# Essays on Climate Change Interactions with Agricultural Land and Water Use

by

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B.A., Obafemi Awolowo University, Ile Ife, Nigeria, 2008

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AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the
requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
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# Abstract

Agriculture and climate change are closely connected as climate change impacts agriculture through crop yield loss, reduction in area harvested and increase in irrigation water use. Agriculture plays both roles in the emission and sequestration of greenhouse gases. This dissertation is divided into two main parts. The first part has two essays that examine the impacts of climate change on winter wheat production and irrigation water use. The second part examines the cost–effectiveness of using lands under the Conservation Reserve Program (CRP) to sequester carbon through tree planting program. This dissertation contributes to the literature by showing how crop yield variability is not the same as production variability. The total impact of climate change is underestimated if climate change impact on yield alone is used. Another contribution to the literature is the modeling of crop abandonment in relation to climate change using correlated random effects fractional probit model. My work also illustrates how irrigation water use will change and how this change will impact the level of water in the aquifer by mid–century.

In my first essay, I examine the impact of climate change on winter wheat production in Kansas. I decompose the total impact of weather variables on wheat production in Kansas through crop abandonment and yield. Using yield impacts alone to measure the climate change impact on production underestimates the total impact of climate change on production. I use the correlated random effects fractional probit model to estimate crop abandonment and account for unobserved heterogeneity between time–invariant variables and yield. The result projects a 16.3% decrease in winter wheat production by mid–century under the Representative Concentration Pathway (RCP) 4.5. I find that 86.72% of the projected decrease in production is due to the reduction in yield while crop abandonment is projected to decrease production by 13.17%. Yield is projected to decrease by 14.12% while

crop abandonment is expected to increase by 18% by mid–century. Majority of damages from climate change are explained by an increase in temperature.

In the second essay, I examine the impact of climate change on groundwater extraction for corn production in Kansas. Using a 24–year panel data of irrigation water use, weather and soil data, I estimate the impact of weather variability on irrigation water use for corn. I include the field–level fixed effects and a quadratic time trend to control for time invariant–variables and technological progress over time. I provide new evidence that shows farmers are less responsive to changing irrigation water use than an irrigation schedule would predict due to changes in weather. The result indicates 9% and 12% increase in irrigation water use by mid–century under RCP 4.5 and 8.5 respectively. The number of water rights that exceed their authorized water quantity will increase by 18.1% on average across different climate models under RCP 4.5. The effect of an increase in irrigation water use on the water level in the aquifer is spatial different. In Southwest Kansas, the historical rate of depletion is 2.05ft/year and by mid-century, the rate of depletion is projected to increase to 2.43 ft/year. In South Central Kansas, historical depletion is around 0.19 ft/year and the rate of depletion is predicted to increase to 1 ft/year by mid-century.

In the third essay, I analyze the cost–effectiveness of carbon sequestration through the afforestation of the Conservation Reserve Program (CRP). I use the correlated random effects probit model (CRE) to estimate the impact of an increase in the Conservation Reserve Program (CRP) payments on land use change. The CRE model allows me to control for unobserved heterogeneity and exploit variation in returns to land over time. Estimation without control for unobserved heterogeneity produces biased estimates with coefficients with the wrong sign. My estimates are used to simulate land use change, carbon sequestered and the marginal cost of carbon at different levels of CRP rent (i.e., the supply curve for carbon sequestration). At the average CRP rent rate of $71.21, 118,046 acres is gained by CRP and 2.1 million tons of carbon is sequestered per year at a marginal cost of $24.6. Increasing the average rent by 30% will add additional 159,736 acres and 0.24 million tons of carbon per year.

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Approved by:

Major Professor
Nathan Hendricks

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crop abandonment is expected to increase by 18% by mid–century. Majority of damages from climate change are explained by an increase in temperature.

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# Dedication

To my loving mother and my beloved wife and children

# Chapter 1

# Introduction

Climate change and agriculture are closely connected. Numerous studies have examined the relationship between climate change and agriculture and how climate change and agriculture impact each other (Hendricks et al., 2018; Howden et al., 2007; Lubowski et al., 2006; Nelson et al., 2009; Rosenberg et al., 1999; Schlenker and Roberts, 2009). Figure 1.1 shows the interaction and impacts of climate change on agriculture, and how agricultural activities contribute both to the emission of greenhouse gases and sequestration of carbon from the atmosphere. The red arrow in figure 1.1 shows that climate change impacts agriculture by affecting yield, area harvested, and irrigation water use.

Climate change impacts agriculture in two main ways: (i) warming and drought conditions increase the chance of crop failure which may result in crop yield loss and reduction in the area harvested, and (ii) the increasing temperature and variability in pattern and amount precipitation impacts crop water demand and use. Extreme climate events do not impact yield alone, but can also cause some area of the field planted to be abandoned. The impact of agriculture on climate change can be divided into two categories: (i) agricultural activities contribute to climate change through land use change and emission of greenhouse gases as a result of deforestation, bush burning and management practices and, (ii) agricultural practices can mitigate climate change through carbon sequestration, such as the afforestation of agricultural lands. About 6% of all greenhouse gas emissions originating in the United

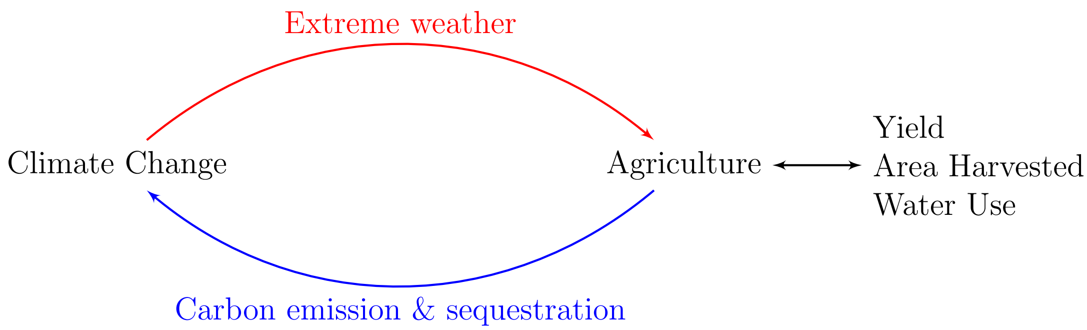


**Figure 1.1**: *The Interaction between Agriculture and Climate Change*

States come from agricultural activities (Denef et al., 2011). Agricultural activities like rice production and deforestation increase carbon emissions which causes climate change while the same agricultural programs like the adoption of conservation practices and afforestation can be used to mitigate climate change (Canadell et al., 2007; Dale, 1997; Guo and Gifford, 2002; Karl and Trenberth, 2003; Lal, 2004).

My first essay analyzes how crop production responds to weather shocks. The IPCC (2013) projects an increase in temperature between 0.9$^o$C and 5.4$^o$C by the end of the century. As the global average surface temperature increases over the 21st century, these changes will create different impacts on agriculture. Corn yield is projected to decrease by 30–46% as a result of warming (Schlenker and Roberts, 2009), and dryland wheat yield is projected to decline by 32% due to reduction in precipitation (Hernandez-Ochoa et al., 2018). Variability created by climate change will perturb cropping patterns and growing season length, reducing crop production as demand for food increases due to population increase (Iizumi and Ramankutty, 2015; Lobell and Burke, 2010).

Therefore, I examine how responsive is wheat production through yield and harvested acres to weather shocks. The majority of existing studies on yield–weather relationship use yield measured as total production divided by area harvested (Berry et al., 2014; Miao et al., 2016; Schlenker and Roberts, 2009). Apart from using this harvested yield information, some of the literature uses yield as the sole source of variation in production (Berry et al., 2014; Gammans et al., 2017). Using these methods underestimate the total effect during extreme weather conditions. I decompose the total impact of climate change on production in Kansas through yield and crop abandonment. There is crop abandonment when a portion of the planted acres are not harvested because the adverse weather shocks reduce the yield below the point where the value of production is less than the cost of harvesting. Kansas is the number one state for winter wheat production in the United States and ranked 49th in the world based on acres planted. I use the correlated random effects fractional probit model to estimate crop abandonment and account for unobserved heterogeneity. I use 18 different general circulation models to project the impact of climate change on winter wheat yield, crop abandonment and production by mid–century. I find that using climate change impacts on yield alone to represent climate change impact on production underestimates the total impacts from climate change.

In the second essay, I examine the impact of climate change on irrigation in Kansas. Irrigation water demand and use will change in the future especially in the High Plains as the variability created by climate change increases. Döll (2002) shows that about two–thirds of the global area equipped for irrigation suffer from increased water requirements due to an increase in temperature. De Silva et al. (2007) shows that a 3.5% increase in potential evapotranspiration will increase irrigation water use by 23% due to rain ending earlier. According to Steward et al. (2013), about 39% of the total water left in the High Plains Aquifer is expected to be depleted over the next 50 years (Steward et al., 2013), while a 35% reduction is expected in the areas of the southern High Plains supported by irrigation due to increase in depletion rate and demand for water (Basso et al., 2013; Döll, 2002; Scanlon et al., 2012). Increase in the global average surface temperature means an increase in crop water demand and use. Gondim et al. (2012), Döll (2002) and Fischer et al. (2007) all project an increase in irrigation water demand as climate changes. With the projected depletion of the Ogallala aquifer in the future, more pressure is expected to be exerted on the aquifer.

In the second essay, I examine the impact of climate change on groundwater extraction for corn production in Kansas. More than 90% of the irrigation water pumped in Kansas is used for agriculture with more than 3.3 million acre–feet of water applied annually to approximately 3 million irrigated acres (Lanning-Rush, 2016). More than 50% of the irrigated acreage is used for corn production in Kansas, while billions of dollars are contributed in revenue annually to the economy through the continued dependence on the aquifer. This narrative will probably change in the future as the aquifer is completely depleted (Scanlon et al., 2012; Steward et al., 2013). This means that any increase in crop water requirements will likely increase irrigation water use which will further put more pressure on the aquifer. I combine farm–level water use information, climate data, soils data and price information to explain how precipitation variability and warming effects of temperature impacts irrigation water use. I provide new evidence that shows how farmers react to increasing irrigation water demand when climate changes. I also simulate how the enforcement of authorized water quantity will reduce irrigation water use if fully enforced. I also assess the impact of climate change on the change in the rate of depletion of the High Plains Aquifer across the major Groundwater Management Districts (GMDs). Irrigation water use is projected to increase as temperature increases by mid–century. The impact of climate change on the level of water in the aquifer varies substantially across the GMDs in Kansas.

In the third essay, I examine how land use change can be used to mitigate climate change. Land use will change due to different reasons especially to meet human development and its nutritional needs as the world population continues to surge.[1] Land use and other activities especially on agricultural land can cause or mitigate climate change. Land use change distorts the dynamics of $CO_2$ exchange between the soil, plant and the environment that occur through photosynthesis and respiration processes. In 2015, land conversion to cropland released 23.2 MMT $CO_2$ equivalent while 75 MMT of $CO_2$ equivalent was sequestrated from land that transitioned to forestry.[2] Trees and other vegetation can sequester carbon in their biomass and soils through the photosynthetic conversion of $CO_2$ to carbon. For instance, one of the aims of the Kyoto Protocol was to reduce climate change by reducing greenhouse gases through forest sequestration.

The third essay examines the cost-effectiveness of mitigating climate change through forest restoration of agricultural land. The Conservation Reserve Program (CRP), one of

[1] More than 50 million acres associated with deforestation will take place in U.S. by 2051 as the population reaches 400 million (Alig et al., 2010) [2] Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2016 at https://www.epa.gov/sites/production/files/2018-01/documents/2018_complete_report.pdf.

the USDA programs established by the Food Security Act of 1985, provides annual rental payments to farmers and landowners to voluntarily retire environmentally sensitive land from agricultural production for the duration of 10 to 15 years. Currently, there are over 23 million acres of land under CRP (USDA-FSA, 2015). Apart from carbon sequestration, reforestation of CRP land has the potential of reducing carbon emissions, erosion and improving water quality (Goodwin and Smith, 2003; Gorte, 2009). I combined a parcel–level data on land use choice and quality from the National Resources Inventory (NRI) with the county–level estimates of annual net returns (per acre) for six major crops and CRP returns between 2000 and 2012 for the Southeastern parts of the United States. I use the correlated random effects probit model (CRE) to estimate the impact of an increase in CRP payments on land use change. I simulate the amount of carbon that will be sequestered on a CRP parcel under the tree–planting program. Carbon flow increases as the CRP return increases. Increasing CRP rent to the social cost of carbon will increase the amount of carbon sequestered. I find that increases in crop prices reduce land enrolled in the CRP program and results in net carbon emissions.

# Chapter 2

# Climate Change Impacts on Wheat Production

## 2.1 Introduction

Changing climatic conditions are becoming one of the major challenges facing agricultural production globally as demand for staple foods increases as the world population moves toward 9 billion by 2050. Despite the fact that advancements in agriculture production have improved agricultural productivity, risk due to climate change has also increased (Ortiz-Bobea et al., 2018; Wang et al., 2015). Wheat is one of the most important staple foods consumed globally, with the USA producing 8% of the world's total production (Bond and Liefert, 2015). With continuous changes in climatic conditions, it may be difficult to guarantee production of staple foods in the future as extreme heat events in the spring and freezing temperatures in the fall are considered to be the largest drivers of winter wheat yield loss (Tack et al., 2015). For example, Kansas, the leading state in winter wheat production abandoned 1.05 million acres (11.1 percent of the planted acres) in 2013 due to below freezing temperature in the second week of April and mostly above normal temperatures throughout June (USDA, 2016).

