accounted for a large share of the increase in total U.S. corn acreage. In 1995, North Dakota corn acreage accounted for less than one percent of total U.S. corn acreage—0.700 million of approximately 71.479 million acres—but grew to account for 3.53 percent of total U.S. corn plantings by 2018—3.15 million of about 89.129 million acres (National Agricultural Statistics Service, 2019). While national corn acreage increased by 17.65 million acres during this period North Dakota corn acreage grew by 2.45 million acres, comprising 13.88 percent of the total national increase in corn acreage.

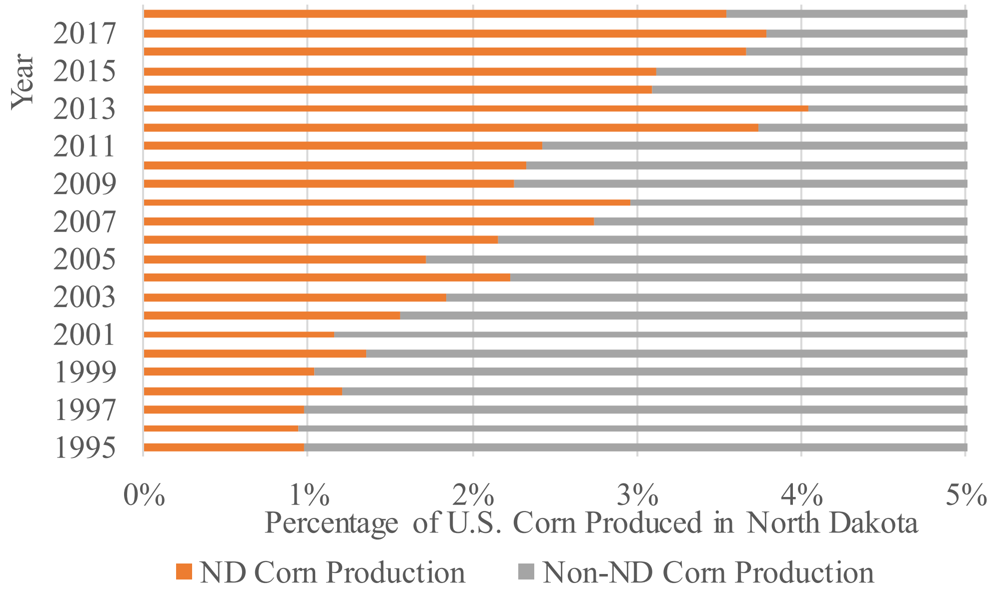

Figure 3. Percentage of corn produced in North Dakota as a percentage of U.S corn production

Whatever the causes, corn acreage in the state has increased more than four-fold since 1995. Given this rapidly increasing intensification of corn production, mostly confined to the southeastern portion of the state, developments in North Dakota present a potentially unparalleled opportunity to study the impacts of agricultural production on regional climate. The purpose of this study is to examine the relationships among corn acreage, commodity markets, climatic variables, and policy developments in energy, agriculture, and trade to determine how factors that influence agricultural production may also be influencing regional weather patterns.

Research objectives

The main objective of this study is to examine the impacts of changing cropping patterns on temperature and precipitation in North Dakota.

The specific objectives are to;

1. Develop and estimate a system of equations to better understand how changing cropping patterns may be contributing to observed changes in temperature and precipitation in North Dakota;
2. Estimate the marginal effects of some explanatory variables on corn acreage, temperature, precipitation, and corn yield.

Organization of study

The first chapter presents a background to the study and the rationale for this research. Chapter two reviews relevant literature on factors that influence weather and climate, acreage response modelling and what previous studies have done on relationship between crop production and weather. The third chapter presents the theoretical and empirical methodology. Chapter four provides a detailed discussion of the research findings. The last chapter concludes the study and offers some policy recommendations and suggestions for future research.

CHAPTER 2. LITERATURE REVIEW

Climate change has been a cause for concern over the years because it poses a great problem to humanity due to the grave consequences that may arise from humanity's failure to address issues of greenhouse gas emissions. The substantial costs from humanity's action or inaction to deal with greenhouse gas emissions presents a big economic problem (Pretis, 2020). Research indicates that rising atmospheric concentration of greenhouse gases and tropospheric sulfates as a result of human activities is responsible for observed changes in global surface temperature (Santer et al., 1996a, 1996b). Hegerl et al. (2007) attribute the observed global warming since the mid-twentieth century to greenhouse gas emissions. Some studies point out that anthropogenic emissions from burning fossil fuels and deforestation are the main causes of global warming experienced over the last fifty years (Gillett at al., 2012, Santer et al., 2013, Scott et al., 2010).

Despite studies suggesting that the Earth has generally experienced increase in temperature research findings from some other studies provide evidence that contradicts this observation. A study by Adegoke et al. (2003) in the United States High plains indicates that there was a decline in average and maximum surface temperatures in irrigated areas whereas non-irrigated areas exhibited an increasing trend in surface temperature. Harding and Snyder (2012) in their study of the Great Plains point out that irrigation has increased evaporation and precipitation. Hubner et al., (2014) also conducted a study in the Great Plains and their findings reveal that irrigation resulted in a net increase in atmospheric moisture and increased July precipitation by almost fifty percent. Jin and Miller (2011), give further evidence that suggests that agricultural intensification through irrigation in the California Central valley has resulted in a decrease in modern-day daily maximum near surface temperature. Wei et al.,

(2013) report that irrigation has significantly increased precipitation over heavily irrigated areas in Asia. Mueller et al. (2016) conclude that changes in climatic conditions in the United States Midwest is as a result of agricultural intensification, which is due in part to increased irrigation leading to increased evapotranspiration and an increase in precipitation. Research findings from Alter et al., (2015) conducted in the Gezira Scheme in East Africa further supports the impact of crop intensification on climate by pointing out that irrigation decreases air surface temperature. The study also indicates that irrigation has increased rainfall to the eastern side of the irrigated areas however there has been a decline in precipitation directly over irrigated areas. Mueller et al. (2017) suggests that agricultural land use can affect climate through intensification of crop production on existing croplands and a corresponding increase in evapotranspiration. Alter et al., (2018) used a model of simulations to assess the effect of agricultural intensification on regional climate. According to the study, observational historical data from the early 1900's indicates that there has been a simultaneous rise in cropland productivity, precipitation and specific humidity in central United States from July to August while surface air temperature has experienced a decline. Results from the study points out that increased agricultural activity has caused surface air temperature to fall by 1ºC while rainfall increased by thirty-five percent in central United States.

Effect of evapotranspiration on climate

Evapotranspiration is an essential physiological process in plants. Evapotranspiration or crop water use represents water lost from the soil through evaporation and water lost from leaves and plant surfaces through transpiration (Mckenzie et al, 2011). Crop water use also includes water utilized by plants for growth. Klocke et al (1990) suggest that evapotranspiration is important because it has a direct relationship with crop yields. This is because maximum yield will not be reached unless maximum evaporation has occurred. Burba and Verma (2005), further point out the importance of evapotranspiration, by suggesting that when it comes to water management evapotranspiration represents an important part of energy and water balance in agricultural systems. The significance of evapotranspiration is further enhanced by its temporal and spatial characteristics that make it essential for studying issues of climate change and irrigation scheduling (Gowda et al. 2008; Lei and Yang, 2010). Weather, crop type, growth stage of crop, cropping density and other factors greatly influence evapotranspiration (Klocke et al. 1990). Photosynthesis, soil moisture and heat transfer are various physiological processes that depend on evapotranspiration (Wever et al. 2002). Evapotranspiration also greatly impacts global energy and water cycles (Miao et al. 2009). Evapotranspiration changes with respect to vegetation, weather conditions and soil characteristics (Baldocchi et al. 2004). Soil moisture greatly influences evapotranspiration (Chen et al. 2009; Niu et al. 2009; Niu et al. 2011). Evapotranspiration can influence regional climate by transferring heat away from the surface of plants and the soil through latent heat transport and due to differences in evaporation rate associated with various grassland uses, the energy budget is changed consequently impacting local climate (Miao et al. 2009). Past research indicates that various uses of land greatly influence microclimate conditions, and this is as a result of evapotranspiration (Hu et al. 2008; Huxman et al. 2004; Keenan et al. 2013; Knapp and Smith ,2001; Niu et al, 2008; Niu et al, 2009; Xu et al; 2013). A study by Klocke et al. (1990) to determine the evapotranspiration rate of some crops at various stages of growth indicates that corn had the highest water use followed by soybean. This means corn has a high evaporation rate and hence is likely to influence regional climates when it is produced intensively.

Effect of surface albedo on weather patterns

In addition to evapotranspiration, local and global climates as well as ecological, biophysical and plant physiological processes are greatly affected by surface albedo (Tooming, 2002; Yin, 1998). Albedo represents the portion of shortwave solar radiation reflected by a surface (Oguntunde and van de Giesen, 2004). Albedo is an important determinant of evapotranspiration, photosynthesis and changes in surface temperature (Giambelluca et al. 1999; Iziomon and Mayer, 2002; Xin, 1998). The albedo of vegetation varies throughout the growing season and never stays the same (Jacobs and van Pul, 1990; Song 1999). The attributes of the soil surface such as soil moisture, soil particles and soil structure determine albedo in the beginning of the season after land preparation. However, the characteristics of the crop or vegetation including, crop height, canopy and leaf area index influence albedo during the growing season. Ross (1975) indicates that during the growing season crops exhibit different albedos because spectral attributes of leaves are not constant over the course of the growing season. These attributes of vegetation provide further evidence to support the two-way causal relationship between crop production and climate.

Climate modeling

Studies on changes in global surface temperature are mostly based on physical simulation models of the climate system and historical data (Kaufman and Stern, 2002). Global Climate Models (GCMs) are the most widely used approach in studying changes in global surface temperature. GCMs are physics-based models that are used in many studies because output from these models are used in econometric analysis of the effect of weather on an economic variable of interest to simulate the future effects of climate change on the economy (Auffhammer et al. 2013). GCMs are used mainly for weather forecasting and to simulate the impact of human activity on future climate. Houghton et al. (1990) indicate that GCMs are particularly not reliable in examining the impact of human activity on climate because the model is plagued with several problems including large natural variability and the chaotic nature of the system. Tol and Vos (1993) recommend the use of simple statistical models to relate global mean surface temperature to carbon dioxide rather than the more complex GCMs. Pretis (2017) points out that economic and environmental systems exhibit a bi-directional relationship and it is important to use an approach that makes provision for climate and economic activity to be combined with the fundamental physical relationship.

Land-use change in North Dakota

The United States has undergone significant conversion of grassland to cropland in recent years. Claassen et al. (2011) attributes this conversion to increased conversion of grassland to cropland in the Northern plains which includes North and South Dakota, Nebraska and parts of other states. Faber et al. (2012) point out that almost twenty-four million acres of grassland, shrubland and wetlands were converted to cropland in the United States with a little over three million acres of habitat lost in North and South Dakota alone from 2008 to 2011. Wright and Wimberly using land cover data from 2006 to 2011 suggest that grassland conversion in the Western Corn Belt was mostly concentrated in North and South Dakota. The study further indicates that not only is grassland being converted to cropland but also corn and soybean production is extending to marginal lands.

North Dakota has experienced notable variation in land use patterns during recent decades. Corn and soybean production have experienced a general increase while wheat production has fallen since 1996 (Feng et al. 2013). North Dakota's changing land use pattern has contributed immensely to increased corn production at the national level. Data from the

National Agricultural Statistics Service (2019) indicates that North Dakota's share of total U.S corn acreage increased from less than a million of approximately seventy-two million acres to a little over three million of approximately eighty-nine million acres from 1995 to 2018. This tremendous increase in North Dakota corn acreage from 1995 to 2018 comprises about fourteen percent of total national increase in corn acreage.

The main drivers of land use change are the same factors responsible for this observed change in corn acreage. These factors include local policy regulations, population growth, and population responses to economic opportunities, weather, and other factors affecting the demand for various land uses (Lambin et al. 2001; Stavins et al. 2008). In North Dakota, output and input prices, technology, farm size, market incentives, government policies, weather patterns, and crop insurance policies are all important factors that impact land use decisions (Wang et al. 2016; Miao et al. 2016). Profit maximizing crop producers are willing to supply more of a crop that is more profitable. Profitability is influenced by the same factors that influence land use decisions. Rashford et al. (2010), allude that land use decisions are significantly influenced by economic returns from alternative uses of land.