I examine how responsive is wheat production through yield and harvested acres to weather shocks. Climate change impacts agriculture in different ways in terms of crop mix, planting date, yield and harvested area (Cho and McCarl, 2017; Deschenes and Greenstone, 2007; Kang et al., 2009; Miao et al., 2016; Nelson et al., 2009; Schlenker and Roberts, 2009; Tack et al., 2015). There are two sources of variation in production: yield and acres harvested. I focus on dryland winter wheat production because 93% of the wheat acres planted in Kansas are under dryland production, which is vulnerable to weather and secondly, winter wheat is almost a year–long production where a lot of things can go wrong between planting and harvesting due to weather shock. Increasingly unfavorable conditions under observed and projected climate change conditions are expected to impact wheat production variability as harvested areas are exposed to more extreme temperature and yield damage (Gourdji et al., 2013). Tack et al. (2015) using experimental yield find freezing temperatures in the fall and extreme heat events in the spring as the largest drivers of yield loss. Zampieri et al. (2017) attribute wheat yield loss to heat waves, drought and water excess at the global, national and subnational scales. Asseng et al. (2015) using 30 different wheat simulation models predict a 6% fall in global wheat production for each 1$^o$C increase in temperature, while Finley (1963) highlights government programs and weather as some of the reasons for the change in harvested acres.

There is a long list of literature that analyzes the impact of weather shocks on yield measured as total production divided by harvested acres (Lobell et al., 2008; Miao et al., 2016; Schlenker and Roberts, 2009). Extreme weather can cause some of the planted acres to be abandoned reducing harvested acres. Then measuring the impact of weather on harvested yield underestimates the impact on total production. According to Schlenker and Roberts (2009), the use of harvested yield presents a selection problem during extremely bad years when yields are close to zero and farmers choose not to harvest. Maunder (2012) explains that yield information that does not consider abandonment can lead to inflated estimates.

A majority of the existing literature uses yield variability as the sole source of variation in production (Asseng et al., 2015; Gammans et al., 2017; Kukal and Irmak, 2018; Schlenker and Roberts, 2009). Schlenker and Roberts (2009) and Gammans et al. (2017) use average growing area and weather impact on yield to estimate the total impact of climate change on production. The use of average acreage ignores the relationship between the area harvested, weather and other factors that may influence production. Kukal and Irmak (2018) use yield variability as production variability. Winter wheat is a long duration crop facing different temperature ranges and damages before harvest (Shroyer et al., 1995), therefore, accounting for crop abandonment is important. Iizumi and Ramankutty (2015) define annual production as a product of harvested yield, harvested area, and cropping intensity. The impact of weather variability on production is extensive for the use of yield variability alone to capture. Maunder (2012) highlight that the portion of the field abandoned are probably the poorest acres which are most sensitive to climate impacts.

I decompose the total impact of weather shocks on production through its impact on harvested yield (total production divided by harvested area) and crop abandonment (the portion of the planted acres not harvested). Only a few studies have estimated the separate responses of production, harvested area and yield to climate (Koide et al., 2013; Lobell et al., 2008). Based on Iizumi and Ramankutty (2015)'s definition of production, cropping intensity is set to one as winter wheat can only be cultivated once in a year. Winter wheat is planted in the fall, goes through vernalization during the winter (Herbek and Lee, 2009), resisting freeze, and reaches maturity in the spring when the conditions are ideal. There can be crop abandonment or crop failure. Crop failure and abandonment are both caused by extreme weather conditions and the distinction between crop failure and abandonment are based on the degree of damage. Mendelsohn (2007) defines the complete loss of crops on a farm as crop failure.

There is crop abandonment when a portion of the planted acres is not harvested because adverse weather shocks have reduced the yield below the point where the value of production is less than the cost of harvesting. Crop abandonment depends mainly on crop performance and the area harvested. Sometimes crop abandonment decision depends on crop's expected price and moral hazard (Chen et al., 2007; Miao et al., 2016), and sometimes it depends purely on the weather (USDA, 2016). Koide et al. (2013) find a positive correlation between area harvested and precipitation for rice production in the Philippines. If the weather is bad during a cropping season, a farmer has to decide either to abandon acres before harvest or harvest yield at a loss. For example, crop abandonment in Kansas is as small as 4% of the total wheat area, but there are some years where loss from crop abandonment is as high as one-quarter of the total area for wheat in Kansas (Figure 2.1).

Depending on the stage of production, a farmer may decide to abandon a portion of the planted acreage if the degree of possible damage by extreme heat or freeze is severe enough. If the damage is early, the farmer can replant with the initial cost at this stage being considered as a sunk cost. Late frost during early grain filling cause yield loss between 13 and 33% as grains was 80% lighter in spikes (Cromey et al., 1998). Barlow et al. (2015) identified freeze to have the greatest impacts on production as it is associated with sterility and the abortion of formed grains around anthesis. Warm temperatures during the winter stop hardening very early, setting the crop for further damage when cold temperatures set in during spring (Li et al., 2015). Extreme drought during major development also results in poor development and reductions in yield. If the damage happens at a later stage, efforts and resources can be diverted to the rest of the field if there is a prospect of better yield.

Farmer's decisions and choices are influenced by uncertainty in weather conditions that determine the performance of the crop. There is a large literature on the nonlinear effects of weather on crop yields, rent and profit (Deschenes and Greenstone, 2007; Hendricks et al., 2018; Lobell et al., 2011; Schlenker and Roberts, 2006, 2009; Tack et al., 2015). Different temperature exposure ranges are needed for optimal winter wheat production (Acevedo et al., 2002; Porter and Gawith, 1999). Bunting et al. (1982) explained that winter wheat is mostly planted when the daily temperature is between 8–16$^o$C while an optimal temperature ranging between 12–15$^o$C is needed for germination (Acevedo et al., 2002). Temperature between 3–10$^o$C is needed during winter for vernalization (Herbek and Lee, 2009; Robertson et al., 2004) and temperature below zero is damaging for yield in the spring (Shroyer et al., 1995). Tack et al. (2015) show that yield will increase when the temperature is between 10–17$^o$C during fall, 5–10$^o$C during winter and 18–34$^o$C during spring. Lobell et al. (2012) using satellite measurements of wheat grown in northern India found temperature above 34$^o$C to accelerate wheat senescence.

Different approaches have been used to measure the nonlinear effects of weather variables on winter wheat. Gammans et al. (2017) use both the step and flexible polynomial functions with a 2$^o$C and 1$^o$C temperature intervals respectively, while controlling for non–monotonic precipitation effects. Tack et al. (2015) use a piecewise linear approach where the authors account for exposure to freezing temperature, and implement time separability to explain how weather variables affect different physiological processes of winter wheat. I modify Tack et al. (2015)'s preferred specification by adding expected wheat price to account for other factors apart from weather shocks that could impact production through yield and crop abandonment. Huang et al. (2010) incorporate state–level prices into the yield equation while using crop stocks as an instrumental variable. Miao et al. (2016) include input prices and expected output prices as other factors that can impact yield and land allocation decisions. Kaufmann and Snell (1997) include price and other social factors to simulate the effect of management decisions by farmers and found that a 1% increase in the use of purchased inputs will increase output, but at a lesser rate than 1%.

I estimate crop abandonment with the correlated random effect fractional probit model to control for unobserved heterogeneity. Fractional probit models allow the use of panel data and controls for time–invariant variables by including the time averages of weather variables (Papke and Wooldridge, 2008; Wooldridge, 2010). Ignoring unobserved heterogeneity results in biased estimates. Parcels may have unobserved characteristics that can influence yield like soil characteristics or be susceptible to flood and be correlated spatially. Fixed effect estimates can also correct the omitted variable bias, but the use of fixed effects in nonlinear estimation gives rise to an incidental parameter problem (Wooldridge, 2010). Cho and McCarl (2017) use of county fixed effect to control for unobserved heterogeneity may have introduced an incidental parameter problem in their analysis. Ji and Cobourn (2018) also use a fractional multinomial logit model to explain the influences of irrigation districts on land allocation, but failed to control for unobserved heterogeneity.

I use 18 different climate models to simulate the impact of climate change on production by mid–century to capture relevant uncertainties. As reported in Wehner et al. (2017), climate change is projected to further increase the duration and intensity of drought over the Southern Great Plains. I project how precipitation variability and increasing temperature will affect production under Representative Concentration Pathways (RCPs) 4.5 and 8.5. I combine my estimates from my historical estimation with the climate change model to project how yield and crop abandonment will change by mid-century by assuming no adaptation (Burke and Emerick, 2016). Temperature is expected to rise in the Southern Great Plains between 2$^o$C (3.6$^o$F) and 2.83$^o$C (5.1$^o$F) by the mid–21st century and by 2.4$^o$C (4.4$^o$F) and 4.67$^o$C (8.4$^o$F) by the late 21st century, with the occurrence of temperature similar to that of 2011 (Reidmiller et al., 2018). According to Wuebbles et al. (2017), the Southern Great Plains is projected to experience an additional 30–60 days per year above 37.78$^o$C (100$^o$F) than it does now by late 21st century if there are no reductions in greenhouse gas emissions.

My key result is that when there is crop abandonment, using yield impacts alone to measure the climate change impact on production underestimate the total impact of climate change on production. Increase in crop abandonment is projected to reduce production by 13.17%, while the reduction in yield is projected to lower production by 86.72%. Production is projected to decline by 16.3% under the RCP 4.5 scenario. From the historical climate, freeze in the fall and spring, and extreme heat in spring are the major cause of crop abandonment, while freeze in the fall and extreme heat in the spring is the major cause of decline in winter wheat yield. For the future projections, the temperature increase will be the main cause of reduction in wheat production. The impact of weather variables on yield is consistent with results from Tack et al. (2015). Increasing temperature by 1$^o$C while holding precipitation constant reduces yield by 6.87%. This result is also similar in magnitude with both US and global aggregate impacts predicted by Liu et al. (2016) and Asseng et al. (2015). A uniform 2$^o$C increase in temperature will reduce abandonment and yield by 5.5% and 14.8% respectively.

## 2.2 Theoretical Framework

Iizumi and Ramankutty (2015) define annual production ($Prod_{it}$) as a product of harvested yield, harvested area, and cropping intensity. For this study, I assume cropping intensity for dryland winter wheat to be one. Let superscript H and P denote harvested and planted.

Harvested yield is defined as production divided by area harvested while planted yield is defined as production divided by area planted. Let $y_{it}^{H}=\dfrac{Prod_{it}}{Acres^{H}}$ be denoted as harvested yield and $y_{it}^{P}=\dfrac{Prod_{it}}{Acres^{P}}$ be denoted as the planted yield. Let $y_{it}$ be explained as a function of weather variables $W_{it}$ (temperature, precipitation) given that other variables are controlled for in the empirical analysis using fixed effects. That is:

$$y_{it} = f(W_{it}). \tag{2.1}$$

Let harvested acres and planted acres be denoted as $Acres^{H}(W_{it})$ and $Acres^{P}$, respectively. Assuming acres planted does not depend on the weather, $\dfrac{\partial Acres^{P}}{\partial W_{it}} = 0$ and the proportion of acres harvested be represented as $A^{R}(W_{it}) = \frac{Acres^{H}(W_{it})}{Acres^{P}}$. Let the proportion of the area not harvested or acreage response ($ca_{it}(W_{it})$) be defined as;

$$ca_{it}(W_{it}) = 1 - A^{R}(W_{it}) \tag{2.2}$$

where

$$A^{R}(W_{it}) = \frac{Acres^{H}(W_{it})}{Acres^{P}}, \tag{2.3}$$

The effect of weather on the area not harvested can be represented as ;

$$\frac{\partial ca_{it}(W_{it})}{\partial W_{it}} = -\frac{\partial A^{R}(W_{it})}{\partial W_{it}} \tag{2.4}$$

Production can be redefined as:

$$Prod_{it}(W_{it}) = y_{it}^{P}(W_{it}) \times Acres^{P} = y_{it}^{H}(W_{it}) \times Acres^{H}(W_{it}) \tag{2.5}$$

where

$$y_{it}^{P}(W_{it}) = y_{it}^{H}(W_{it}) \times \frac{Acres^{H}(W_{it})}{Acres^{P}} \tag{2.6}$$

Note that $A^{R}(W_{it}) = 1 - ca_{it}(W_{it})$

$$y_{it}^{P}(W_{it}) = y_{it}^{H}(W_{it}) \times (1 - ca_{it}(W_{it})). \tag{2.7}$$

$y_{it}^{H} \times ca_{it}(W_{it})$ is the production loss, which is defined as the product of the area of the planted acres not harvested and yield that should have been realized. The impact of weather production can be measured by differentiating equation 2.7. More than 32% of yield variability is explained by climate variability (Ray et al., 2015), while winter wheat is expected to reduce between 10 and 20% by 2090 due to climate change (Chen et al., 2004). Taking the derivative of equation 2.7 gives the total impact of climate change on production. The total impact of climate change on production is the sum of climate change impact on yield and harvested acres;

$$y_{it}^{H'}.A_{it}^{R} - ca_{it}^{'}.y_{it}^{H} = y_{it}^{P'} \tag{2.8}$$

The primes denote first derivatives. If the total planted area is harvested ($A_{it}^{R} = 1$), crop abandonment equals zero ($ca_{it} = 0$), climate change impact on production is the same as its impact on yield ($y_{it}^{H'} = y_{it}^{P'}$). If the total planted area is not harvested ($A_{it}^{R} < 1$), crop abandonment is not equal to zero ($ca_{it} \neq 0$), and climate change impact from harvested yield understate the total impact of climate change on production ($y_{it}^{H'} < y_{it}^{P'}$).