A major determinant of changes in cropping or land use patterns in North Dakota is farm policy (Feng at al. 2013). Some of these policies are in the form of government payments, including federal crop insurance, disaster aid, and marketing loans that incentivize crop producers to convert grassland to cropland or switch from one type of crop to another because these payments help to reduce risk (Claassen et al. 2011). Changes in crop prices and price volatility are critical variables in land allocation decisions of crop producers (Haile, Kalkuhl and Von Braun, 2015). Feng and Babcock (2010) indicate that crop producers increase land allocation for those crops that have higher expected prices relative to other crops. Biofuel demand is also a major contributor to the conversion of grassland to cropland because it increases the prices of crops such as corn and soybean (Claassen et al. 2011; Fargione et al. 2009; Rashford et al. 2011; Wallander, Claassen, and Nickerson 2011). The rising demand for biofuel, especially corn ethanol, is greatly influenced by oil prices, biofuel and energy policy mandates, as well as government subsidies (Hertel, Tyner, and Birur 2008). A major factor influencing the demand for biofuels and simultaneously increasing conversion of grassland to cropland is biofuel policy, specifically the Energy Policy Act of 2005 and the Energy Independence and Security Act of 2007. The Energy Policy Act of 2005 was expanded into Energy Independence and Security Act of 2007 which requires transportation fuel to contain minimum volume of renewable biofuel. The Renewable Fuel Standard set in these energy policies has significantly influenced corn production. Wright and Wimberly (2013) point out that rising crop prices are expected to continue increasing the changes in cropping and land use patterns.

Climatic variables such as temperature and precipitation are also important in crop production. Climatic variables such as rainfall, temperature, seasonal water balance and length of growing seasons are important to crop production (Prentice et al., 1992; Woodward et al., 1995). According to the North Dakota Agricultural Weather Network (2019) optimal temperatures for growing corn and soybean range between 50 ºF (10 ºC) and 86 ºF (30 ºC). Schenkler and Michael (2009) suggest that corn and soybean yields increase until 29 ºC and 30ºC respectively however anything in excess of these temperatures will cause yields to fall. Increased rainfall during planting time has a negative impact on yields while increased rainfall a few weeks after planting has a positive impact on yields (Chmielewski and Kohn 1999; and Hakala et al. 2012). Higher rainfall during the late growing season causes crop yields to decrease. Climate is an important part of crop production because many physiological processes in crops depend on rainfall and temperature. However, recent evidence suggests that some areas in the United States, specifically the Corn Belt, have experienced significant changes in climate because of cropping intensification. This gives the impression that there is a two-way causal relationship between climate and agricultural intensification.

According to Malhi et al (2008) activities such as fertilization, irrigation, forestry and grazing are major determinants of land cover and land management intensity. Over the last three to four decades there has been tremendous greening of the earth as a result of increased levels of carbon dioxide (Zhu et al. 2016). The increase in atmospheric carbon dioxide levels has resulted in a phenomenon called carbon fertilization effect. Carbon fertilization effect refers to the rise in the rate of photosynthesis due to high atmospheric carbon dioxide levels. An increase in atmospheric carbon dioxide often results in increased reproduction and vegetative biomass growth (Baker and Boote, 1996). Baker and Boote (1996) indicate that higher atmospheric carbon dioxide conditions end up increasing water-use efficiency in crops due to a decrease in transpiration. A host of factors including plant species, temperature, water availability and nutrients all impact carbon fertilization.

Acreage response modeling

Turner II et al. (1993) suggest that land use change is often expressed as a relationship between socio-economic and biophysical factors. To model the impact of crop intensification on climate a regression-based model is used in this study. A common model that has used been over the years to understand the relationship between crop production and other variables such as climate, prices and policy is the acreage response model. Acreage response has been a topic that has been well covered over the years since the model was popularized by Nerlove (1956). The general supply response model developed by Nerlove (1956) has been adopted and modified by various studies since the 1950s ranging from a single equation to a system of supply equations (Barten and Vanloot, 1996; Bewley et al, 1987; Coyle, 1993). Also, other studies have expanded the scope of acreage response models by including different variables in addition to the more traditional variables specified in acreage response models. The various modifications that have been made to the acreage response models over the years to capture the effect of other notable variables on the type and acreage of crops being grown. Many studies have used a variety of variables as the dependent variable including yield, planted and harvested acreage to represent supply in acreage response models (Coyle, 1993; Haile, Kalkuhl and Von Braun, 2014).

A very important variable to consider in modeling acreage response is expected price. Many studies give credence to the fact that expected price is an essential variable that cannot be excluded from acreage response modelling (Chavas and Holt, 1990; Choi and Helmberger, 1993; Krause et al. 1996; Krause and Koo, 1996;). However, there is no standard measure for expected price. Expected price is preferred to observed price because during decision making on planting, output prices are not known. Houck and Subotnik (1969) in their analysis of the impact of policy changes on both soybean acreage used previous years' prices as expected prices for the current period. Houck and Ryan (1972) studied acreage supply relationships for corn in the United States between 1948 and 1970. This study modelled the relationship between planted acreage of corn prices and expected prices, using previous crop year prices as a proxy for expected price. Ryan and Abel (1973) in their study of oats and barley acreage response to government programs also used one-year lagged market prices for barley and oats as a proxy for expected prices. Krause and Koo (1996) examined acreage response for minor oilseeds in the Northern plains to expected revenues and price risk using data from 1962-1993. Expected gross revenue is defined in the study as a product of expected price and expected yield of the minor oil seeds. The price-risk variable represents the weighted variance of price received by oil seed producers in the previous three years around the expected prices in those years. The findings indicate that flax seed and sunflower acreage are significantly and positively affected by their own expected revenue and negatively affected by own price risk. Krause et al. (1996) analyzed regional and United States acreage response for program-planted, program-complying and nonprogram-planted wheat to expected price of wheat, expected price of competing crops, government programs and risk. The price and risk variables used in this study are as defined by Krause and Koo (1996). Krause et al. (1996) indicates that the expected price of wheat has a strong negative effect on program-complying wheat acreage, whereas price risk has a positive impact on program-complying wheat acreage and a negative effect on nonprogram-planted acreage. All these studies discussed utilized past market price as the measure for expected price. Futures prices have also been extensively used as a proxy for expected market prices in many studies. Gardiner (1976) suggests that the use of futures prices as a proxy for expected prices is appropriate because it represents the price expected by producers during decision making. Futures prices incorporate variability in factors such as weather, currency exchange rates, trade subsidies and tariffs (Davison and Crowder, 1991). Morzuch et al. (1980) assessed wheat acreage supply response for major producing states in the United States under changing farm programs. Futures prices were used as the proxy for expected prices. The results reveal that relative price of wheat had a positive effect on wheat acreage. Choi and Helmberger (1993) using futures price studied the relationship between soybean acreage, futures price and other variables using a simultaneous equation model since the variables ae endogenous. The study concludes that futures prices are good for forecasting and suitable for making acreage decisions. Regardless of the work done to support the use of futures prices other studies express concerns about how good futures prices are for forecasting. Chavas et al. (1983) suggest that it is very unlikely for futures prices to totally reflect all the information in the market. In their quest to address these problems associated with futures prices, the study developed an acreage supply response for United States corn and integrated both futures price and lagged cash price. Their findings raised doubts about the use of futures prices especially in the presence of government support programs. The research however indicates that futures price can be a good proxy for expected prices in the absence of government programs. Though there have been some misgivings about how to measure expected prices, most research supports the importance of expected price in the decision-making process of producers.

While some previous studies have ignored the effect of climate in their acreage response models, others (Smithers and Smit, 1997) have studied how climate change may influence the types of crops being planted and the price of these crops. Schenkler and Roberts (2009) used a Ricardian economic model to analyze the effect of climate on crop production. Weersink et al., (2010) also examine the effect of weather, price and other variables on yield distribution and crop area allocation.

The impact of agricultural support policies on supply has also been investigated (Holt, 1999). Because of the crucial role these policies play in changing prices and reducing price and yield risk they have been extensively studied (Chavas and Holt, 1990, 1996; Krause et al., 1995; Lin and Dismukes, 2007). Timilsina et al. (2010) also examined the effect of biofuel policy on land use change and food supply. Results from the study reveals that cropland expansion due to increased biofuel demand has caused a decline in forest, and pastureland, food supply and has resulted in increased prices of feedstock items.

It is important that any acreage response model developed in this study is supported by a reliable theoretical framework. Many studies have made a case for various theoretical frameworks to adequately analyze acreage response modelling. A commonly used approach is the profit function concept from the theory of production. Lee and Helmberger (1985) utilized this approach in their study of supply response of corn and soybeans in the presence of farm programs. Chembezi and Womack (1992) also examined the impact farm programs on acreage response of corn in the Corn Belt and Lake states and for wheat in the Northern plains using the concept of profit maximization. Findings from the study reveal that expected market price negatively impacts program planted acres while nonprogram-planted acres are positively influenced by expected market price. Weersink, Cabas and Olale (2010) used the profit maximization framework to examine the impact of weather on the distribution of yield and the effect on acreage allocation decisions of crop farmers in Ontario. The study estimated acreage response functions using predicted parameters of yield distributions and expected distribution of crop price to highlight the significance of expected yield in area allocation decisions. Findings from the study indicate that even if crop prices remain the same climate will influence crop area. The expected utility function is another approach that has been employed by various researchers to study acreage response especially when risk is a variable of interest. In their analysis of the planting decisions of risk averse farmers between corn and soybeans, Chavas and Holt (1990) used a Von-Neumann Morgenstern utility function to represent the preferences of these farmers. Holt and Moschini (1992) developed a multivariate ARCH-M and GARCH-M framework to investigate different methods of modelling risk response in commodity supply models. The study assumes that producers have a constant absolute risk aversion utility function and that price risk is normal. Results from the study indicate a small and negative effect of price risk on acreage response. Krause and Koo (1996) also employed the utility function approach used by Chavas and Holt (1990) to study acreage response of minor oilseeds to various economic variables including price risk and expected revenues. Liang et al. (2011) also follow the utility function framework to study factors that influence crop prices and yields in southeastern U.S.

Seemingly unrelated Tobit regression model

For this study the most appropriate model is a seemingly unrelated Tobit regression model. The decision to utilize this model is because some dependent variables in some of the econometric equations cannot have values less than zero and since we have more than one equation the error terms in the various equations are likely to be correlated. Tobin (1958) was the first to use a Tobit model in his study to examine the linear relationship between household expenditure on durable goods which is the non-negative dependent variable and a vector of explanatory variables. Amemiya (1984) indicates that Tobit models with observations outside a specified range are totally lost are referred to as truncated and in instances where one can at least observe the exogenous variables it is known as censored Tobit model. In situations where there is more than endogenous variable, simultaneity and censoring are likely to happen (Chen and Zhou, 2011). A seemingly unrelated regression model with censored dependent variables is classified as a seemingly unrelated Tobit regression Tobit model (Zellner, 1962; Greene, 2003; Zellner and Ando, 2010). In this this type of model there are several equations with each equation having a different dependent variable while independent variables may be the same or vary across equations (Zellner, 1962). There are many ways of estimating seemingly unrelated Tobit regression Tobit models a common parameter estimation procedure is maximum likelihood estimation. (Brown and Lankford, 1992; Kamakura and Wedel, 2001: Wales and Woodland, 1983).

This study seeks to contribute to existing literature by using acreage response modelling and rainfall and temperature forecasting to examine how the factors that influence land use change specifically increased corn production in North Dakota may be responsible for the observed changes in climate patterns in North Dakota. The research gives importance to how drivers of acreage response decisions have directly or indirectly caused some variations in precipitation and temperature in North Dakota. The subsequent chapter gives a detailed explanation about how this study will be conducted.

CHAPTER 3. MODEL DEVELOPMENT

This chapter presents the theoretical underpinnings of models developed to describe the responses of corn and hard red spring wheat (HRSW) acreage to farmers' crop price and crop yield expectations, including effects of rainfall, temperature, and policy on expected yields and prices in North Dakota. These acreage response models are jointly estimated with models quantifying the impacts of aggregate crop selection on weather patterns in North Dakota from 1998 to 2018. Explanatory variables used in the models include expected prices of crops, production costs, thirty-year temperature and precipitation averages, energy policy and agricultural policy.

Theoretical model

The basic theoretical justification for the acreage response equations is the law of supply. That is, profit maximizing farmers are willing to supply more of a commodity given increased profitability relative to other commodities, *ceteris paribus*, by increasing resources—particularly land—allocated to production of the crop. Thus, acreage supply functions for a group of crops can be expressed as follows:

$$A_{ikt} = X_{A,ikt}\beta_{A,i} + \varepsilon_{A,ikt} \tag{1}$$

where A_{ikt} denotes planted acreage of crop *i* at location *k* in year *t*; $X_{A,ikt}$ is a collection of explanatory variables with known values specific to site *k* and year *t* that affect the relative expected profitability of crop *i* (e.g. expected commodity prices, expected production costs, expected precipitation and temperature, policy, etc.); $\beta_{A,i}$ is the vector of parameters to be estimated relating planted acreage of crop *i* to its particular set of explanatory variables; and $\varepsilon_{A,ikt}$ represents an unexplained random disturbance following a normal distribution with a mean of zero and variance of σ_{ik}^2.

Selection of specific variables for inclusion in $X_{A,ikt}$ should be based in economic theory. For example, a farmer's decision to increase acreage of crop *i* in year *t* ought not be based only on the expected price, expected yield, and production costs of crop *i* but also on the expected prices, expected yields, and expected production costs of the *J* alternative crops that could be planted instead. Additional variables that may impact productivity and profitability of each crop are related to rotational considerations for suppression of pests and disease; thus, the acreages of crops *i* and *j* at location *k* in year (*t* – 1) are likely to influence the acreage of crop *i* planted there in year *t*. Additionally, certain types of land cover (such as open water and wetlands) preclude agricultural use of any kind. The extent of these types of land cover may, in turn, depend upon precipitation at or near location *k* in year *t*.