I divide equation 2.8 by $\frac{y^p}{y^p}$ where $y^p$ is defined by equation 2.6 ($y^p = \frac{y_{it}^{H}(W_{it}) \times Acres^{H}(W_{it})}{Acres^{P}}$).

$$\frac{y_{it}^{H'}}{y_{it}^{H}} - \frac{ca_{it}^{'}}{A_{it}^{R}} = \frac{y_{it}^{P'}}{y_{it}^{p}} \tag{2.9}$$

In other words, the percent change in production is equal to the percent change in harvested yield plus the percent change in acres harvested. Equation 2.9 shows the contribution of each component of production.$\frac{y_{it}^{H'}}{y_{it}^{H}}$ represents the impact of climate change on production, while $\frac{ca_{it}^{'}}{A_{it}^{R}}$ represents changes in harvested acres production. $\frac{y_{it}^{P'}}{y_{it}^{p}}$ represents the total impact of climate change on production.

## 2.3 Data

### 2.3.1 Yield Information

I used a panel data set of USDA data on production, planted and harvested acres for dryland winter wheat producing counties in Kansas from 1981 to 2007. There is limited production information for the winter after 2007 due to a change in the method of reporting production information. Since planted yield per net–planted was not reported for all counties and years for every county where I have crop abandonment data, I used the harvested yield. Therefore, the harvested yield will be referred to as yield. Table 4.2 shows the production data. The average yield between 1981–2007 is 35.05 bu./acres, while the average crop abandonment between the same period is 11%.

### 2.3.2 Weather Information

I use the daily weather data from PRISM[1] to construct the weather variables from September to May following Tack et al. (2015). Following Tack et al. (2015) and assuming temperature and precipitation effects are additive, I divide the growing season into three periods; Fall (September–November), Winter (December–February) and Spring (March–May). I exclude the weather information during the final parts of the growing season because of harvest in Kansas typically starts in the month of June. More details on how the degree days and freeze variables are constructed are explained in details in section 2.4.2. The average minimum temperature in the winter is –6.25$^o$C compares to the minimum temperature of 6.1$^o$C in the fall and 5.13$^o$C in the spring (Table 2.6). I aggregate the total precipitation received during each period. Less precipitation is received during the winter when compared to the other two periods. Figures 2.2 and 2.3 show the distributions of average temperature and precipitation across counties in Kansas between 1981 and 2007.

[1] PRISM Climate Group, Oregon State University, http://prism.oregonstate.edu

### 2.3.3 Soil Information

I use detail soil data from the gSSURGO (gridded Soil Survey Geographic) database created by NRCS.[2] I include root zone available water, which is the volume of plant available water that the soil can store within the root zone based on all map unit earthy major components. Other soil characteristics included as controls are: soil organic carbon, bulk density, electrical conductivity, the proportion of cropland with a pH less than 6, and the proportion of cropland with a pH greater than 7.5. These soil characteristics were chosen to represent indicators of the five functions of soil: sustaining biological diversity and productivity (D); regulating water (W); filtering, buffering, and degrading organic and inorganic materials (F); storing and cycling nutrients and carbon (N); and providing physical stability (S) (Hendricks, 2018; NRCS, 2018).

Soil organic carbon (SOC) is the source and sink of principal plant nutrients, absorbing water at low moisture potentials to increase plant available water capacity (Lal, 2004). Bulk density reflects the soils ability to function for structural support, water and solute movement, and soil aeration (NRCS, 2018). Soil pH generally refers to the degree of soil acidity or alkalinity which impacts soils physical, chemical, and biological properties and processes, as well as plant growth. Electrical conductivity is used as an indirect indicator of the amount of nutrients available for plant uptake and salinity levels (NRCS, 2018). Table 2.6 has the descriptive statistics of each of the soil variables.

### 2.3.4 Price Information

I used the Chicago Mercantile Exchange (CME) expected price of wheat which is the average daily settled price between August and September for July contract. To reduce any concern of endogeneity, I use winter wheat price prior to the start of the growing season so that the total area of acres planted is exogenous to price set by the CME. According to Hendricks et al. (2014), using expected price information before that start of the growing season may reduce endogeneity as these prices are exogenous factors that affect planting area.

[2] Read Hendricks et al. (2018) for more information about the soil data

## 2.4 Econometric Model

I modify the approach by Tack et al. (2015) by including expected wheat price to measure changes in farmers practices in response to changes in price. I separately estimate the nonlinear effect of weather variables on (1) yields and (2) crop abandonment.[3] Let 1, 2 and 3 denote fall, winter, and spring respectively. I explain yield and crop abandonment as a function of weather variables and expected wheat price. For the yield model estimation, time–invariant variables such as soil controls are controlled with fixed effects. The yield model is specified as;

$$y_{it} = \sum_{\mathbf{s=1}}^{\mathbf{3}} \mathbf{X_{it}}\beta_{\mathbf{s}} + \delta_i + \tau(t) + \gamma Wprice_t + \varepsilon_{it}. \tag{2.10}$$

where $y_{it}$ is in log form to remove the skewness in yield distribution across counties, $\delta_i$ is the county fixed effect used to control for time–invariant heterogeneity like soil quality, $\tau(t)$ is the linear and quadratic time trend specified to capture changes in management practices like planting date and technological change. $\gamma$ is the coefficient of the expected wheat price. According to Miao et al. (2016), expected output price and management practices are other factors that can influence crop yield. $\varepsilon_{it}$ is the error term, clustered at the county level. $\beta_s$ is the vector of parameters to be estimated for each of the growing periods, while $X_{it}$ is the vector of degree days, freeze variables, and precipitation.

I construct the degree days as a sinusoidal interpolation of minimum and maximum temperature exposure within each day (Schlenker and Roberts, 2009; Tack et al., 2015). Following Tack et al. (2015), a piecewise linear regression is estimated using equation 2.10 over different possible thresholds within each period. There is no guidance in the literature on what thresholds bounds should be within each growing periods. The same principle used by Tack et al. (2015) was adopted by restricting the lower threshold at least five degrees above zero and ten degrees below the maximum observed temperature, while the upper threshold is restricted to be five degrees above the lower threshold and five degrees below

[3] I use the harvested yield instead of the planted yield. Planted yield information are missing for some counties for some years.

the maximum for fall and spring.

I select the optimal thresholds for the harvest yield model from the model with the best fit based on r–squared. For crop abandonment, I use the same thresholds from the yield model. I use these thresholds to construct temperature exposure for each period during the growing season. I define the low degree days for each period as the degree days between zero and lower threshold. The medium degree days measures the degree days between lower and upper threshold, while the high degree days measures degree days above the upper threshold. I construct the freeze variables as exposure in days to freezing temperature. The beneficial temperatures within each period vary across the growing season (Table 2.6). The critical temperature for wheat in the fall is 15$^o$C, 11$^o$C in the winter and 30$^o$C in the spring. These thresholds appear consistent with Porter and Gawith (1999) regarding the effects of temperature exposure on wheat development.$\sum_{s=1}^{3} X_{it}$ is defined as

$$\sum_{s=1}^{3} X_{it} = \sum_{s=1}^{3} \beta_{1s} Freeze_{it} + \sum_{s=1}^{3} \beta_{2s} DDLow_{it} + \sum_{s=1}^{3} \beta_{3s} DDMedium_{it} + \sum_{s=1}^{3} \beta_{4s} DDHigh_{it} + \sum_{s=1}^{3} \beta_{5s} Prec_{it} + \sum_{s=1}^{3} \beta_{6s} Prec_{it}^2. \tag{2.11}$$

The crop abandonment model has the same variables as the yield model except with the inclusion of soil control variables. Since $ca_{it}$ is between $0 < ca_{it} \leq 1$, I use the correlated random effect fractional probit to model the nonlinear relationship between weather and crop abandonment. The notation $\Phi(.)$ denotes the cumulative normal distribution. $\beta_s$ can be estimated consistently with a standard probit model by imposing some condition on the correlation between the unobserved effect and the covariates. (Chamberlain, 1980; Mundlak, 1978; Wooldridge, 2010). This is called correlated random effects. The inclusion of county fixed effects in the fractional probit model introduces an incidental parameter problem if $T$ is fixed and $N \longrightarrow \infty$. The crop abandonment model is specified as;

$$E(ca_{it}) = \Phi(\sum_{\mathbf{s=1}}^{\mathbf{3}} \mathbf{X_{it}} \beta_s + \tau(t) + \delta_i + \gamma Wprice_t). \tag{2.12}$$

By assuming a conditional normal distribution with linear expectation and constant variance (Chamberlain, 1980; Wooldridge, 2010), I control for $\delta_i$ by introducing $\overline{X_i} \equiv T^{-1}\sum_{t=1}^{T} X_{it}$ into equation 4.3 to consistently estimate $\beta_s$ as well as the estimators of the average partial effects (APEs). By introducing $\overline{X_{is}}$ into equation 4.3, it means any remaining unobserved heterogeneity is uncorrelated with the weather variables.

$$E(ca_{it}) = \Phi(\sum_{\mathbf{s=1}}^{\mathbf{3}} \mathbf{X_{it}}\beta_{\mathbf{s}} + \tau(t) + \gamma W price_t + \theta\chi_i + \rho_s \sum_{s=1}^{3} \overline{X_i}). \tag{2.13}$$

$\chi_i$ is a vector of soil control variables described in the data section.

### 2.4.1 Warming Scenarios

I use eqs. (2.10) and (2.13) to simulate the impact of an increase in temperature on yield and crop abandonment for each $1^oC$ increase in temperature up to $5^oC$. I simulate the effect of drought defined by tenth-percentile precipitation outcome of average precipitation received. I also simulate the combined effects of drought and with different ranges of temperature increase (Tack et al., 2014). The impact on yield is specified as the relative change in winter yield due to increase in temperature;

$$Impact_y = e^{(X_i - X_0)\hat{\beta}_i} - 1, \tag{2.14}$$

while the impact on crop abandonment is specified as;

$$Impact_{ca} = \Phi\left(.\right)_i - \Phi\left(.\right)_o \tag{2.15}$$

Where $i$=1, 2, 3, 4 and 5 are the warming scenarios in degrees Celsius and $X_0$ and $\Phi\left(.\right)_o$ are the baseline scenarios.

### 2.4.2 Climate Change Projection

I use data from 18 different climate models to construct climate variables which are aggregated to growing periods and used to project change in crop abandonment and yield under the Representative Concentration Pathways (RCPs) 4.5 and 8.5 by mid–century (2034-2065). I use the downscaled Coupled Model Intercomparison Project (CMIP5) daily climate projections for two main reasons. Downscaled CMIP5 was used to inform the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment and secondly, the data are downscaled, which resolves any issue of aggregation bias raised by Auffhammer et al. (2013). I make a bias correction to account for bias in certain climate models. Bias–corrected projections are obtained by using the mean difference between variables constructed from historical simulated data by the climate models and the observed data from the PRISM to adjust the future data projection around the bias (Hawkins et al., 2013). Data between 1981–2005 are used to correct future projections.

Other challenges associated with the use of a single projection of future climate are resolved by using an ensemble average (Auffhammer et al., 2013; Burke et al., 2015). I report a simulation with an ensemble average by averaging the predicted change in each variable across all models. I also report simulation for each climate change models to show the level of uncertainty across different climate models under RCP 4.5 and 8.5 respectively. The list of the 18 climate models and institutions are listed in table A. The use of an ensemble average smooths out the uncertainty and extreme projections from different models.

## 2.5 Result and Discussion

The results of crop abandonment and yield response to weather effects are shown in tables 2.5 and 2.6. Table 2.5 shows the parameter estimates from the fractional probit, average partial effects (APEs) and the fixed effects linear probability model. The APEs from the fractional probit are similar in sign and the coefficients are close in magnitude to the coefficients from the linear fixed model.

The major drivers of crop abandonment are freeze in the fall and spring, and extreme heat in the spring. An additional day of freezing temperatures in the spring is associated with a 1.04 percentage point increase in crop abandonment while exposure to freezing temperatures in the fall will increase abandonment by 0.85 percentage points. Crop abandonment is highly sensitive to increased exposure to a temperature above $30^oC$. An additional degree day above $30^oC$ will increase crop abandonment by 1.33 percentage points. Wheat is sensitive to freeze temperature as cold temperatures cause injury like leaf chlorosis and death of growing points after hardening in the fall and dehardening in the spring (Warrick and Miller, 1999).

Both the linear and quadratic coefficients of precipitation are significant for fall and spring. Precipitation has an inverted U shape in all the periods. At sample means, a 1mm increase in precipitation in the fall and the spring season will reduce abandonment by 0.08 and 0.04 percentage points respectively.

Table 2.6 shows the weather effects on winter wheat yield. The major driver of yield loss is exposure to freezing temperatures during fall and extreme heat in the spring. Spring is when plants grow to maturity after dehardening in the winter. An additional day of freeze in the fall reduces harvested yield by 3.54%. Freezing temperatures during the spring also lower yield by 1.66%. Freeze impact from the fall is consistent, but smaller in magnitude when compared to the impact associated with yield reduction in Tack et al. (2015).[4] Gammans et al. (2017) also find exposure to a temperature below -6$^o$C in the fall to have a negative effect on yield. Freezing temperatures during the spring bring about freeze injuries ranging from leaf chlorosis to floret sterility that have moderate to severe effects on yield (Shroyer et al., 1995). According to Warrick and Miller (1999) and Shroyer et al. (1995), the duration of injury depends on the duration of exposure and how cold the temperature is.

Extreme heat in the spring lowers harvested yield by 4.53%. Extreme heat in the fall and winter also have a minimal impact on yield. A temperature exceeding $11^oC$ during the winter reduces yield by 0.79%. Extreme heat damage is most common during grain filling when the kernels are shriveled and prematurely ripe. High temperature hastens the decline in photosynthesis and leaf area, decreases shoot and grain mass as well as weight and sugar

[4] Tack et al. (2015) associate a 9% reducing in yield with freeze in the fall

content of kernels, and reduces water-use efficiency (Shah and Paulsen, 2003).

Precipitation has a statistically significant inverted–U shape in all the seasons. Increase in precipitation through all the growing season is important as it all increase yield. For the fall, the yield-maximizing level is 14.09 inches, 4.81 inches in the winter and 8.49 inches for the spring.

### 2.5.1 Warming Scenario

I simulate the impact of an increase in temperature on crop abandonment and yield to understand the impact of warming, while holding precipitation constant. A uniform temperature increase of $2^{o}$C or less will reduce crop abandonment as the impacts from warming offset damages from exposure to freezing temperature. Although not significant, a $2^{o}$C increase in temperature will reduce area crop abandonment by less than 5.5%. Beyond $2^{o}$C, the net warming impacts outweigh the benefits from the reduced damage from exposure to freezing temperature. A $3^{o}$C increase in temperature will increase crop abandonment by 11.2% (figure 2.4).

I also simulate the impact of drought, while holding temperature effects constant. Crop abandonment increase by 31.6% when only 10 percentile of the historical average precipitation is received. The red bar of figure 2.4 shows how crop abandonment will increase by 22.1% when there are drought and temperature increase of $2^{o}$C.

For winter wheat yield, a $1^{o}$C and $2^{o}$C uniform increase in temperature reduces yield by 6.1% and 14.8% respectively (figure 2.5). My predicted yield reduction under $1^{o}$C is similar in magnitude with both US and global aggregate impacts predicted by Liu et al. (2016) and Asseng et al. (2015). The effect from drought why holding the temperature constant is 27.5% which is a bit higher in magnitude when compared to the estimate from Tack et al. (2014). The difference in impact can be attributed to the type of yield used in these estimations. Under the combined scenarios of $2^{o}$C increase in temperature and drought, winter wheat yield is reduced by 38% (figure 2.5).

### 2.5.2 Climate Projection

I combine the climate projections with my empirical models to project the impact of climate change on crop abandonment and winter wheat yield by mid–century (eqs. (2.10) and (2.13)). To derive the impact of climate change on crop abandonment and winter wheat yield, I predict crop abandonment and yield by using the historical climate (1981–2007) and the projected climate data from 18 different climate models under scenarios RCP 4.5 and 8.5. The projection for the mid–century is done at 2007 technology.

The ensemble average of the crop abandonment varies across years at mid–century and is higher in almost all years above the historical climate (Figure 2.6). The variation in crop abandonment from one year to another reflects climate variability and the effects of extreme weather conditions by mid–century. On average, crop abandonment is expected to increase by 1.9 and 3.9 percentage points under RCP 4.5 and 8.5 respectively. In some models, crop abandonment is high as 60 percent increase for some years above the historical climate (figures 2.15).

Figure 2.7 shows the winter wheat yield projection by year for the mid–century. The yearly projections are all below the historical climate outcomes. Winter wheat yield is expected to decrease by an ensemble average of 14.12% and 19.71% under RCP 4.5 and 8.5 respectively (Figure 2.16). Gammans et al. (2017) projected a yield decrease between 3.5% to 12.9% for winter wheat by 2037–2065 for France. In some models, the yield is as low as 10 bushels per acre for some years (figures 2.7).

Figures 2.15 and 2.16 show the level of uncertainties in change in crop abandonment and yield across the 18 climate models from the baseline. Most of the models project an increase in crop abandonment under both scenarios except for MRI-CGM3, MIROC-ESM, and CNRM-CM5 that project reduction in crop abandonment (figure **??**). For yield, all these models project reduction in yield which is as high as 21% under RCP 4.5.

Next, I isolate the source of change in crop abandonment and winter wheat yield: (i) degree days (ii) freeze variables, (iii) precipitation. To decipher the contribution of each variable, I simulate crop abandonment and yield using degree days while I assume no change in freeze variables and precipitation relative to the reference period (1981–2007). Similar procedures are repeated for freeze variables and precipitation. Each impact is bootstrapped with 500 replications to obtain their confidence interval.

Figures 2.10 and 2.11 show the contributions of each climate characteristics to the overall impact on crop abandonment and yield. The middle dot indicates point estimates and the bars represent the 95% confidence interval generated using 500 bootstrap replications. Summing the relative change in crop abandonment and yield across sources does not equal the relative change in crop abandonment or yield due to the functional form used. For the crop abandonment, the cumulative normal distribution of a sum of different values is not the same as the sum of separate cumulative normal distributions $-\Phi(a+b) \neq \Phi(a) + \phi(b)$. For yield, the relative change nearly adds to the total effect.

Crop abandonment is estimated to increase by 18% by mid–century under RCP 4.5 (fig. 2.10). The impact from an increase in temperature through degree days and freeze variables on crop abandonment are different. An increase in temperature through degree days alone will increase crop abandonment by 74%, while exposure to freezing temperature will reduce crop abandonment by 34%. The impact from the warming effects due to temperature increase offsets the damage from exposure to freezing temperature, therefore reducing crop abandonment by 40%. Precipitation is expected to reduce abandonment by 0.01%. This result implies that the projected increase in crop abandonment will be induced by an increase in temperature. it is also interesting that the damage from temperature increase through degree days far outweighs the benefits gained in reducing damage from exposure to freezing temperature.

Winter wheat yield is expected to reduce by 14.12% by mid–century under RCP 4.5 (Figure 2.11). Increase in temperature will reduce yield by 23% through degree days and increase yield by 13% by offsetting damage from exposure to freezing temperature. Reduction in precipitation will reduce yield by 3%. According to Tack et al. (2015), additional rainfall in the spring can partially offset the negative effects of warming.

Next, I examine the relative change in crop abandonment and winter wheat yield across counties in Kansas by mid-century. To calculate the relative change, I estimate the change in crop abandonment and yield between mid–century and the reference period, divided by the average crop abandonment and yield from the reference period weighted by production in each county. Figure 2.12 shows the relative change in crop abandonment by county under RCP 4.5 in reference to the historical climate. The variation across counties can be attributed to the spatial differences in soil characteristics and weather conditions across counties. Crop abandonment is reduced in the northern counties of Kansas as the region is much colder and warming impacts from the temperature increase offset the damage from the cold condition by mid–century. This is different for counties in the south as the hot conditions are aggravated by increases in temperature. Figure 2.13 shows the relative change in yield by the county under RCP 4.5. Unlike crop abandonment, the distribution of yield impacts across counties is more concentrated within regions. The counties within the Southwest and South–central regions of Kansas are expected to have the highest relative change in yield with respect to the historical climate.

### 2.5.3 Climate Change Impact on Production

I decompose the impact of climate change on production through yield and acreage response by mid–century (Figure 2.14). I use equation 2.9 to estimate the total impact on production as a sum of the relative change in yield and relative change in the proportion of the acres harvested. Winter wheat production is expected to reduce by 16.3% and 24.1% by mid–century under RCP 4.5 and 8.5 respectively. Crop abandonment is expected to lower production by 13.17%, while the remaining 86.72% is explained by yield variability. Using yield impacts alone to measure the climate change impact on production when there is crop abandonment underestimates the impact by an average of 13.17% under RCP 4.5.

## 2.6 Conclusion

The primary contribution of this paper involves the decomposition of climate change impact on production through yield and acreage. I use a fractional probit model that allows the control of unobserved heterogeneity. I use 18 general circulation models to project crop abandonment and winter wheat yield for the mid–century, isolating the source of change in crop abandonment and yield. I also examine the relative change in the spatial distribution of crop abandonment and yield across counties in Kansas by mid–century (2034–2065).

I nd that freeze in the fall and spring, and extreme heat in spring are the major driver of crop abandonment while freeze in the fall and extreme heat in the spring are the major cause of decline in winter yield under the historical climate. By midcentury, increasing temperature will cause most of the change in yield and abandonment. A uniform $2^o$C increase in temperature will reduce yield by 15.48%. Increase in crop abandonment will account for 13.17% reduction in winter wheat production. By midcentury, production is projected to decrease by 16.3% under RCP 4.5.

There are some important caveats in my analysis. I do not factor yield improvement from technological advancement in the future as I project the impacts from climate change. The predicted impacts may be smaller with the adoption of heat–tolerant winter wheat varieties. My analysis does not consider the fertilization effects of $CO_2$ on winter wheat production. Winter wheat water use efficiency is high under higher levels of $CO_2$ (Eitzinger et al., 2003). Another limitation is that I only analyze winter wheat production using Kansas information. Abandonment could be less important for other crops with shorter duration compared to winter wheat which has an almost a year production period with different temperature thresholds for optimal production. One area of research interest is to examine the impact of climate over a bigger study area, examining how crop insurance affects crop abandonment.

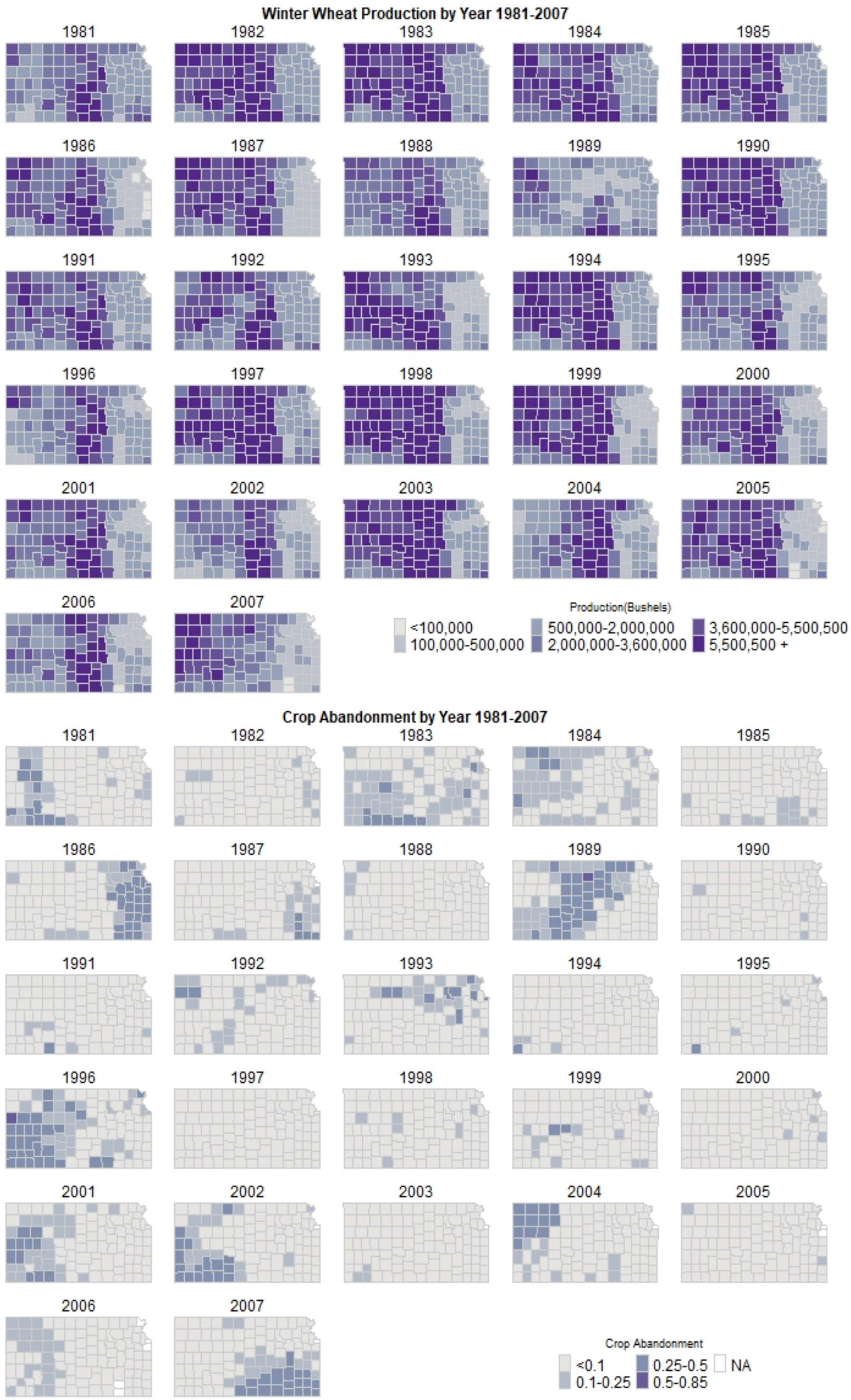


**Figure 2.1**: *The figure shows the distribution of winter wheat production and abandonment in Kansas between 1981–2007. The upper panel shows the average production by county by year while the second panel shows the distribution of winter wheat abandonment by year.*

**Table 2.1**: *Descriptive Statistics of Production and Price Variables*

| Measures | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Harvested Yield(bu./ac) | 35.05 | 10.12 | 9 | 80.35 |
| Planted Yield(bu./ac) | 31.94 | 11.12 | 2.11 | 76.39 |
| Harvested Area (,000 Acres) | 90.62 | 68.15 | 0.20 | 505.60 |
| Planted Area (,000 Acres) | 101.58 | 73.84 | 0.20 | 524.00 |
| Production (,000 bu.) | 3,222.31 | 2,656.68 | 6.00 | 22000 |
| Abandonment* | 0.11 | 0.12 | 0.00 | 0.85 |
| Expected Price ($) | 3.68 | 0.68 | 2.55 | 5.01 |

Note: Crop abandonment has no unit. Planted and harvested yield represent yield calculated from production divided by planted and harvested acres respectively over years. The data is from 105 counties in Kansas between 1981–2007.