Given the physical relationship for yield, it can be expressed as a function of environmental variables and economic variables. The biophysical components and economic variables affecting yield can be expressed as follows;

$$Y_{ikt} = X_{Y,ikt}\beta_{y,i} + \varepsilon_{y,ikt} \tag{2}$$

where Y_{ikt} denotes yield of crop *i* at location *k* in year *t*; $X_{Y,ikt}$ is a collection of independent variables with known values specific to site *k* and year *t* that impact yield of crop *i* (e.g. carbon dioxide, precipitation and temperature, policy, etc.); $\beta_{Y,i}$ is the vector of parameters to be estimated relating yield of crop *i* to its particular set of explanatory variables.

Ample evidence demonstrates that land use and land cover influence local and regional climate due to varied light reflectance and evapotranspiration. For example, cropping activities that leave bare soil exposed in spring absorb more visible light, which is re-emitted as infrared heat (Oguntunde and van de Giesen, 2004). On the other hand, crops with high evapotranspiration rates may cause local cooling because evapotranspiration is an endothermic reaction. Crops with higher evapotranspiration rates increase local relative humidity and may result in higher regional precipitation levels (Alter et al., 2015; Alter et al., 2018; Mueller et al. 2016; Mueller et al. 2017). Thus, each of the alternative crops has unique effects on local climate and, via annual changes in acreage at the regional scale, is likely to impact regional climate in different ways during different parts of the growing season each year. Changes in temperature and precipitation during the months of the growing season from year to year can be modeled as in equations (3) and (4).

$$\dot{T}_{jkt} = X_{\dot{T},jkt}\beta_{\dot{T},j} + \varepsilon_{\dot{T},jkt} \tag{3}$$

$$\dot{P}_{jkt} = X_{\dot{P},jkt}\beta_{\dot{P},j} + \varepsilon_{\dot{P},jkt} \tag{4}$$

In the equations above, $\dot{T}_{jkt}$ is the difference between the average monthly temperature at location *k* in month *j* in year *t* and the 30-year normal[1] average monthly temperature at location *k* in year *t*; $\dot{P}_{jkt}$ is the difference between total precipitation at site *k* in month *j* of year *t* and the 30-year normal of total precipitation at site *k* in month *j*; $X_{\dot{T},jkt}$ and $X_{\dot{P},jkt}$ are matrices of independent variables that may theoretically influence inter-annual variations in temperature and precipitation, with known values in month *j* at location *k* in year *t*; $\beta_{\dot{T},j}$ and $\beta_{\dot{P},j}$ are unknown parameters to be estimated to quantify the potential effects of the independent variables on variations in temperature and precipitation; and $\varepsilon_{\dot{T},jkt}$ and $\varepsilon_{\dot{P},jkt}$ are random disturbances following normal distributions with means at zero and variances $\sigma^2_{\dot{T},jk}$ and $\sigma^2_{\dot{P},jk}$.

Empirical model

For this study a Seemingly Unrelated Tobit Regression model consisting of two acreage response equations, two yield equations, four temperature equations and four precipitation

[1] The 30-year normal for each climate variable is calculated by averaging its values from 1980 to . . .

equations is developed and estimated using Maximum Likelihood Estimation. The reasons for choosing this model are that the dependent variables in the acreage response equations cannot have values less than zero and the error terms in the various equations are likely to be correlated. The two acreage response equations consist of one equation for corn acreage and another for hard red spring wheat (HRSW) acreage. The two yield equations consist of one equation for corn price and one for HRSW. The four temperature equations are developed for four different months; June, July, August and September. These months are selected for the study because crop water use in the Corn belt is highest during this period (DeAngelis et al. 2010). The precipitation equations follow the same idea as the temperature equations. The SUR Tobit model is expressed as;

$$\begin{bmatrix} Z_{1t} \\ Z_{2t} \\ Z_{3t} \\ Z_{4t} \\ Z_{5t} \\ Z_{6t} \\ Z_{7t} \\ Z_{8t} \\ Z_{9t} \\ Z_{10t} \\ Z_{11t} \\ Z_{12t} \end{bmatrix} = \begin{bmatrix} X_{1t} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & X_{2t} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & X_{3t} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & X_{4t} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & X_{5t} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & X_{6t} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & X_{7t} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & X_{8t} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & X_{9t} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & X_{10t} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & X_{11t} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & X_{12t} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_5 \\ \beta_6 \\ \beta_7 \\ \beta_8 \\ \beta_9 \\ \beta_{10} \\ \beta_{11} \\ \beta_{12} \end{bmatrix} + \begin{bmatrix} U_{1t} \\ U_{2t} \\ U_{3t} \\ U_{4t} \\ U_{5t} \\ U_{6t} \\ U_{7t} \\ U_{8t} \\ U_{9t} \\ U_{10t} \\ U_{11t} \\ U_{12t} \end{bmatrix} \quad (5)$$

Where $Z_{1t}\ldots, Z_{12t}$ are the latent variables of the dependent variables for all twelve equations to be determined using the SUR Tobit model for all cross-sectional units in year *t*. $Z_{1t}\ldots, Z_{4t}$ are the latent variables for corn acreage, HRSW acreage, corn yield and HRSW yield. $Z_{5t}\ldots, Z_{8t}$ are the latent variables for temperature deviations from the thirty-year normal in June, July, August and September respectively. $Z_{9t,}\ldots, Z_{12t}$ are the latent variables for precipitation deviations from the thirty-year normal in May, June, July and August respectively. $X_{1t,}\ldots, X_{12t}$ represents the explanatory variables for each cross-sectional unit at time t. $\beta_1\ldots, \beta_{12}$ are vector of parameters relating explanatory variables to the vector of latent variables. $U_{1t}\ldots, U_{12t}$ are vectors of errors at time t, which are normally distributed with zero mean and variance ϑ. The relationship between the latent variable Z_{kt} and the observed variable V_{kt} can be expressed as follows;

$$V_{kt} = \begin{cases} Z_{kt} & \text{iff } Z_{kt} > 0 \\ 0 & \text{iff } Z_{kt} \leq 0 \end{cases}, \quad (6)$$

Data and variable selection

In this section the types, sources and method of data collection are presented. Data used in this study covers a period from 1998-2018. Data for the estimation of the model are acreage planted for corn, soybean and spring wheat, yield for corn, soybean and spring wheat. Other data used include 30-year normal for temperature and precipitation, monthly temperature and precipitation, temperature and precipitation deviations from 30-year normal, corn storage. Also, data on conventional biofuel mandates and prevented planting are used in the study. Data used covers all 53 counties in North Dakota. However, all counties are broken down into different cross-sectional units laid out in a 50 square-mile grid resulting in 1,355 cross sectional units for the study.

Crop acreages used in the study are derived from the US Department of Agriculture's (USDA) Cropland Data Layer files produced annually. The Cropland Data Layer files classify all land by crop each year at a resolution of 30m. The acreage data are aggregated at a resolution of 16km. Crop yields used are county-level yields obtained from the USDA's National Agricultural Statistics Service (NASS) Quick Stats database. Also, data for corn in storage representing national-level corn supply at the end of March and December were obtained from USDA-NASS.

Prices used in the model are futures contract prices for corn, spring wheat and soybean. Prices used are not those received by farmers rather they represent farmers' springtime expectations about prices at harvest. The December futures contract price for corn is used as the expected price for corn and it was obtained from the Chicago Board of Trade. For spring wheat, the December futures contract price is used, and it was obtained from the Minneapolis Grain Exchange. The November futures contract prices are used as the expected prices for soybean and they were obtained from the Chicago Board of Trade. All futures contract prices were obtained from their respective sources via DTN ProphetX. Operating cost data used represent expected costs from the North Dakota State University Extension's projected crop budgets prepared for the various budget regions in the state. All prices and costs are in US dollars and were adjusted for inflation using the GDP implicit price deflator from the St. Louis Federal Reserve Economic Data using 2018 as the base year.

All temperature and precipitation data were obtained from Oregon State University's PRISM Climate group. The 30-year normal are average values for temperature and precipitation computed at the end of each decade after the preceding 30 years. The 30-year normal used in the study were computed from 1981 to 2010. Temperature and precipitation deviations were obtained by subtracting the 30-year normal for temperature and precipitation from the mean monthly temperature and precipitation data recorded from 1998-2018. To capture agricultural policy, we use prevented planting under the Common Crop Insurance Policy. A dummy variable is used to represent availability of prevented planting coverage, with years preceding 2006 taking on a value of zero while 2006 onwards are assigned a value of one. The Renewable Fuel Standard (RFS) program established under the Energy Policy Act of 2005 and expanded by the Energy Independence and Security Act of 2007 is used to represent the energy policy variable in this study. The volume of ethanol produced in million liters is used to capture the impact of this policy. Data for the RFS is obtained from the United States Environmental Protection Agency website. Data on global carbon dioxide emissions is obtained from the Global Monitoring Laboratory (GML) of the National Oceanic and Atmospheric Administration (NOAA).

Spatial dependence

The various cross-sectional units in this study are likely to exhibit spatial dependence because observations at one location depend on variables at other locations. Anselin (1988) suggests that spatial dependence may be caused by some spillover effects and this becomes problematic as a result of misspecification and may end up violating the standard assumptions of regression. Lesage (1999) attributes spatial dependence to two factors. First, measurement error associated with collecting data concerning spatial may happen if the administrative boundaries for gathering information do not closely follow the fundamental procedure for creating the sample data. The second reason is that, a modelling problem may arise due to the spatial dimension of socio-demographic, economic or regional activity (Lesage, 1999). To address problems of spatial dependence a spatial weight matrix can be used to separate the effects of the other independent variables from any spatial dependencies that may exist between dependent variables. The spatial weight matrix measures the interaction among units. Lam and Qian (2017) point out that many estimation procedures assume that the spatial weight matrix is known. Selection of a spatial weight matrix is contingent on individual specifications and may be computed by using the inverse of certain distance measures (Lam and Qian, 2017). This study adopts the inverse distance weighted matrix in developing weight matrices for corn, wheat and soybean.

Marginal effects and elasticities

To better understand the impact of crop production and precipitation, it is important to calculate the marginal effect of corn on the weather variables. Also, of interest in this study is the marginal effect of carbon dioxide on yield, the marginal effect of crop prices on yield and planted crop acreage. The following formula is used to compute the expected values of temperature and precipitation variables:

$$\hat{V}_{jkt} = E[V_{kt}|X_{kt}], \tag{7}$$

$$\hat{V}_{kt} = \phi\left(\frac{X_{kt}}{\sigma_i}\right)\left(\beta X_{kt} + \sigma_i\left(\frac{\varphi\left(\frac{\beta X_{kt}}{\sigma_i}\right)}{\phi\left(\frac{\beta X_{kt}}{\sigma_i}\right)}\right)\right)', \tag{8}$$

where $\hat{V}_{kt}$ is a dependent variable at location k in year t, ϕ is the normal cumulative distribution function (cdf), φ is the normal probability distribution function (pdf), β is the vector of estimated coefficients, X_{kt} represents the explanatory variables and σ_i is the estimated standard error. The marginal effects and elasticities are calculated using the following formulae:

$$\hat{M}_{kt} = (\partial V_{kt}/\partial W_{kt})\phi(\beta X_{kt}/\sigma_i) \tag{9}$$

$$\hat{\eta}_{kt} = \hat{M}_{kt}\left(\hat{W}_{kt}/\hat{V}_{kt}\right) \tag{10}$$

$\hat{M}_{kt}$ is the marginal effect of an independent variable on our predicted variable of interest, W_{kt} is the independent variable of interest whose marginal effect is being investigated at location k in year t, $\hat{\eta}_{kt}$ is the elasticity measure, all other variables are the same as earlier explained. To estimate the standard errors for the marginal effects Monte Carlo simulation is used in the study. The approach used in this study is that developed by Krinsky and Robb (1986) where random draws are simulated from the joint distribution for all parameter estimates from the model. The simulation is done 10,000 times. Marginal effects and elasticities are averaged over the study period for the state and 95% and 99% confidence band are used to test the statistical significance of the marginal effects and elasticities.

Principal component analysis

Due to the likelihood of the problem of multicollinearity, Principal Component Analysis (PCA) is employed to remedy this problem. PCA uses orthogonal transformation to change correlated variables into a set of uncorrelated variables. The newly formed uncorrelated variables are called principal components. The basic concept is to decrease the many dimensions of a data set that includes many interrelated variables while retaining as much variation as possible from the data set (Wu et al, 2010). Principal component analysis is a commonly used approach in weather forecasting and climate studies (Jolliffe, 1993). Principal components scores can be expressed as (Jolliffe, 1982):

$$P_{qt} = \Sigma_{j=i}^{J} a_{jq} Z_{jt} \tag{11}$$

P_{qt} represents the value of principal component q in year t; a_{jq} is the j^{th} element of the eigenvector for the q^{th} principal component, and Z_{jt} is the standardized value of the natural log of variable j in year t. Principal component scores are functions of the standardized values of all the original variables. The first principal component has the highest eigenvalue after the orthogonal transformation. The eigenvalue represents proportion of the variation in the independent variables explained by the principal component. The principal component that explains the next highest proportion of the variation becomes the second principal component and so on and so forth. The principal components were created using the "PRINCOMP" procedure in SAS software package.