**Table 2.2**: *Descriptive Statistics of Weather Variables*

| Tmin ($^oC$) | | | Tmax ($^oC$) | | | Aggregate Precipitation (mm) | | |
|---|---|---|---|---|---|---|---|---|
| Fall | Winter | Spring | Fall | Winter | Spring | Fall | Winter | Spring |
| 6.10 | -6.25 | 5.13 | 20.52 | 6.88 | 19.39 | 165.62 | 78.66 | 230.51 |
| (1.87) | (2.02) | (1.93) | (1.58) | (2.33) | (1.79) | (98.35) | (48.59) | (95.34) |

Note: Weather variables are aggregated over the growing season. Standard deviation is in bracket.

**Table 2.3**: *Optimal Thresholds from Piecewise Linear Models*

| Variables | Threshold | mean ± SD. |
|---|---|---|
| Degree Days low:Fall | 0–10 $^oC$ | 716.86 ± 49.74 |
| Degree Days Medium:Fall | 10–15 $^oC$ | 243.47 ± 26.99 |
| Degree Days High:Fall | 15+ $^oC$ | 277.57 ± 53.34 |
| Degree Days low:Winter | 0–5 $^oC$ | 172.66 ± 38.54 |
| Degree Days Medium:Winter | 5–11 $^oC$ | 95.48 ± 31.79 |
| Degree Days High:Winter | 11+ $^oC$ | 30.71 ±18.71 |
| Degree Days low:Spring | 0–20 $^oC$ | 1077.61 ± 113.24 |
| Degree Days Medium:Spring | 20–30 $^oC$ | 75.77 ± 27.09 |
| Degree Days High:Spring | 30+ $^oC$ | 2.02 ± 2.95 |

Note: The thresholds were estimated through piecewise regression over all possible thresholds. The optimal thresholds for yield' model was selected from the models that maximize the r–squared. Seasons are September-November (Fall), December-February (Winter), and March-May (Spring).

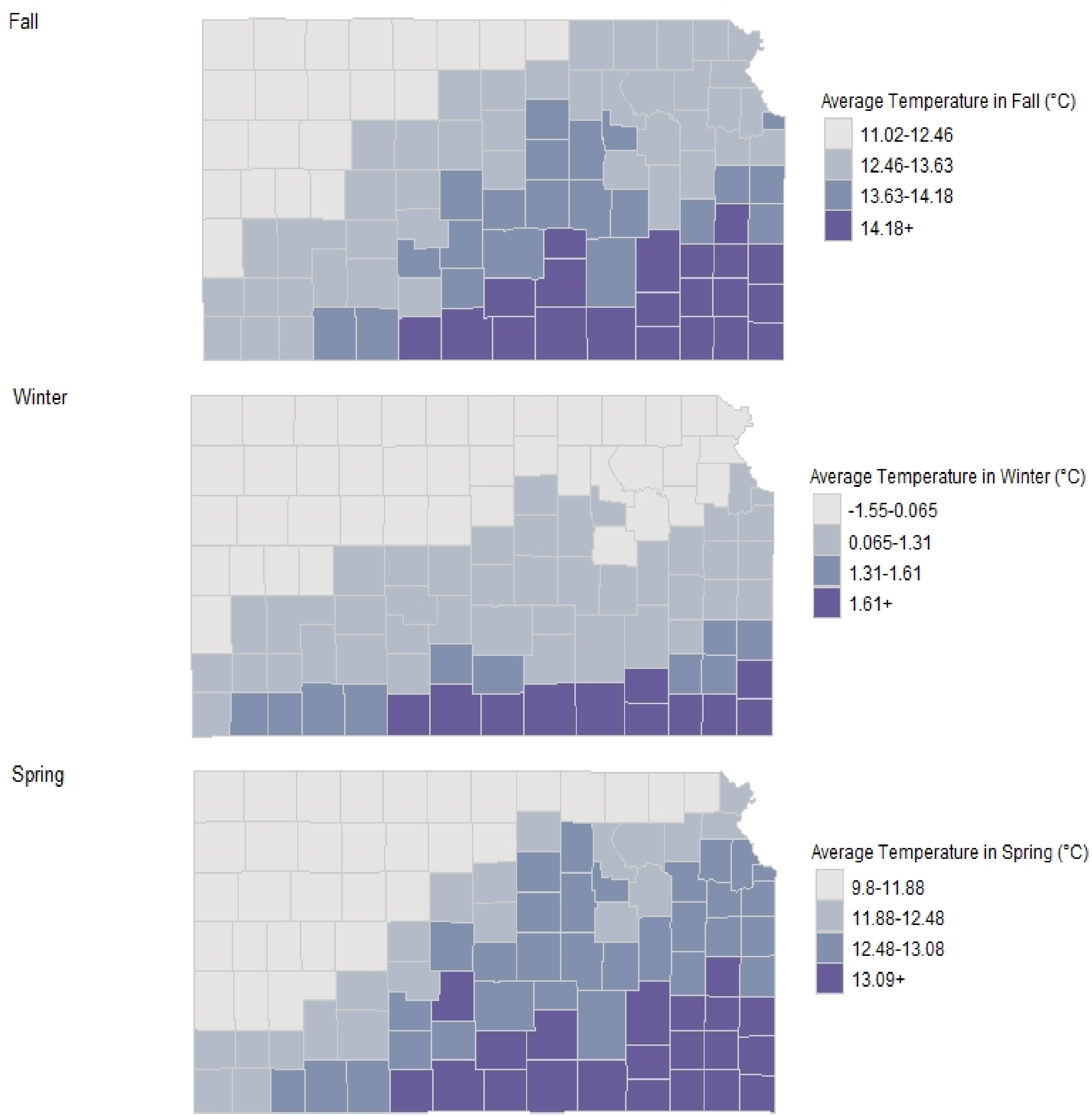


**Figure 2.2**: *The figure shows the average temperature by county in Kansas between 1981–2007. The first panel shows the average temperature for the fall season (September-November), the second panel shows the average temperature in the winter( December–February) and the last panel shows the average temperature spring (March–May).*

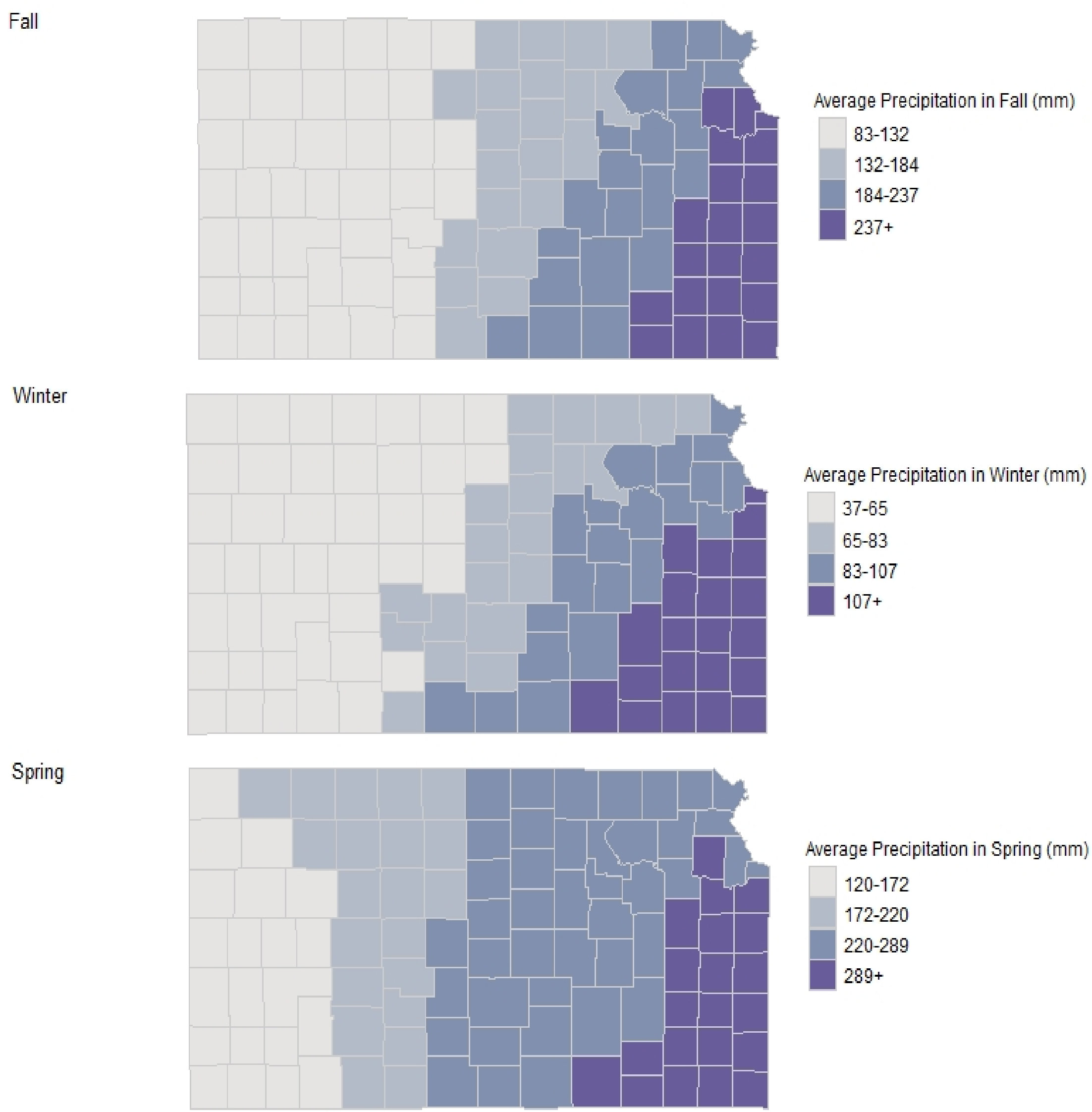


**Figure 2.3**: *The figure shows the average precipitation by county in Kansas between 1981–2007. The first panel shows the average precipitation for the fall season (September-November), the second panel shows the average precipitation in the winter( December–February) and the last panel shows the average precipitation spring (March–May).*

**Table 2.4**: *Descriptive Statistics of Soil Variables*

| Measures | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Rootznaws (mm) | 247.34 | 39.71 | 160.28 | 311.74 |
| Soil organic carbon (kg/$m^3$) | 11.51 | 2.94 | 5.63 | 81.89 |
| Bulk density | 1.38 | 0.06 | 1.21 | 1.54 |
| Electrical conductivity (EC) | 0.39 | 0.32 | 0.00 | 1.19 |
| pH less than 6 | 0.04 | 0.10 | 0.00 | 0.62 |
| pH greater than 7.5 | 0.44 | 0.41 | 0.00 | 1.00 |

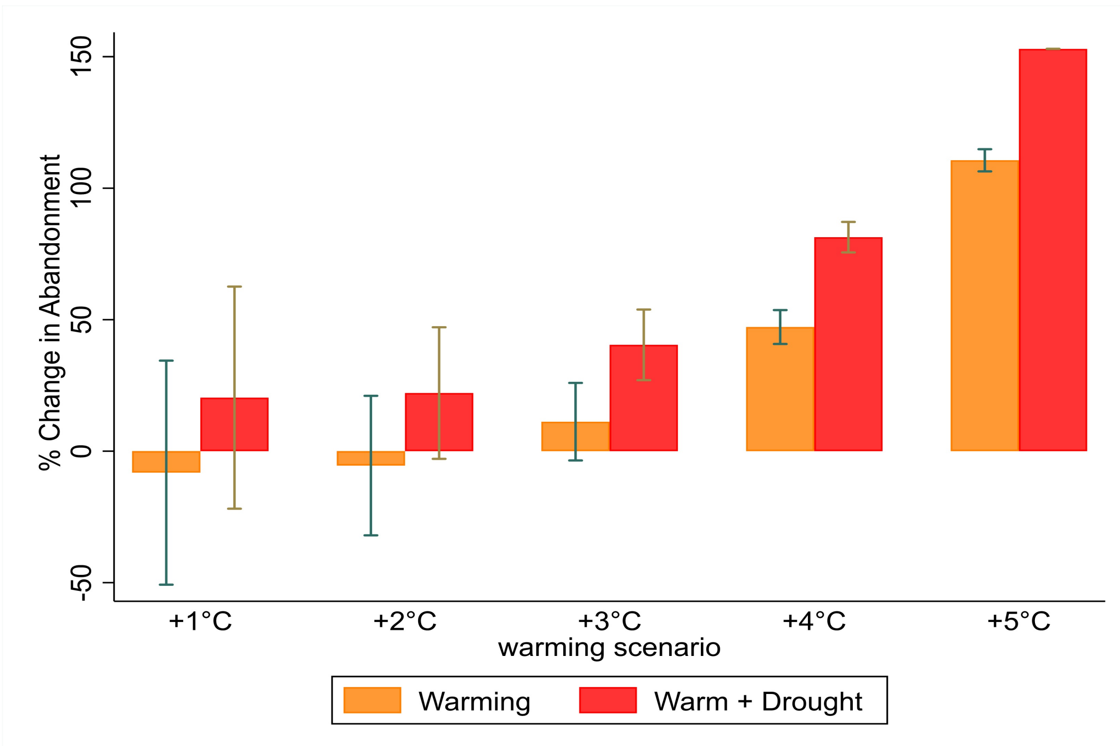


**Figure 2.4**: *The figure shows the predicted impact of the combined effects from an increase in temperature and decrease in precipitation on crop abandonment. The first bar (orange), shows the predicted impact of an increase in temperature alone across different periods during the growing season on crop abandonment. The second bar shows the added effects of temperature increase and tenth-percentile of the average precipitation received. Tenth-percentile of the average precipitation received is used to represent drought. Impacts are reported as the percentage change point in crop abandonment relative to historical climate. Bars show 95% confidence intervals using the standard error clustered by county and obtained by 500 bootstraps.*

**Table 2.5**: *Specification Measures of Weather Effects on Crop Abandonment*

| Estimation Methods | (1) Fractional probit Pooled QMLE | | (2) Linear Fixed Effects |
|---|---|---|---|
| Variables | Coefficient | APE | Coefficient |
| Freeze Days :Fall ($^oC$) | 0.0485*** | 0.0085*** | 0.0079*** |
| | (0.0113) | (0.0020) | (0.0020) |
| Freeze Days:Winter ($^oC$) | 0.0053 | 0.0009 | 0.0006 |
| | (0.0100) | (0.0017) | (0.0022) |
| Freeze Days:Spring ($^oC$) | 0.0594*** | 0.0104*** | 0.0115*** |
| | (0.0085) | (0.0016) | (0.0014) |
| Degree Days low:Fall ($^oC$) | 0.0007 | 0.0001 | 0.0000 |
| | (0.0015) | (0.0003) | (0.0003) |
| Degree Days Medium:Fall ($^oC$) | 0.0006 | 0.0001 | 0.0003 |
| | (0.0026) | (0.0005) | (0.0005) |
| Degree Days High:Fall ($^oC$) | 0.0007 | 0.0001 | 0.0001 |
| | (0.0005) | (0.0001) | (0.0001) |
| Degree Days low:Winter ($^oC$) | -0.0017 | -0.0003 | -0.0003 |
| | (0.0028) | (0.0005) | (0.0006) |
| Degree Days Medium:Winter($^oC$) | 0.0018 | 0.0003 | 0.0003 |
| | (0.0020) | (0.0004) | (0.0004) |
| Degree Days High:Winter($^oC$) | -0.0025 | -0.0004 | -0.0004 |
| | (0.0021) | (0.0004) | (0.0004) |
| Degree Days low:Spring($^oC$) | 0.0024*** | 0.0004*** | 0.0004*** |
| | (0.0004) | (0.0001) | (0.0001) |
| Degree Days Medium:Spring($^oC$) | -0.0075*** | -0.0013*** | -0.0014*** |
| | (0.0011) | (0.0002) | (0.0002) |
| Degree Days High:Spring($^oC$) | 0.0759*** | 0.0133*** | 0.0161*** |
| | (0.0074) | (0.0012) | (0.0013) |
| Precipitation(mm):Fall | -0.0044*** | -0.0008*** | -0.0009*** |
| | (0.0005) | (0.0001) | (0.0001) |
| Precipitation(mm) Squared:Fall | 0.0000*** | 0.0000*** | 0.0000*** |
| | (0.0000) | (0.0000) | (0.0000) |
| Precipitation(mm):Winter | -0.0010 | -0.0002 | -0.0002 |
| | (0.0007) | (0.0001) | (0.0002) |
| Precipitation(mm) Squared:Winter | 0.0000 | 0.0000 | 0.0000 |
| | (0.0000) | (0.0000) | (0.0000) |
| Precipitation(mm):Spring | -0.0021*** | -0.0004*** | -0.0004*** |
| | (0.0006) | (0.0001) | (0.0001) |
| Precipitation(mm) Squared:Spring | 0.0000*** | 0.0000*** | 0.0000*** |
| | (0.0000) | (0.0000) | (0.0000) |
| Wheat price ($) | -0.0323 | -0.0057 | -0.0032 |
| | (0.0284) | (0.0050) | (0.0064) |
| Soil Control | Yes | | No |
| County Fixed effect | No | | Yes |
| Quadratic Trend | Yes | | Yes |

Note: *,** and *** indicate significance at 0.1 and 0.05 and 0.01 level. Figures in the parenthesis are standard errors clustered by county. The standard errors for the APEs are obtained from 500 bootstrap replications.

**Table 2.6**: *Specification Measures of Weather Effects on Yield*

| Variables | (1) Coefficient |
|---|---|
| Freeze Days :Fall ($^oC$) | -0.0354*** |
| | (0.0045) |
| Freeze Days:Winter ($^oC$) | -0.0003 |
| | (0.0038) |
| Freeze Days:Spring ($^oC$) | -0.0166*** |
| | (0.0030) |
| Degree Days low:Fall ($^oC$) | -0.0046*** |
| | (0.0007) |
| Degree Days Medium:Fall ($^oC$) | 0.0040*** |
| | (0.0009) |
| Degree Days High:Fall ($^oC$) | -0.0001 |
| | (0.0001) |
| Degree Days low:Winter ($^oC$) | -0.0025** |
| | (0.0011) |
| Degree Days Medium:Winter($^oC$) | 0.0069*** |
| | (0.0007) |
| Degree Days High:Winter($^oC$) | -0.0079*** |
| | (0.0009) |
| Degree Days low:Spring($^oC$) | -0.0015*** |
| | (0.0002) |
| Degree Days Medium:Spring($^oC$) | 0.0041*** |
| | (0.0005) |
| Degree Days High:Spring($^oC$) | -0.0453*** |
| | (0.0028) |
| Precipitation(mm):Fall | 0.0025*** |
| | (0.0002) |
| Precipitation(mm) Squared:Fall | -0.0000*** |
| | (0.0000) |
| Precipitation(mm):Winter | 0.0031*** |
| | (0.0004) |
| Precipitation(mm) Squared:Winter | -0.0000*** |
| | (0.0000) |
| Precipitation(mm):Spring | 0.0032*** |
| | (0.0004) |
| Precipitation(mm) Squared:Spring | -0.0000*** |
| | (0.0000) |
| Wheat price ($) | 0.0088 |
| | (0.0115) |
| Soil Control | No |
| County Fixed effect | Yes |
| Quadratic Trend | Yes |

Note: *,** and *** indicate significance at 0.1 and 0.05 and 0.01 level. Figures in the parenthesis are standard errors clustered by county.

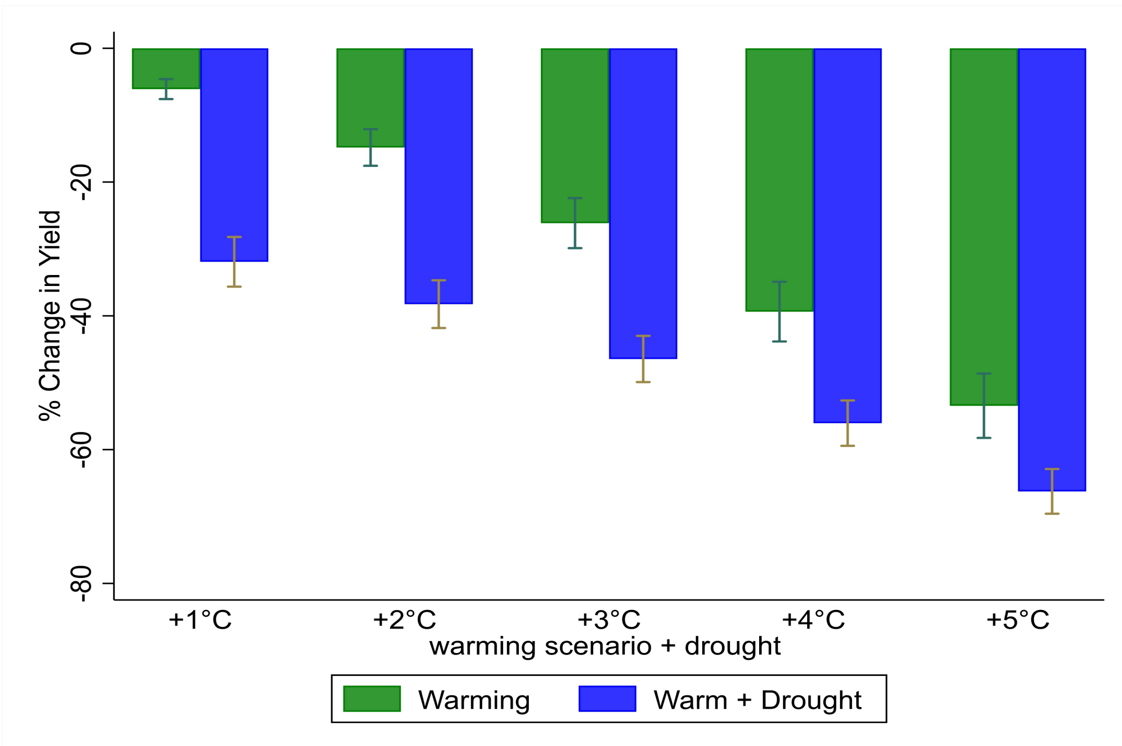


**Figure 2.5**: *The figure shows the predicted impact of an increase in temperature across different periods during the growing season on yield. Impacts are reported as the percentage change in yield relative to historical climate. Bars show 95% confidence intervals using standard error clustered by county.*

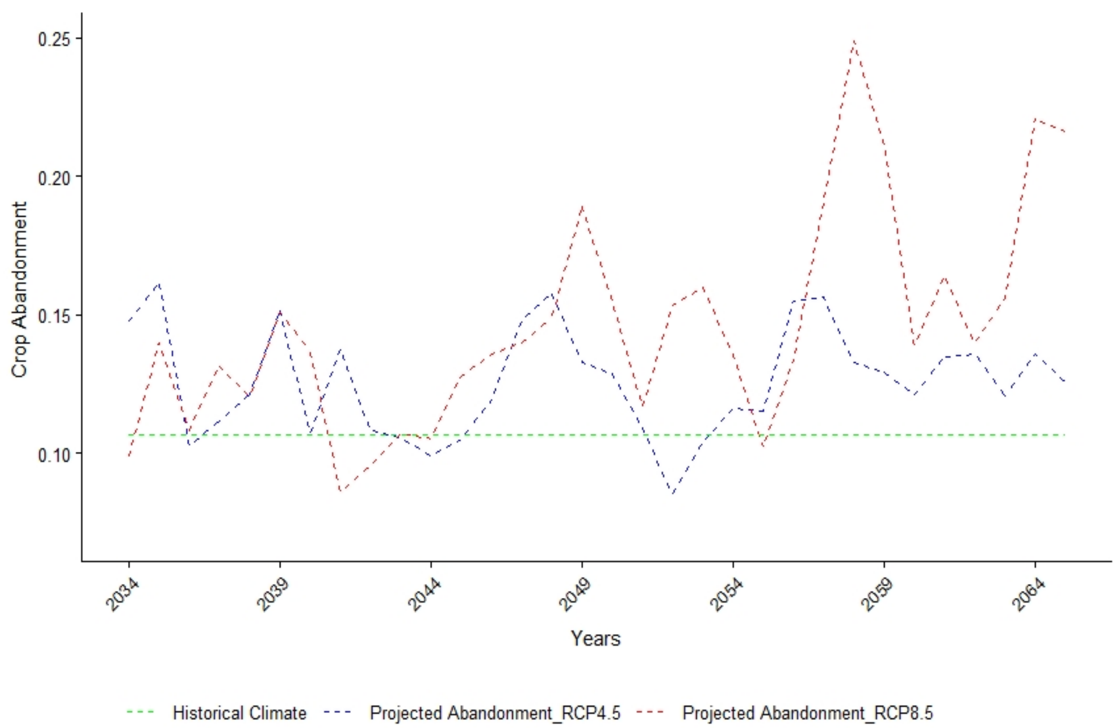


**Figure 2.6**: *The graph shows the projected winter wheat abandonment by year under scenarios RCP 4.5 and RCP 8.5. The dashed green line is the average crop abandonment under the historical climate between 1981–2007.*