CHAPTER 4. RESULTS AND DISCUSSION

In this chapter, the summary statistics of the variables used are presented as well as estimates for the seemingly unrelated regression model. The results of the regression model consist of estimates for twelve regression equations. Also, some maps are presented to illustrate the spread and distribution of corn in North Dakota. The descriptive statistics including the mean, standard deviation, minimum and maximum of the variables used are presented in Table 1. Estimates for the seemingly unrelated Tobit regression model are presented in table 2. These parameter estimates were obtained using full information maximum likelihood estimation.

Summary statistics

The average acreage of corn, soybeans and HRSW across the various cross-sectional units from 1998-2018 is 564.71, 1,181.84 and 1,914.87 hectares respectively. Water bodies on average occupy about 902.49 hectares across the various cross-sectional units in North Dakota. The minimum acreage for corn, HRSW, soybeans and water are zero. Expected revenue for corn, soybean and HRSW was obtained by multiplying the expected yield (previous year's yield) with expected price. Average yield across the cross-sectional units were 6.03 megagrams per hectare for corn, 2.53 megagrams per hectare for HRSW and 1.89 megagrams per hectare for soybean. Corn had the highest expected revenue of $2,495.41 per hectare among all three crops while soybean had the least with $1,634.02 per acre. The highest temperatures were recorded in July while the highest precipitation was recorded in June. Average annual U.S. ethanol production is 32,529.14 million liters. Annual global carbon dioxide emissions were about 386.52 parts per million (ppm) on average. The average operational cost of corn, soybean and HRSW are $498.25per hectare, $298.13 per hectare and $298.13 per hectare respectively.

Table 1. Descriptive statistics for variables

Variable	Mean	Minimum	Maximum	Standard Deviation
Acreage				
Corn (ha)	564.71	0.00	7,137.09	923.31
HRSW (ha)	1,914.87	0.00	8,433.64	1,460.68
Soybean (ha)	1,181.84	0.00	9,894.69	1,718.89
Water (ha)	902.49	0.00	10,534.77	1,178.20
Yield				
Corn (Mg/ha)	6.03	0.00	13.04	1.85
HRSW (Mg/ha)	2.53	0.47	4.79	0.77
Soybean (Mg/ha)	1.89	0.67	3.32	0.48
Price				
Corn ($/Mg)	17,318.49	12,033.69	26,881.03	4,527.74
HRSW ($/Mg)	24,168.90	15,917.73	47,889.90	7,844.41
Soybean ($/Mg)	36,942.12	22,575.32	61,357.94	10,504.29
Expected Revenue				
Corn ($/ha)	1,030.53	190.88	2,495.41	437.00
HRSW ($/ha)	600.90	82.36	1,737.83	282.09
Soybean ($/ha)	701.86	193.20	1,634.02	296.64
Operational Cost				
Corn ($/ha)	498.25	236.23	1,021.17	193.85
HRSW ($/ha)	296.60	139.54	571.67	112.18
Soybean ($/ha)	298.13	195.21	481.10	77.07
Temperature				
June (ºC)	17.34	12.28	22.00	1.48
July (ºC)	21.04	15.72	26.06	1.51
August (ºC)	1.83	13.44	24.44	1.47
September (ºC)	14.69	9.50	19.11	1.59
Precipitation				
June (cm)	9.58	0.84	35.26	4.29
July (cm)	6.65	0.20	27.58	3.63
August (cm)	5.82	0.00	29.64	3.73
September (cm)	4.72	0.00	22.10	3.22
Ethanol Production (million liters)	32,529.14	5,318.50	60,911.06	21,348.40
CO_2 (ppm)	386.52	367.10	408.75	12.84

Spatial distribution of corn acreage, rainfall and temperature in North Dakota

From Figure 4. it is observed that corn acreage in 1998 the western part of North Dakota was relatively small averaging between 0.00 – 105.30 hectares. However, moving from the western part towards the more southern areas corn acreage was relatively higher than the western and northern parts of North Dakota. The eastern part of the state had the highest concentration of corn production with some cross-sectional units growing as much as 5,500.08 hectares of corn. It can also be inferred from Figure 4. that from 1998-2018 cross-sectional units in the northeastern corner of the state experienced a tremendous decline in corn acreage with some places reducing by as much as 1,776.15 hectares. Some areas along the midwestern portion of the state experienced some significant increase in corn acreage especially the midwestern parts of North Dakota over the period. Corn acreage experienced some increments between 2,753.92-5,271.39 hectares across some cross-sectional units in the midwestern part of the state.

It can be inferred from Figure 5. that areas in the eastern portion of the state especially the southeastern areas experienced the most rainfall during the month of June of about 10.67 cm. During the month of July, the eastern part of the state generally experiences the most the most rainfall a little below rainfall values in June. The month of August depicts a fall in rainfall from July with the northeastern parts experiencing the most rainfall. North Dakota recorded the least rainfall among these four months being considered in the study in September when the season begins to change towards fall. The highest rainfall values were recorded in the southeastern part of the state where corn production is high. The highest temperature values in the state were recorded in the month of July. Most areas along the southern part experience temperatures in excess of 23 ºC. Temperatures during the month of June tend to be cooler than July because it represents a transition from spring to summer. Temperature in September is somewhat the lowest among the four months. Areas in the northern part of the state experience cooler weather compared to the southern part. This month marks the beginning of fall which is the transition from summer to winter.

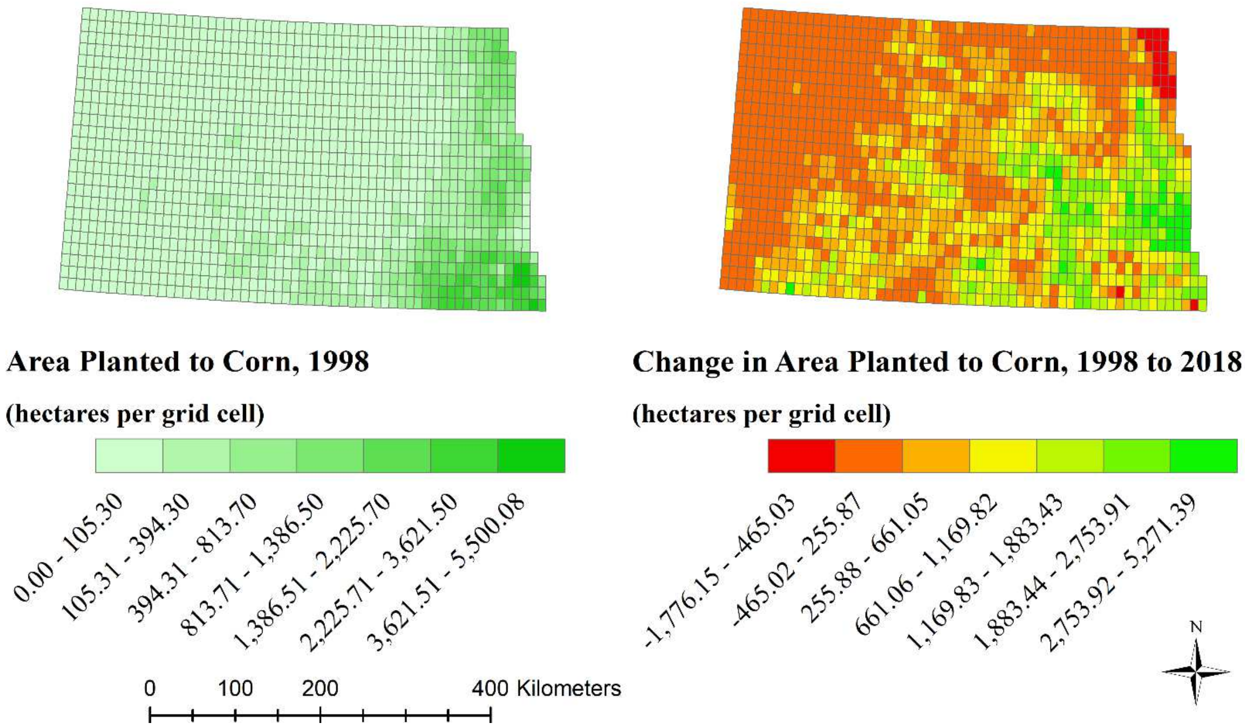

Figure 4. Spatial distribution of corn acreage in 1998 and changes in corn acreage from 1998-2018

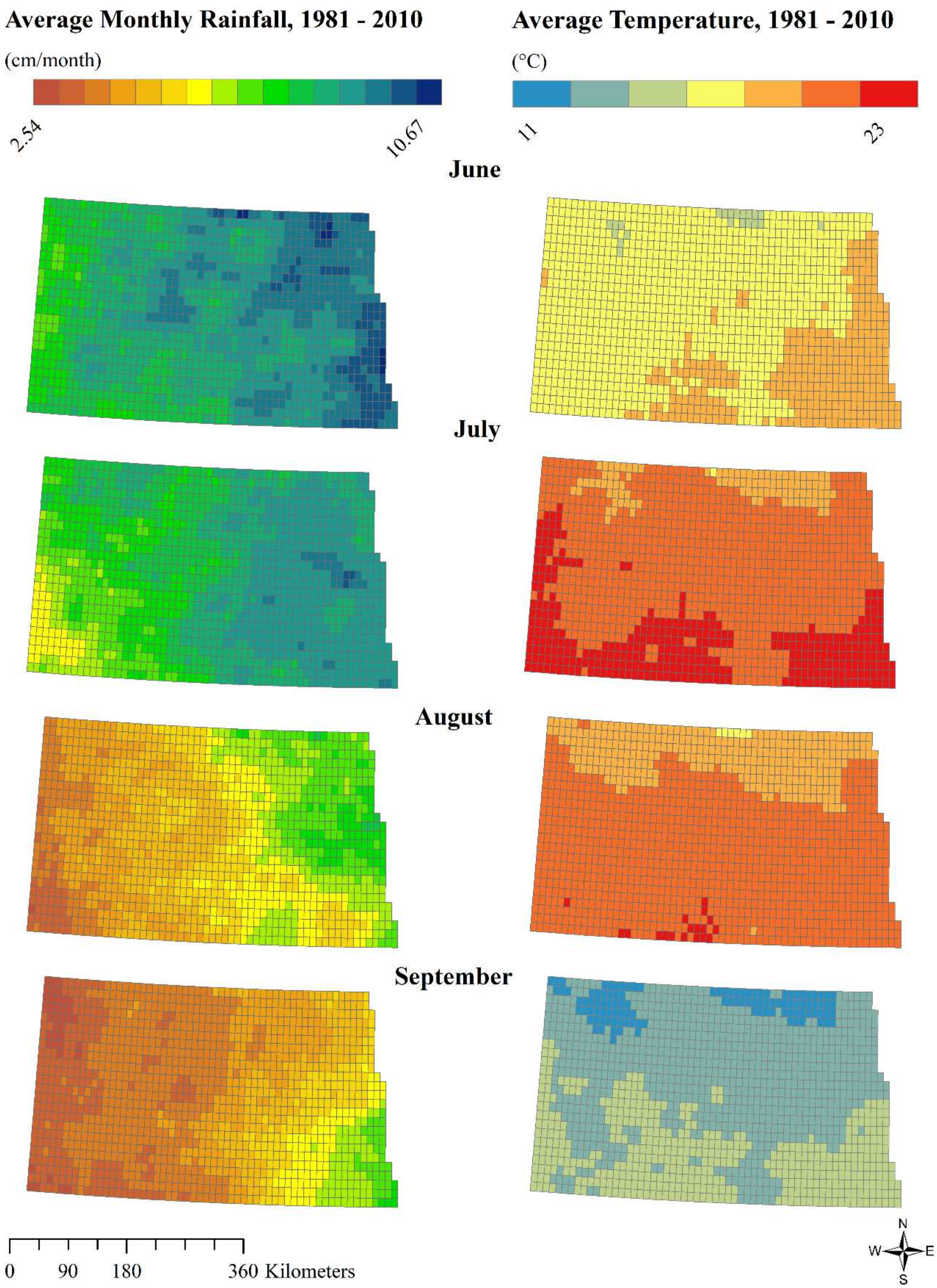

Figure 5. Rainfall and temperature distribution in North Dakota

Seemingly unrelated Tobit regression estimates

The seemingly unrelated Tobit regression model parameter estimates, and goodness of fit statistics are presented in table 2. The Wald test statistic is 207,939.54 and is distributed Chi-square with 270 degrees of freedom. The p-value of the Wald Chi-square statistic is 0.001 which is less than the generally used criterion of 0.05. Hence the null hypothesis is rejected in favor of alternate hypothesis. This means that all statistically significant variables included in the model improve the fit of the model. Parameter estimates for principal components developed for use in each of the twelve regression equations are excluded from our table of parameter estimates because these components were created to correct the problem of multicollinearity. These principal components serve also as a control for other independent variables whose effect were not directly captured in the regression model. The square terms of some independent variables included in the regression model enable the estimation of marginal effects of specific variables of interest.