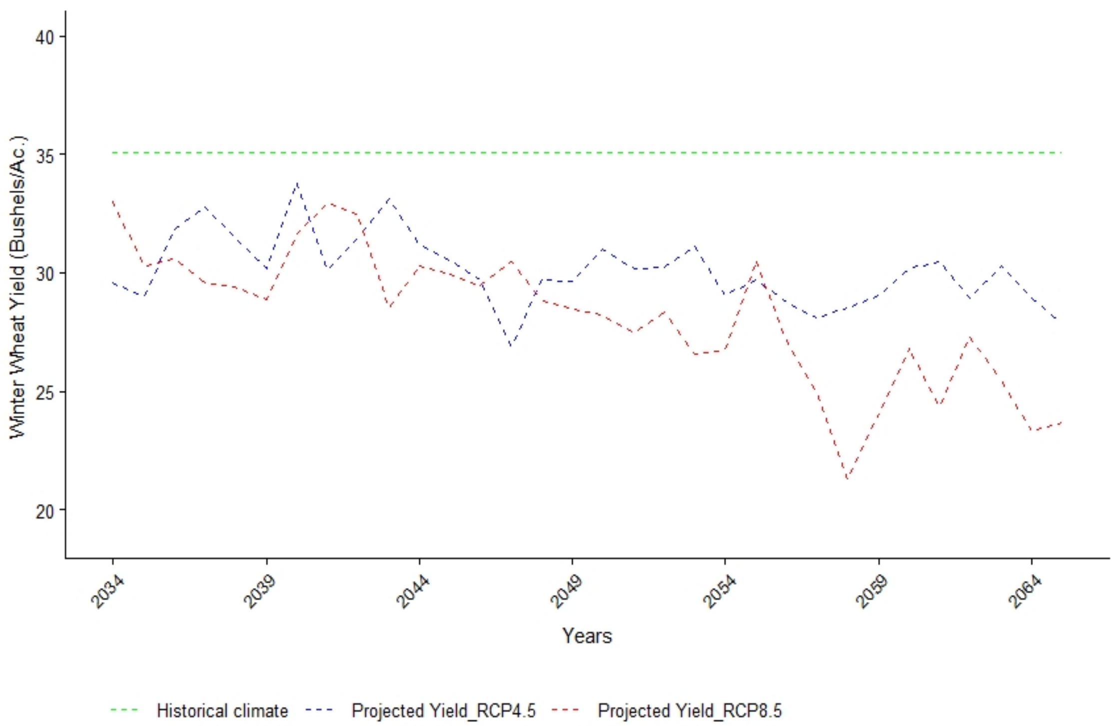


**Figure 2.7**: *The graph shows the projected winter wheat yield by year under scenarios RCP 4.5 and RCP 8.5. The dashed green line is the average yield under historical climate between 1981–2007.*

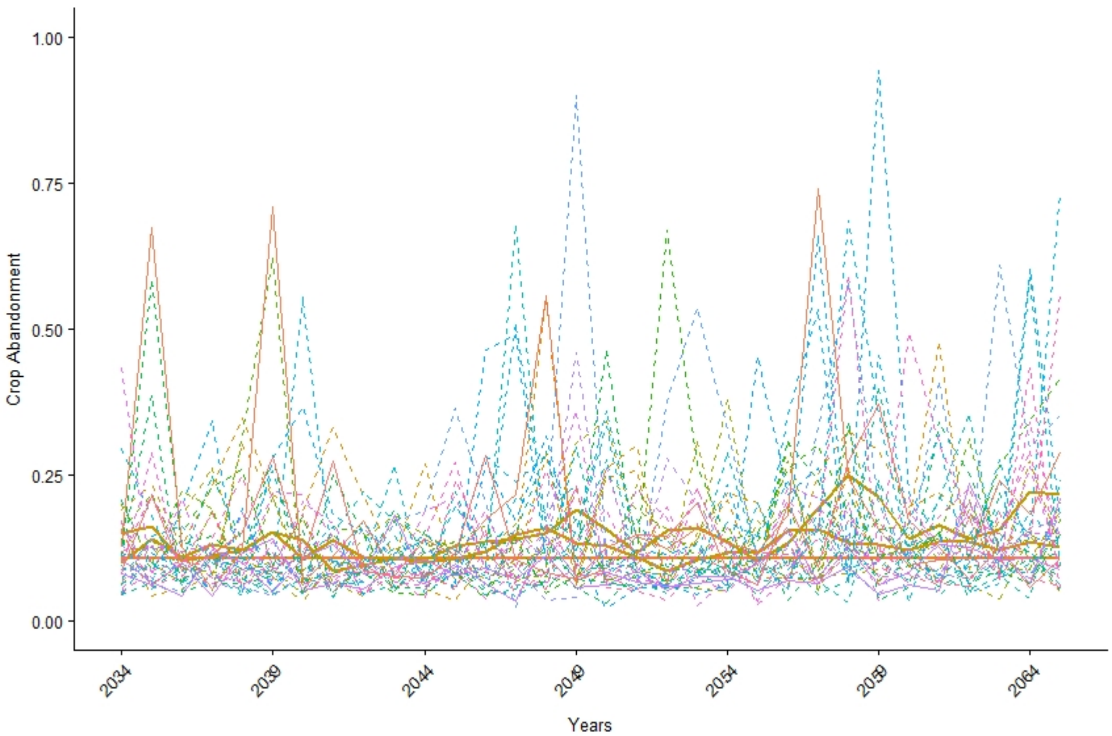


**Figure 2.8**: *The graph shows the projected winter wheat abandonment by each of the 18 climate models by year under scenarios RCP 4.5 and RCP 8.5. The horizontal line is the average crop abandonment under the historical climate between 1981–2007.*

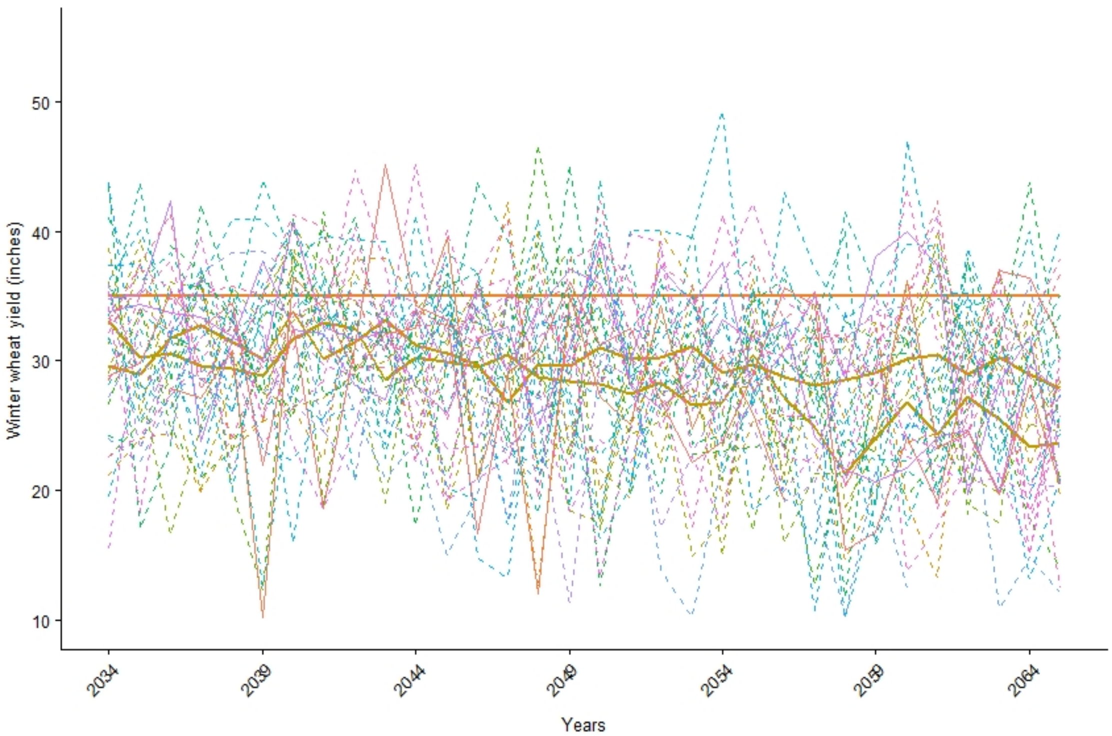


**Figure 2.9**: *The graph shows the projected winter wheat yield by each of the 18 climate models by year under scenarios RCP 4.5 and RCP 8.5. The horizontal line is the average yield under historical climate between 1981–2007.*

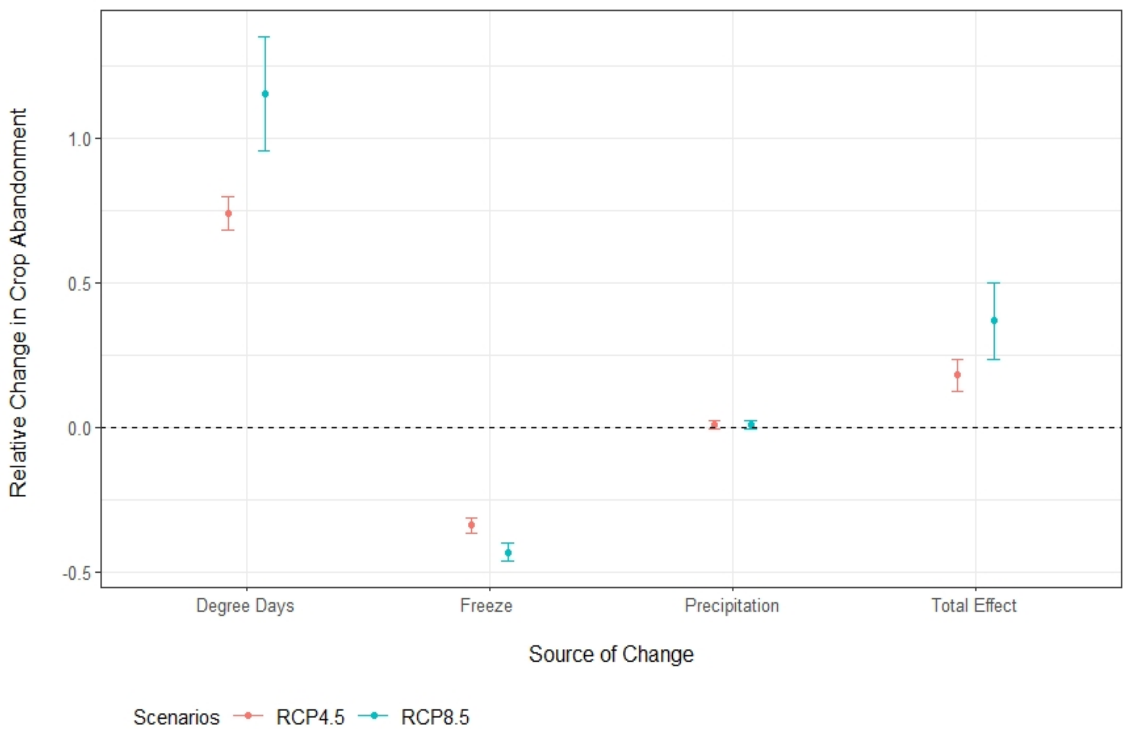


**Figure 2.10**: *The graph shows the source of change in crop abandonment under RCP 4.5 and 8.5 respectively. The dot indicates the point estimates, and whiskers show the 95% confidence interval after adjusting for spatial correlation. This is an ensemble average from 18 different climate models.*

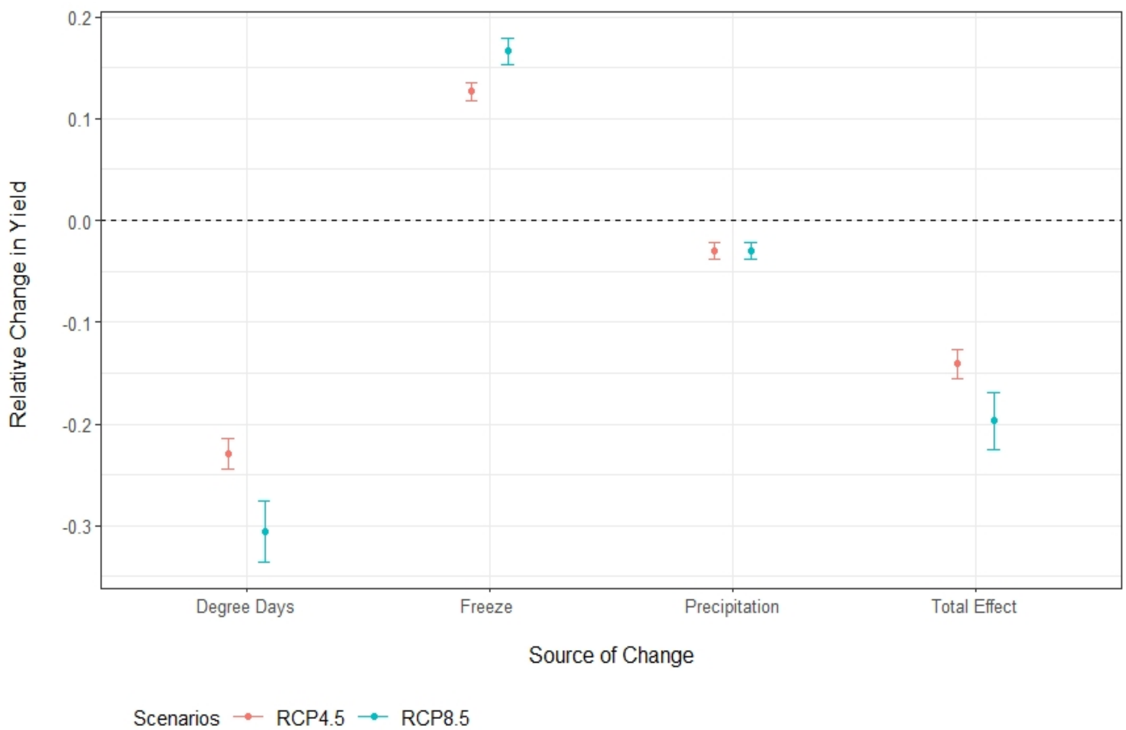


**Figure 2.11**: *The graph shows the source of change in winter wheat yield under RCP 4.5 and 8.5 respectively. A dot indicates the point estimates and whiskers show the 95% confidence interval after adjusting for spatial correlation.*