It is evident from the findings that June precipitation deviations are positively and significantly influenced by time, square of corn acreage and water acreage. Corn acreage, square of water acreage and weighted water acreage have a significant negative effect on June precipitation deviations. The negative effect of corn acreage is contrary to findings from studies suggesting that corn production has increased rainfall in the summer months over the U.S. Midwest. It can also be ascertained that with each passing year temperature deviations in June tend to increase holding all other factors constant. The positive sign on the coefficient of corn acreage squared indicates that even though corn acreage has a negative impact on June temperature deviations, it is likely that at higher acreages of corn plantings June precipitation deviations are likely to rise. All variables mentioned are statistically different from zero at significance level (α) = 0.05 or better. Carbon dioxide emissions have a significant ($\alpha = 0.05$) positive effect on June temperature deviations however all other explanatory variables as indicated by the regression model do not have a statistically significant effect on June temperature deviations. The positive effect of carbon dioxide on June temperature deviations supports the notion that increases in global temperature over the years is as a result of increasing greenhouse gas emissions.

July precipitation deviations exhibited a significant negative relationship with time, corn acreage and water acreage. The negative sign on the coefficient of corn acreage does not meet the expectation of the study as research suggests rising corn production has led to an increase in July rainfall. According to the regression results carbon dioxide negatively affects July temperature deviations which does not meet our expectation. Corn acreage has a significant positive impact on July temperature deviations. The positive sign on the coefficient for corn acreage contradicts the what was expected because it is expected that increases in corn acreage should cause temperature deviations to fall. August precipitation deviations are positively influenced by time, corn acreage and square of water acreage. However, the parameter estimate for corn acreage is statistically not significant. It can be inferred that with each passing year actual August precipitation rises above the 30-year precipitation average, holding all factors constant.

August temperature deviations are significantly and positively affected by carbon dioxide, water acreage and square of corn acreage. Corn acreage negatively affects August temperature deviations however the parameter estimate is not significant. The square term of corn acreage nevertheless has a positive sign indicating that at higher acreages of corn plantings August temperature deviations are likely to fall. The sign on the carbon dioxide parameter estimate suggests that carbon dioxide tends to increase temperatures beyond the 30-year normal temperature and this effect meets the expectation of the study.

September precipitation deviations are positively influenced by time, square of corn acreage, square of water acreage. While corn acreage and water acreage negatively influence September precipitation deviations. Corn acreage despite being significant does not influence September precipitation deviations positively and this is contrary to the expectation of the study. However, the square of corn acreage has a significant positive effect on September precipitation deviations. This means at higher acreages of corn plantings it is possible for corn acreage to increase actual rainfall values above the 30-year normal. September temperature deviations are positively influenced by carbon dioxide emissions, square of corn acreage and water acreage. This positive impact of carbon dioxide emissions is supported by research that points out that increasing carbon dioxide emissions has resulted in actual temperature values to rise above the 30-year temperature normal. This positive effect of carbon dioxide is statistically significant. Corn acreage exhibits a positive relationship with September temperature deviations which contradicts the expectation of the study however the parameter estimate is not statistically significant.

Corn acreage is positively influenced by the prevented planting insurance policy, lagged corn acreage, lagged soybean acreage, expected soybean revenue as a proportion of corn revenue, operational cost of HRSW as a proportion of corn revenue and operational cost of corn as a proportion of expected corn revenue. Water acreage, expected revenue of HRSW as a proportion of corn revenue and operational cost of soybean as a proportion of corn revenue all have a significant negative effect on corn supply. Prevented planting insurance policy's positive impact on corn acreage indicates the importance of how crop insurance incentivizes corn producers to grow more corn. Lagged corn acreage has a significant positive effect on corn acreage because if a producer grows corn this year it is likely they would grow corn in the current season. Lagged HRSW acreage's negative sign suggests that if a farmer planted HRSW last year it is unlikely that the farmer would grow corn in the current season however this parameter estimate is not statistically significant. Since soybean is planted in rotation with corn in North Dakota it is likely that a producer that planted soybean in the previous season would plant corn in the current season. Water acreage's negative effect on corn acreage suggests that areas covered by water are unsuitable for corn production. Ethanol production's negative impact on corn acreage is unexpected because policies that boost ethanol production motivate farmers to grow more corn.

HRSW acreage is significantly and positively impacted by prevented planting insurance policy, previous year's HRSW acreage and previous year's soybean acreage. Previous year's corn acreage and water acreage all have a significant negative effect on HRSW acreage. The negative effect of ethanol production on HRSW acreage indicates that ethanol policy causes farmers to allocate more area to corn production thereby reducing acreage allocated to HRSW. This negative effect of ethanol production is not statistically significant. It can also be ascertained from the results that areas occupied by water make HRSW cultivation impossible.

Expected revenue of soybean relative to corn revenue and expected revenue of HRSW relative to corn yield all have a significant negative effect on corn yield. Corn yield is however positively affected by carbon dioxide and previous year's corn yield. The positive effect of carbon dioxide is expected because plants make use of carbon dioxide in the process of photosynthesis. HRSW yield is negatively impacted by carbon dioxide and previous year's HRSW yield and expected revenue of corn relative to expected HRSW. The negative effect of carbon dioxide on HRSW is what is unexpected because it is used as a raw material in photosynthesis and as such is expected to boost yield.

Table 2. Parameter estimates from the seemingly unrelated Tobit regression

Variable	Parameter Estimate	Standard Error	P-value
June precipitation deviations			
Year	0.0383438	0.0047715	0.000
Corn acreage	-0.0003028	0.0001083	0.005
Corn acreage squared	8.92E-08	1.75E-08	0.000
Weighted corn acreage	-0.000156	0.0000845	0.065
Water acreage	0.0002901	0.0000555	0.000
Water acreage squared	-3.79E-08	8.47E-09	0.000
Weighted water acreage	-0.0005336	0.0000623	0.000
Constant	-75.65004	9.565671	0.000
June temperature deviations			
Carbon dioxide	0.0418841	0.0005242	0.000
Corn acreage	-5.12E-06	0.000023	0.824
Corn acreage squared	3.52E-09	3.68E-09	0.339
Weighted corn acreage	0.0000141	0.0000173	0.415
Water acreage	0.0000123	0.0000111	0.267
Water acreage squared	-1.69E-09	1.70E-09	0.319
Weighted water acreage	0.0000213	0.0000128	0.096
Constant	-16.37492	0.1973195	0.000
July precipitation deviations			
Year	-0.053084	0.0045418	0.000
Corn acreage	-0.0004311	0.000098	0.000
Corn acreage squared	-2.00E-08	1.60E-08	0.210
Weighted corn acreage	-0.0002386	0.0000751	0.001
Water acreage	-0.0002056	0.0000494	0.000
Water acreage squared	3.15E-08	7.51E-09	0.000
Weighted water acreage	0.0000681	0.0000577	0.238
Constant	106.1151	9.107955	0.000

Table 2 Parameter estimates from the seemingly unrelated Tobit regression (continued)

Variable	Parameter Estimate	Standard Error	P-value
July temperature deviations			
Carbon dioxide	-0.0304005	0.0007268	0.000
Corn acreage	0.000048	0.0000217	0.027
Corn acreage squared	-9.85E-09	3.60E-09	0.006
Weighted corn acreage	0.0001493	0.0000159	0.000
Water acreage	-9.12E-06	0.0000119	0.445
Water acreage squared	3.89E-10	1.80E-09	0.829
Weighted water acreage	0.0002504	0.0000141	0.000
Constant	11.82022	0.274796	0.000
August precipitation deviations			
Year	0.079518	0.0050959	0.000
Corn acreage	0.0001638	0.0000977	0.094
Corn acreage squared	-3.00E-08	1.60E-08	0.060
Weighted corn acreage	-0.0004314	0.0000745	0.000
Water acreage	-0.0000926	0.0000481	0.054
Water acreage squared	2.25E-08	7.34E-09	0.002
Weighted water acreage	-0.0005984	0.000054	0.000
Constant	-158.468	10.22172	0.000
August temperature deviations			
Carbon dioxide	0.0061906	0.0009009	0.000
Corn acreage	-0.0000132	0.0000261	0.613
Corn acreage squared	2.57E-08	4.27E-09	0.000
Weighted corn acreage	-0.0001849	0.0000197	0.000
Water acreage	0.0000447	0.0000129	0.001
Water acreage squared	-5.76E-09	1.98E-09	0.004
Weighted water acreage	-0.0001325	0.0000149	0.000
Constant	-2.377944	0.3434213	0.000
September precipitation deviations			
Year	0.2106829	0.0072635	0.000
Corn acreage	-0.0002637	0.0000863	0.002
Corn acreage squared	6.46E-08	1.39E-08	0.000
Weighted corn acreage	-0.0005171	0.0000676	0.000
Water acreage	-0.0000837	0.0000409	0.041
Water acreage squared	2.67E-08	6.26E-09	0.000
Weighted water acreage	-0.0009059	0.0000522	0.000
Constant	-421.4863	14.58006	0.000

Table 2. Parameter estimates from the seemingly unrelated Tobit regression (continued)

Variable	Parameter Estimate	Standard Error	P-value
September temperature deviations			
Carbon dioxide	0.0317729	0.0010262	0.000
Corn acreage	6.31E-06	0.0000411	0.878
Corn acreage squared	1.28E-08	6.54E-09	0.050
Weighted corn acreage	0.0000443	0.0000312	0.155
Water acreage	0.0000639	0.0000198	0.001
Water acreage squared	-1.25E-08	3.02E-09	0.000
Weighted water acreage	0.0004551	0.0000219	0.000
Constant	-12.14598	0.3930255	0.000
Corn acreage			
Prevented planting	168.7587	14.94364	0.000
Ethanol production	-0.0014738	0.0002982	0.000
Lagged corn acreage	0.6523049	0.0044892	0.000
Lagged HRSW acreage	-0.0034222	0.0019217	0.075
Lagged soybean acreage	0.1024089	0.0025489	0.000
Expected soybean revenue relative to expected corn revenue	326.9149	51.13116	0.000
Square of expected soybean revenue relative to expected corn revenue	-173.7135	28.70019	0.000
Expected HRSW revenue relative to expected corn revenue	-547.5394	46.37045	0.000
Square of HRSW revenue relative to expected corn revenue	312.5286	28.9025	0.000
Operational cost of corn relative to expected corn revenue	465.3121	55.06666	0.000
Operational cost of soybean relative to expected corn revenue	-935.7417	72.48128	0.000
Operational cost of HRSW relative to expected corn revenue	423.5236	116.0618	0.000
Water acreage	-0.0396701	0.0055806	0.000
Water acreage squared	4.30E-06	8.45E-07	0.000
Weighted water acreage	0.0384356	0.007172	0.000
Constant	20.83354	25.46679	0.413

Table 2. Parameter estimates from the seemingly unrelated Tobit regression (continued)

Variable	Parameter Estimate	Standard Error	P-value
Corn yield			
Carbon dioxide	0.4060175	0.0523999	0.000
Carbon dioxide squared	-0.0004816	0.0000677	0.000
Lagged corn yield	0.2597606	0.0074873	0.000
Expected soybean revenue relative to expected corn revenue	-2.201099	0.1297786	0.000
Square of expected soybean revenue relative to expected corn revenue	1.002017	0.0671976	0.000
Expected HRSW revenue relative to expected corn revenue	-0.3509389	0.1214792	0.004
Square of HRSW revenue relative to expected corn revenue	0.627577	0.0725636	0.000
Water acreage	0.0000205	0.0000157	0.192
Water acreage squared	-1.36E-09	2.42E-09	0.573
Weighted water acreage	0.000316	0.0000206	0.000
Constant	-79.74462	10.13974	0.000
HRSW acreage			
Prevented planting	256.1191	26.17805	0.000
Ethanol production	-0.0003778	0.0005979	0.527
Lagged HRSW acreage	0.7219327	0.0039223	0.000
Lagged corn acreage	-0.106986	0.008924	0.000
Lagged soybean acreage	0.0496179	0.0053745	0.000
Expected soybean revenue relative to expected HRSW revenue	39.08798	27.567	0.156
Square of expected soybean revenue relative to expected HRSW revenue	-7.985374	5.297739	0.132
Expected corn revenue relative to expected HRSW revenue	-124.1717	27.31131	0.000
Square of expected corn revenue relative to expected HRSW revenue	5.556142	4.789238	0.246
Water acreage	-0.1251513	0.0107938	0.000
Water acreage squared	6.81E-06	1.63E-06	0.000
Weighted water acreage	-0.2217912	0.0145618	0.000
Constant	850.1841	33.63079	0.000

Table 2. Parameter estimates from the seemingly unrelated Tobit regression (continued)

Variable	Parameter Estimate	Standard Error	P-value
HRSW yield			
Carbon dioxide	-0.0885641	0.0217106	0.000
Carbon dioxide squared	0.0001473	0.0000281	0.000
Lagged HRSW yield	0.1003454	0.0070112	0.000
Expected soybean revenue relative to expected HRSW revenue	0.041356	0.0152856	0.007
Square of expected soybean revenue relative to expected HRSW revenue	-0.0059735	0.0026886	0.026
Expected corn revenue relative to expected HRSW revenue	0.1893702	0.0137702	0.000
Square of expected corn revenue relative to expected HRSW revenue	-0.0248108	0.0023752	0.000
Water acreage	4.22E-06	6.49E-06	0.515
Water acreage squared	3.06E-10	9.94E-10	0.758
Weighted water acreage	0.0000192	8.09E-06	0.018
Constant	14.17719	4.201052	0.001
N = 28,455	**Wald X^2 (270) = 207,939.54**		

Estimation of marginal effects of independent variables on dependent variables

To obtain the marginal effects of predictor variables on an independent variable in the study, Monte Carlo simulation was used to make random draws from the joint normal distribution of parameter estimates from the seemingly unrelated Tobit regression model. The simulated vector of parameter estimates was substituted into equation 8. together with predictor variables and then averaged by location over the entire period of the study. Figure 6. to figure 19. present graphs to illustrate the marginal effects of some dependent variables on monthly temperature deviations and precipitation deviations, corn yield and corn acreage.

From figure 6. it is evident that the effect of corn acreage on June precipitation deviations is statistically insignificant at lower levels of acreage of corn planted. However, at about 2,500 hectares an increase in corn acreage leads to a statistically significant increasing marginal response from June precipitation deviations across the various cross-sectional units in North

Dakota. This gives an indication that corn acreage to some extent causes rainfall to rise in North Dakota. As presented in figure 7. the marginal effect of corn acreage on June temperature deviations exhibits a positive. However, this impact is not statistically significant.

In July, figure 8. shows that corn acreage elicits a significant decreasing marginal response from precipitation deviations. Any increase in corn acreage tends to push actual July precipitation values further below the 30-year precipitation average. This relationship is unexpected since research suggests that corn acreage has increased rainfall in these areas. Figure 9. shows that at lower levels of acreage planted of corn (0 to about 5,000 hectares) temperature deviations exhibits a decreasing marginal response to corn acreage. The effect at these levels is statistically insignificant. However, above 5,000 hectares of corn acreage a one hectare increase in corn acreage causes July temperature deviations to fall by about 0.060 ºC to 0.110 ºC across the various cross-sectional units of the study and this effect is statistically significant. This decreasing relationship is expected as some studies have suggested that corn production has resulted in a decrease in temperature in some parts of the U.S.

August precipitation deviations as illustrated in figure 10. is negatively influenced by corn acreage. However, this negative marginal response is not statistically significant at any level of corn acreage. August temperature deviations also fail to meet expectations of the study as illustrated by figure 11. This is because an increase in corn acreage by one hectare causes temperature deviations to rise by 0.038 ºC - 0.397 ºC and this effect is only statistically significant at corn acreage levels above 1,000 hectares. Figure 12. shows that one hectare increments in planted acreage of corn causes September precipitation deviations to rise but this is only significant at levels of corn acreage above between 0-1,000 hectares and above 3,000 hectares. This result is as expected because increasing corn acreage has positive effect on rainfall as suggested by a plethora of studies. From figure 13. a one hectare increase in planted acreage of corn is shown to cause September temperature deviations to rise. However, this marginal effect is statistically insignificant at lower levels of corn acreage (less than 2,000 hectares). This observation goes contrary to the expectation of the study. When global carbon dioxide concentration increases by one ppm HRSW yield rises by about 0.02 to 0.03 Mg/ha (figure 14.) while global carbon dioxide concentration causes corn yield to fall by about 0.01 to 0.05 Mg/ha (figure 15.). The marginal effect of carbon dioxide on yield is statistically significant for both corn and HRSW.

As illustrated in figure 16. the price of corn has a negative marginal effect on corn yield such that a $1.00 increase in the price of a megagram of corn will cause corn yield to fall. Figure 17. shows that a unit price increase by $1.00 will cause corn acreage by about 66.20 to 334.74 hectares. This own-price marginal effect is statistically significant. Corn acreage has a negative marginal response to soybean price (figure 18.). At about $420.00 per megagram a $1.00 increase in the price of soybean will cause corn acreage to fall but this relationship is not statistically significant at price levels between $420 to $540 $ per megagram. As shown by figure 19. a $1.00 increase in the price of a megagram of wheat will cause corn acreage to rise. However, at prices between $300.00 to $400.00 per megagram this cross marginal effect is not statistically significant.

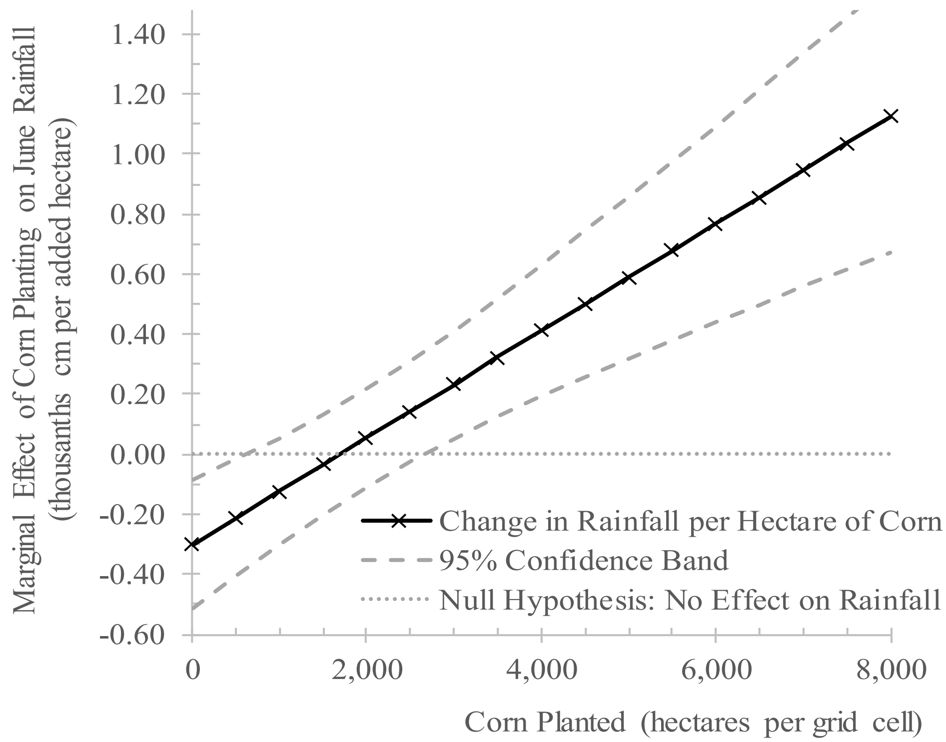

Figure 6. Marginal effect of planted area of corn on June precipitation

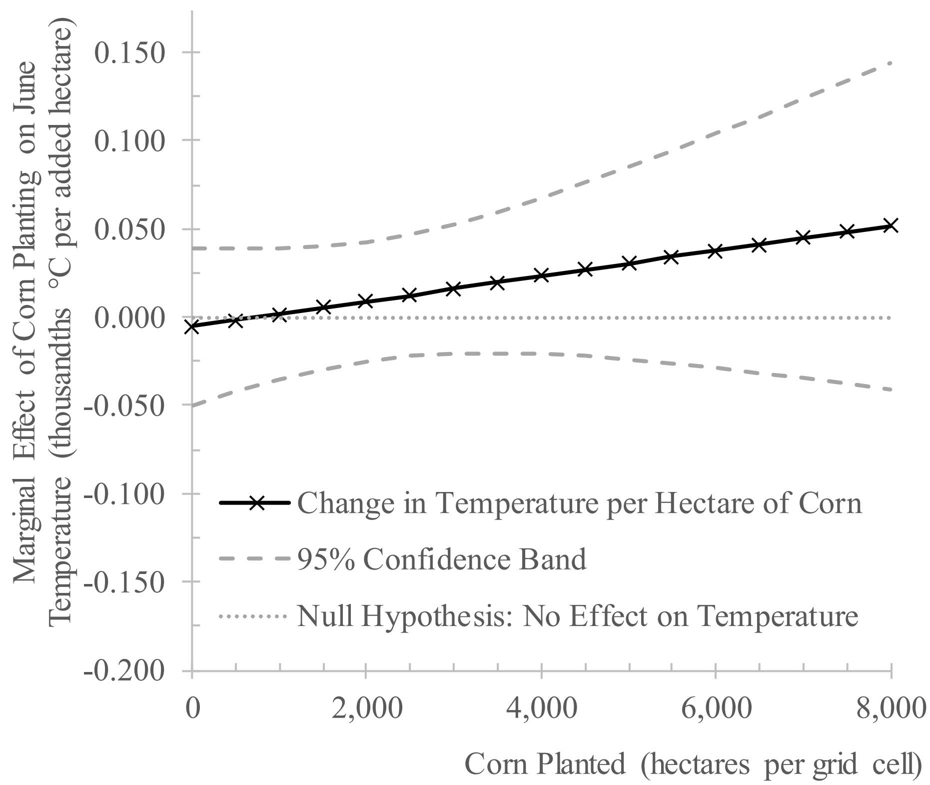

Figure 7. Marginal effect of planted area of corn on June temperature

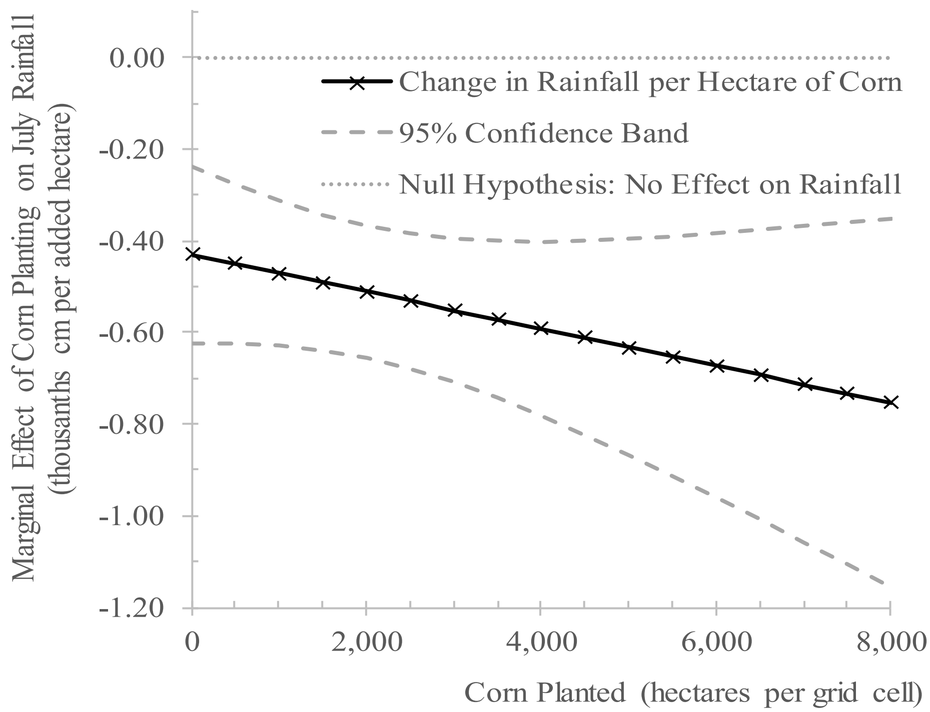

Figure 8. Marginal effect of planted area of corn on July precipitation

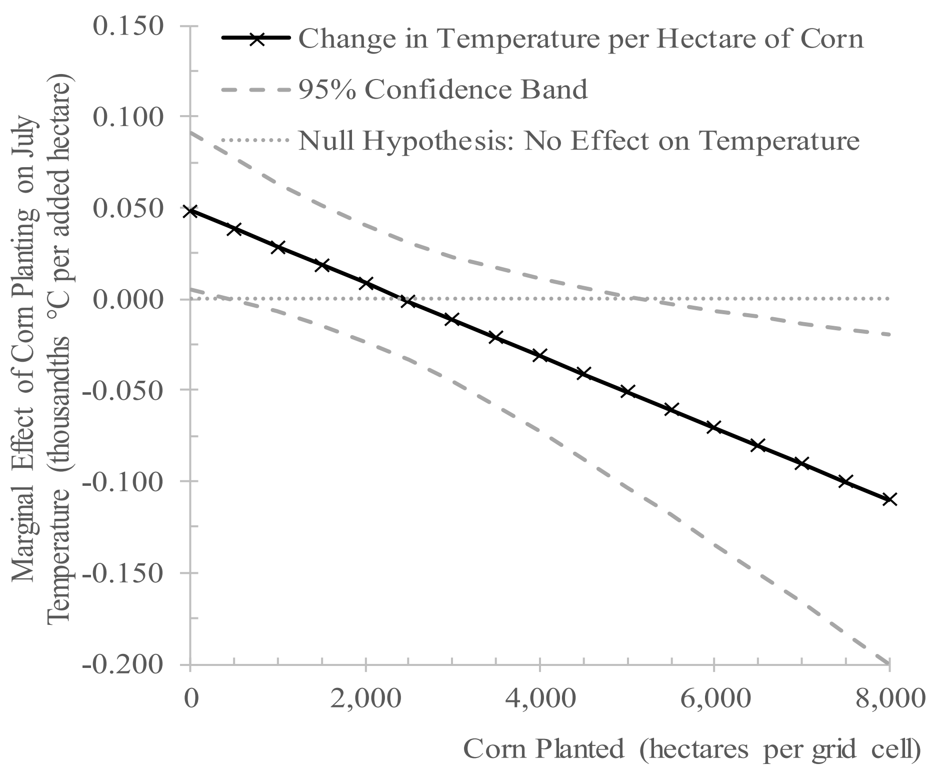

Figure 9. Marginal effect of planted area of corn on July temperature

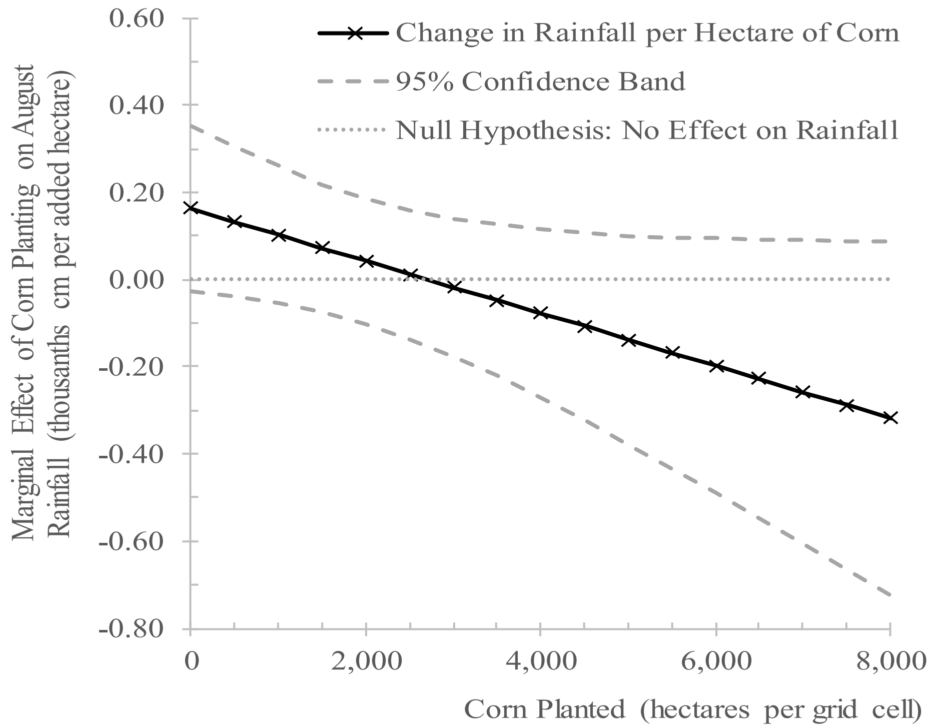

Figure 10. Marginal effect of planted area of corn on August precipitation

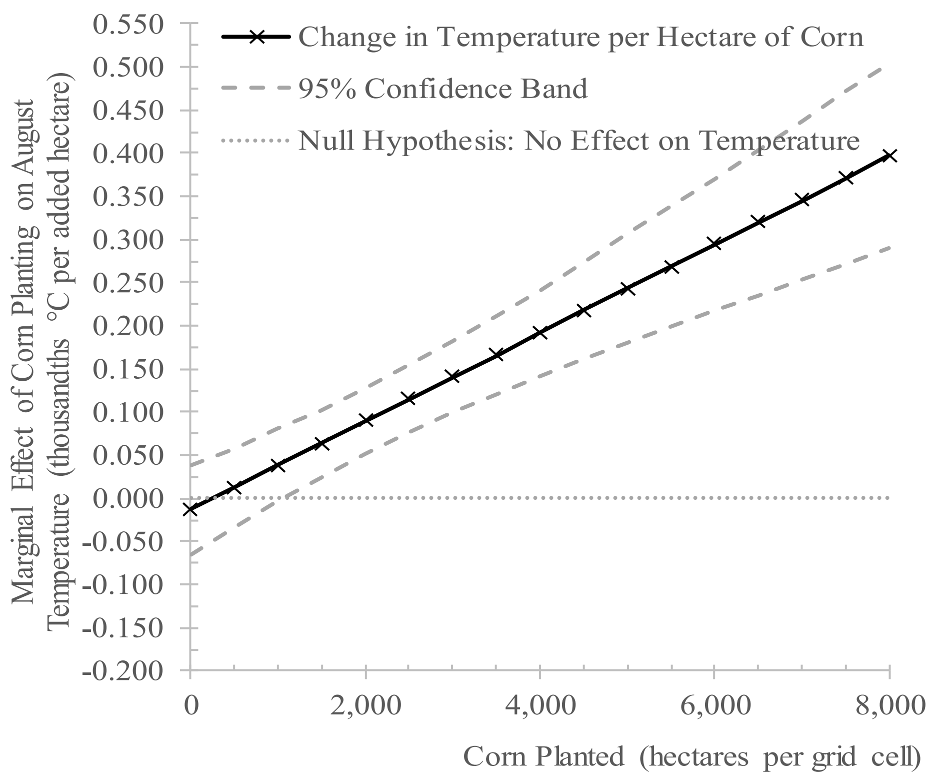

Figure 11. Marginal effect of planted area of corn on August temperature

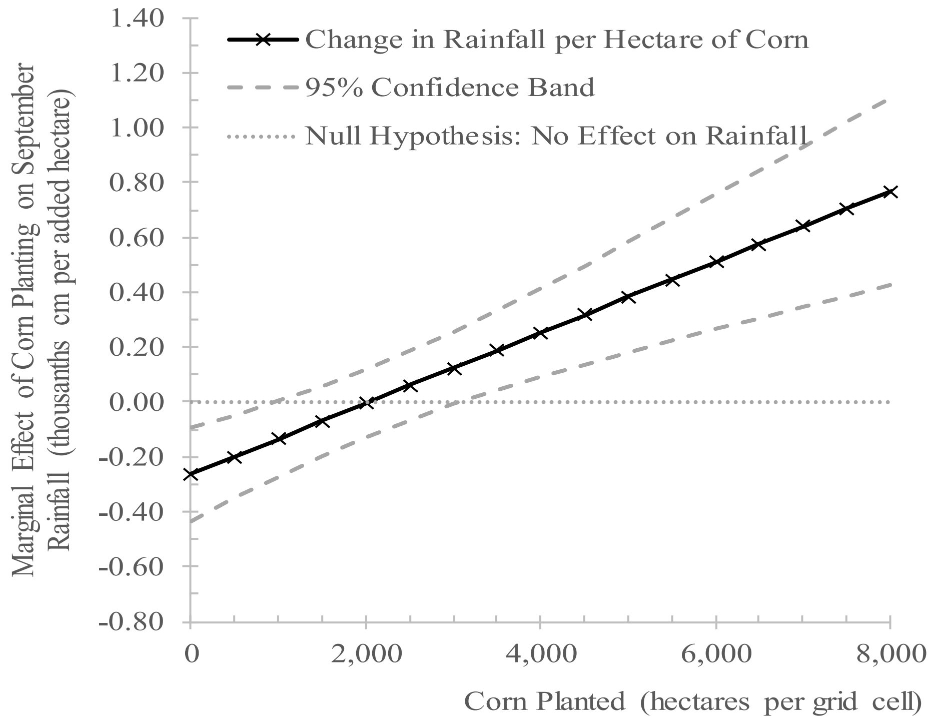

Figure 12. Marginal effect of planted area of corn on September precipitation

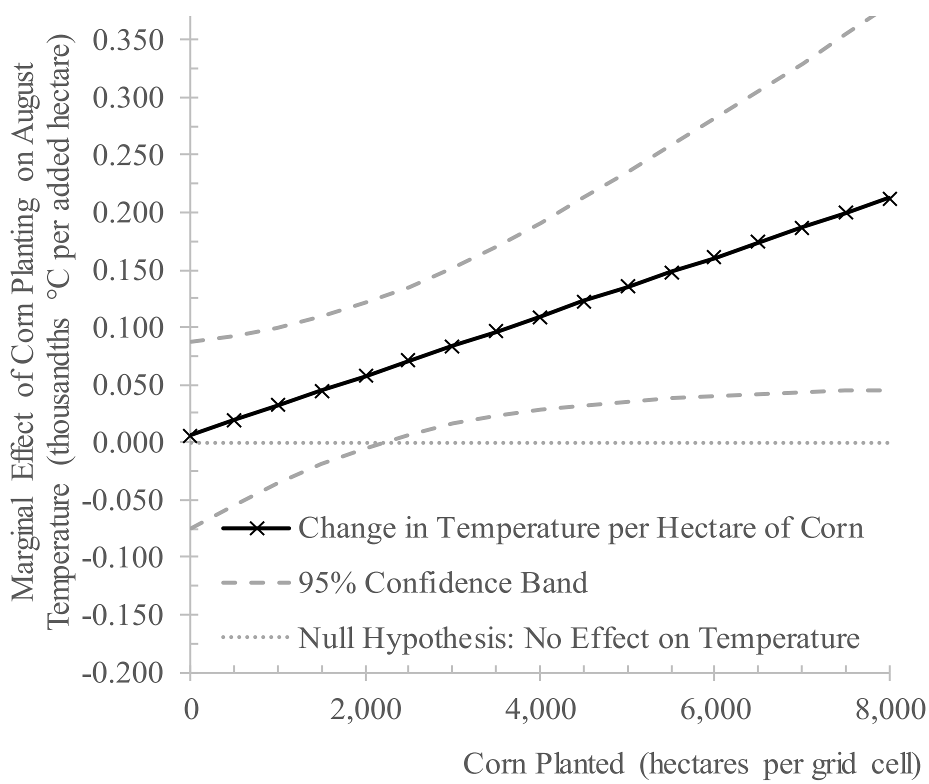

Figure 13. Marginal effect of planted area of corn on September temperature

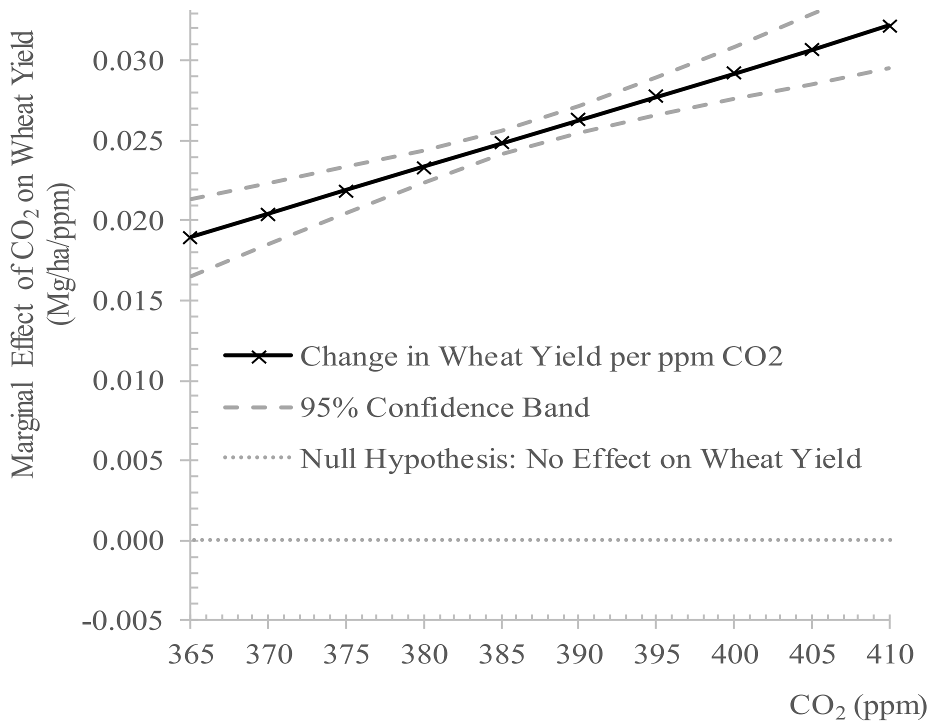

Figure 14. Marginal effect of carbon dioxide on HRSW yield

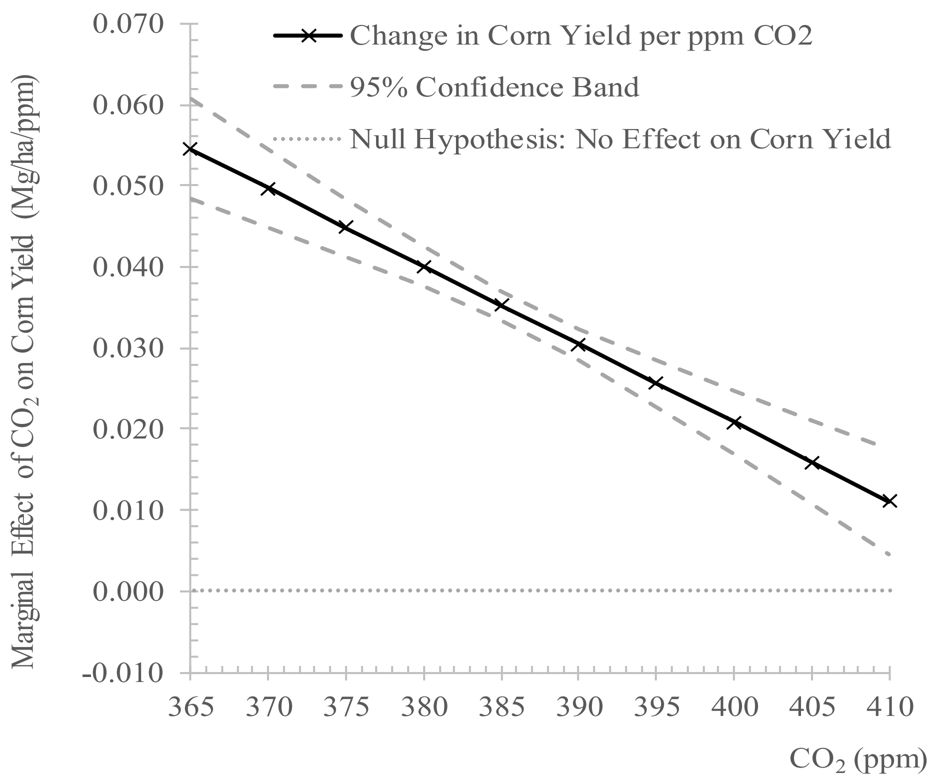

Figure 15. Marginal effect of carbon dioxide on corn yield

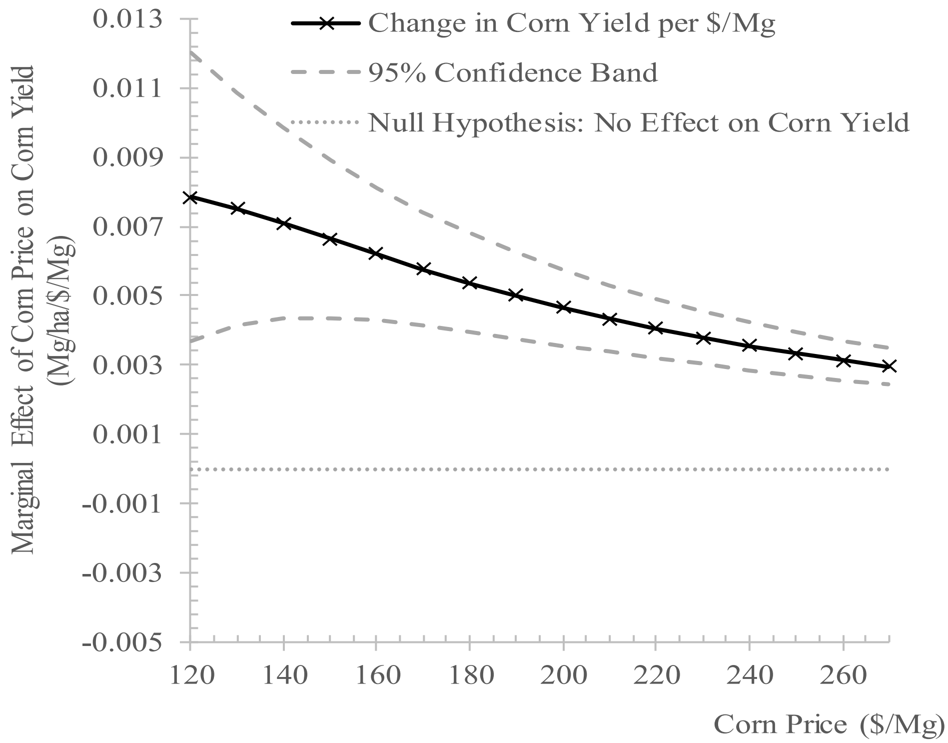

Figure 16. Marginal effect of corn price on corn yield

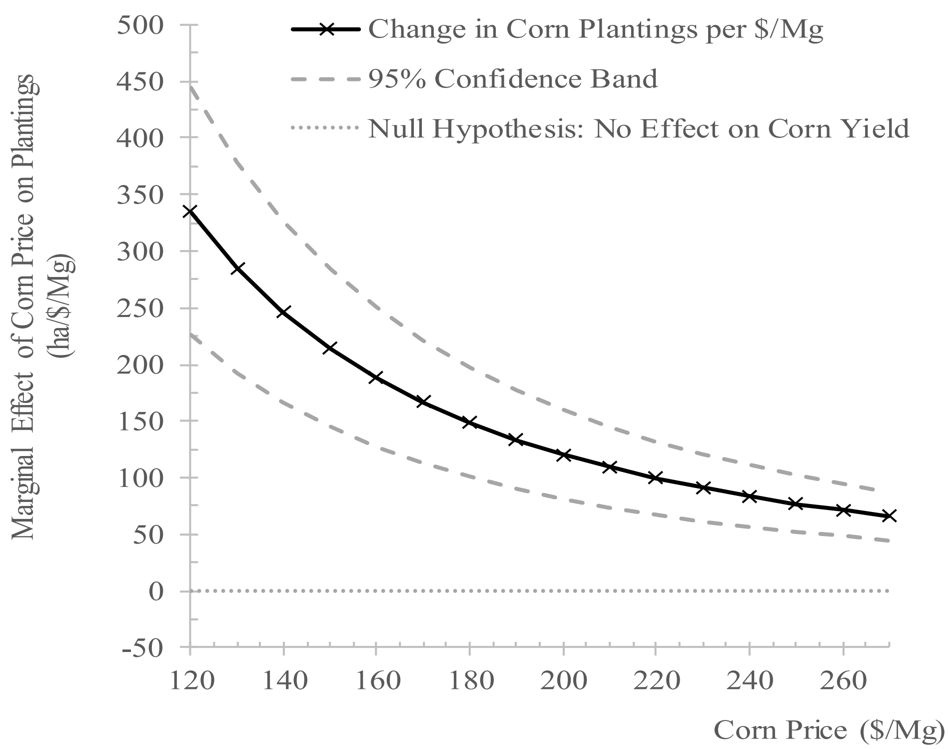

Figure 17. Marginal effect of corn price on corn planting

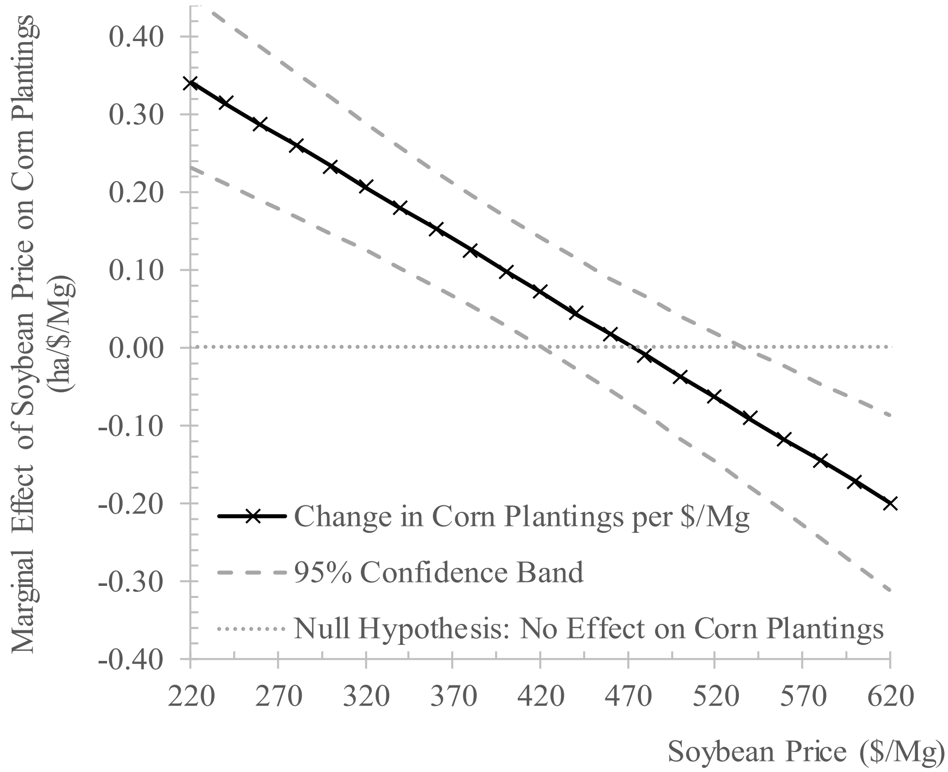

Figure 18. Marginal effect of soybean price on corn planting

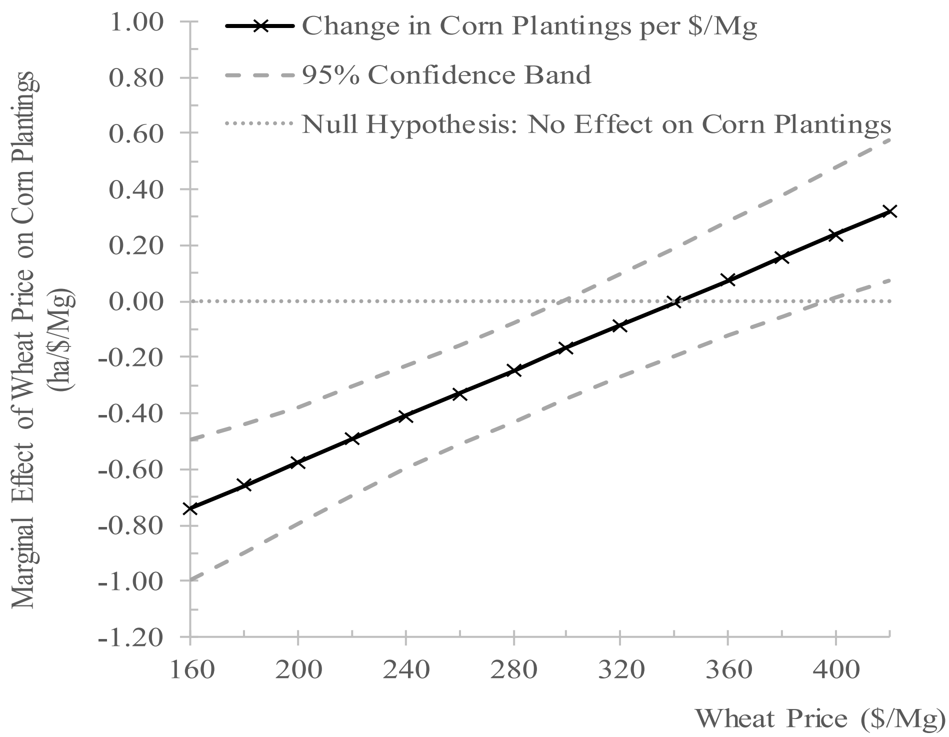

Figure 19. Marginal effect of wheat price on corn planting

CHAPTER 5. CONCLUSIONS

The purpose of this study was to examine how changing cropping patterns especially increased corn production may be contributing to changes in rainfall and temperature during the months of June, July, August and September. This was done by developing a seemingly unrelated Tobit regression model to analyze the connection among acreage, yield, expected prices, operational costs, greenhouse gas emissions, temperature, precipitation, agricultural policy and energy policy. Twelve regression equations were estimated consisting of two acreage equations, two yield equations, four temperature equations and four rainfall equations. The model was estimated using full information maximum likelihood estimation. The study used data covering the period 1998-2018. Principal component analysis was used to control for multicollinearity. Also, some variables used in the development of principal components but were not used directly in the regression estimation include latitudes, longitudes, actual temperature and rainfall values. Marginal effects and elasticities were estimated to better understand and quantify the relationships that exists among some variables.

Findings from the study indicate that temperature and precipitation are to some extent impacted by corn production. Corn acreage had a negative effect on August precipitation deviations. However, in instances where there was a negative relationship between corn acreage and precipitation, the estimation of the marginal effects reveals that at higher acreages corn plantings are likely to increase rainfall as shown in the case of the months of June and September. These findings are in line with results from other studies that indicate that increasing corn production may be responsible for rising rainfall in the U.S. Midwest. Also, it can be inferred from the study that corn acreage causes June, August and September temperatures to fall but this effect is not statistically significant and could be as a result of the significant negative effect of carbon dioxide on temperature in these months. These negative effects of carbon dioxide on monthly average temperatures were unexpected, but a reasonable *post hoc* explanation (that needs to be tested) is that CO_2 fuels photosynthesis, which is itself an endothermic (cooling) chemical process because it converts solar radiation into stored glucose and cellulose rather than re-emitting it as heat. The impact of carbon dioxide on global temperatures cannot be overstated as the findings show it is a major contributor to rising global temperatures. An important aspect of this study was to determine how factors that influence agricultural production may also be influencing regional weather patterns. As shown by the study, government policies that increase the price of corn are likely to increase corn production and this may in turn have an impact on local weather patterns. Also policies that cause farmers to switch from producing crops that are substitutes to corn in order to allocate more acreage to corn production are likely to influence local weather patterns.

This study provides several important ideas for future research. This study was conducted in North Dakota because the state has experienced some tremendous increase in corn production over the last two decades; however, future studies may want to examine the impact of increasing crop production at the regional level covering the entire U.S. Midwest. It could provide an interesting challenge since there has not been much variation in corn production over the period in most of other states in the region. Also, effects of topography and the direction of the prevailing wind may be included in future research.

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