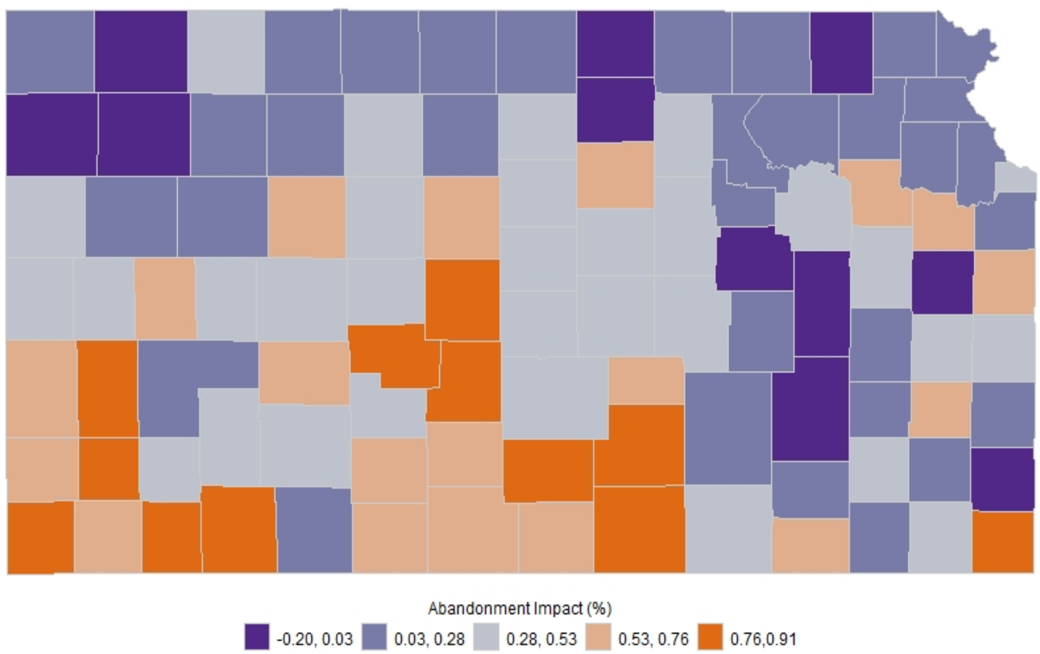


**Figure 2.12**: *The figure shows the percentage change in an ensemble average of crop abandonment by mid–century from the historical abandonment (1981-2007) under RCP 4.5.*

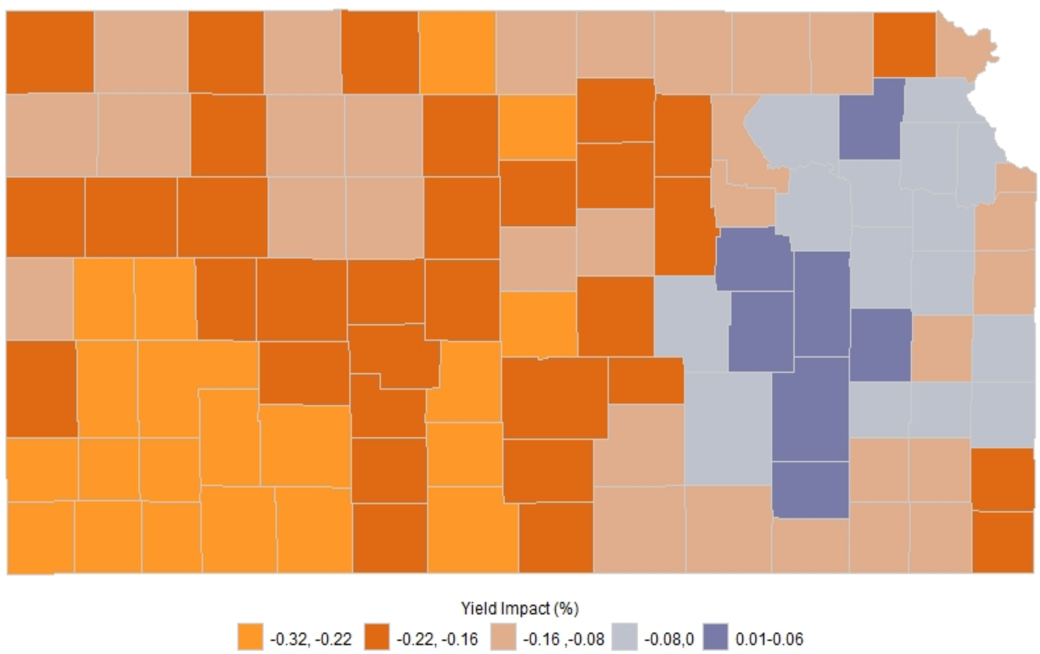


**Figure 2.13**: *The figure shows the percentage change in ensemble average harvested yield by mid–century from the historical yield(1981-2007) under RCP 4.5.*

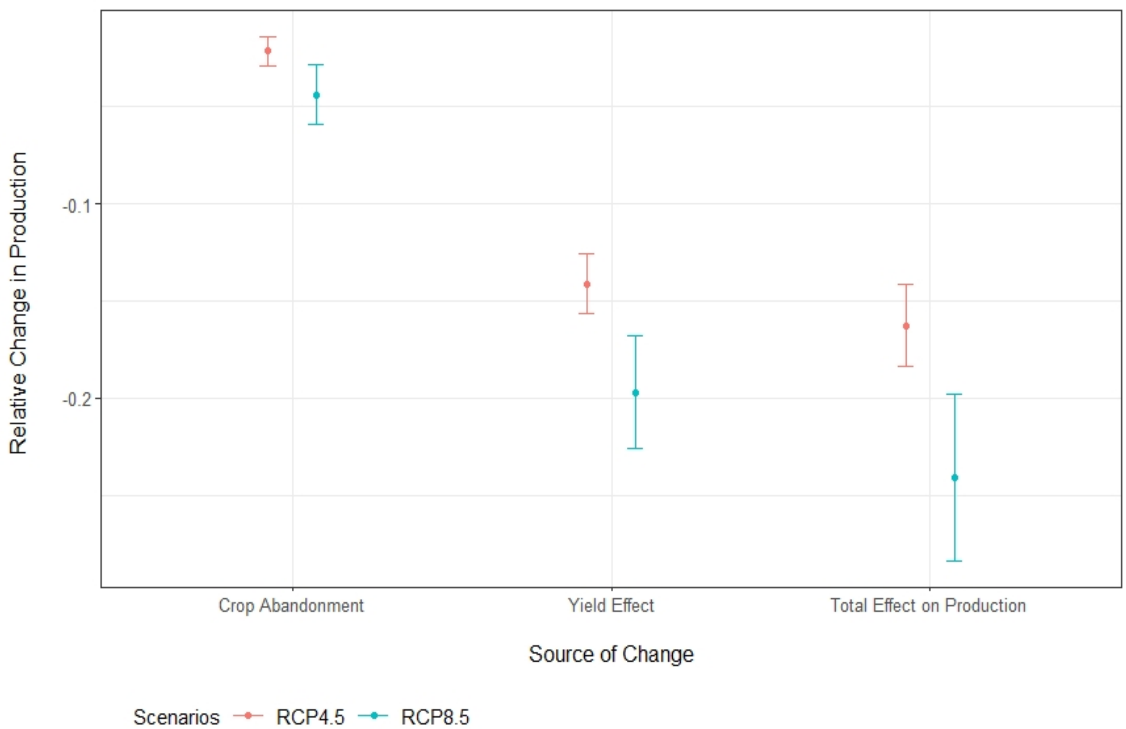


**Figure 2.14**: *The graph shows the source of change in production under RCP 4.5 and 8.5 respectively. The dot in the error bar represents the point estimates while the bars represent the 95% confidence interval generated from 500 bootstrap replications.*

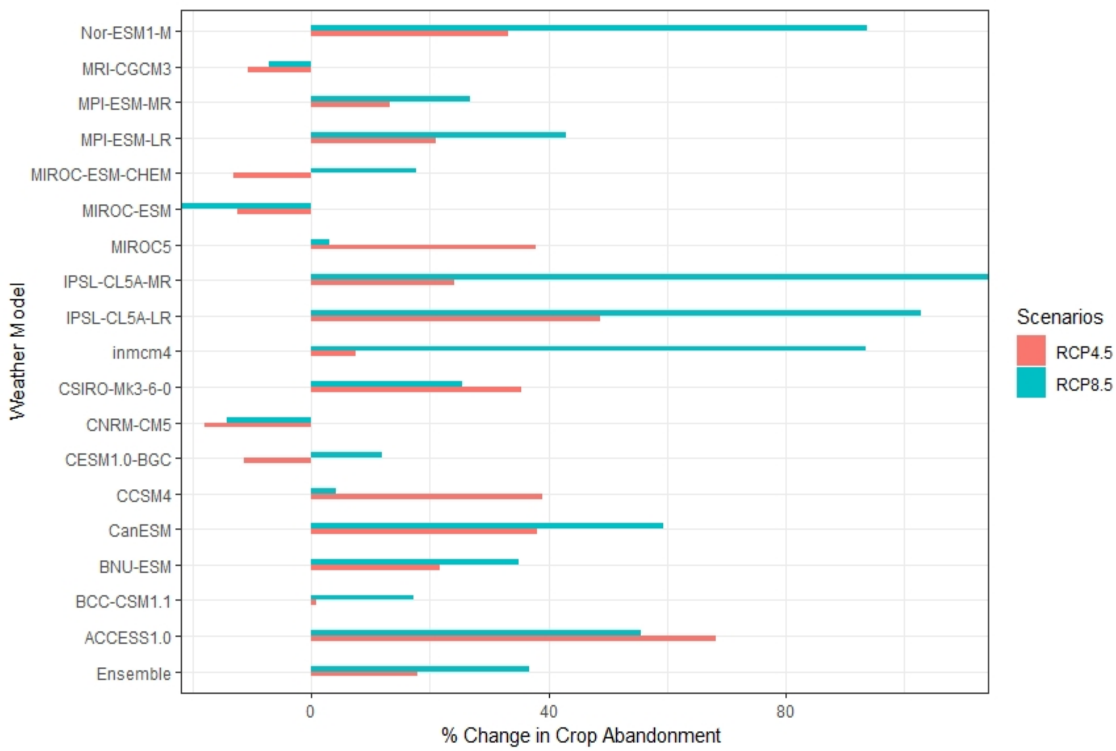


**Figure 2.15**: *The figure shows the percent change in crop abandonment across 18 general circulation models under RCP 4.5 and 8.5 respectively.*

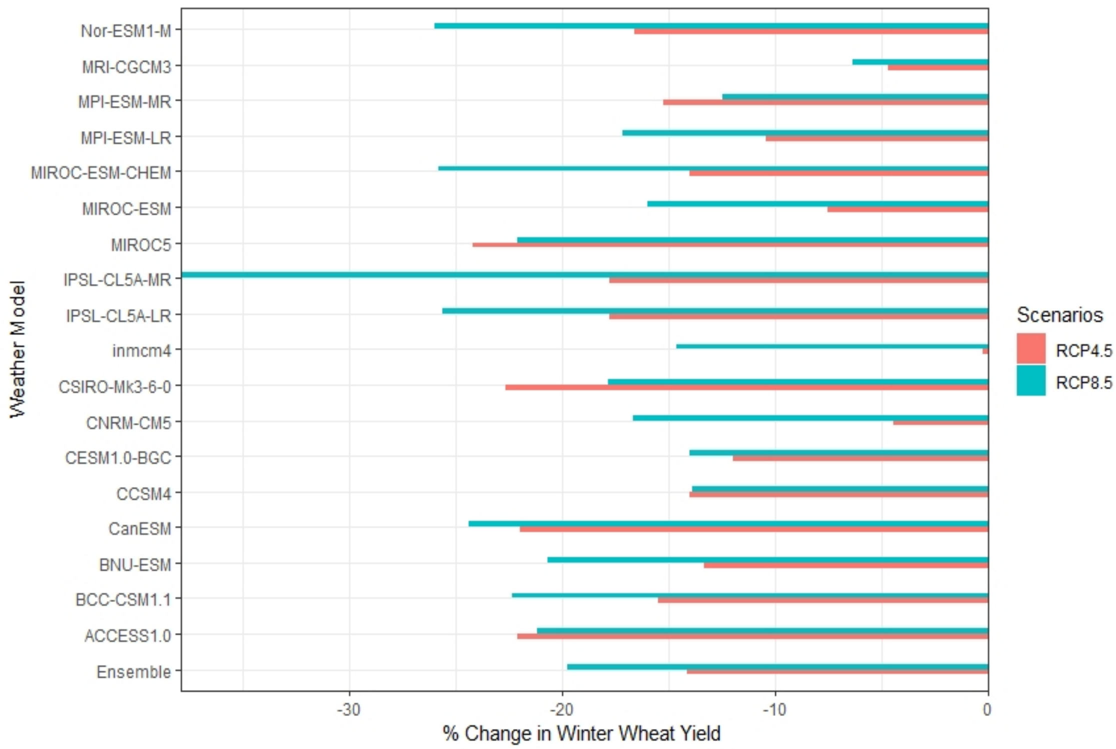


**Figure 2.16**: *The figure shows the percent change in winter wheat yield across 18 general circulation models under RCP 4.5 and 8.5 respectively.*

# Chapter 3

# Impact of Climate Change on Groundwater Extraction for Corn Production in Kansas

## 3.1 Introduction

Irrigated agriculture has expanded over the last 50 years especially in Western Kansas due to continuous improvement in technology, high crop prices and drought (Blanc et al., 2014; Clark, 2009; Rogers et al., 2008; Sampson and Perry, 2018). The survival of this billion dollar industry is being threatened mainly by the continuous depletion of the High Plains Aquifer (HPA) that provides supplementary water to mitigate adverse effects from weather shocks. The aquifer continues to decline as the estimated average annual natural recharge to the aquifer in Kansas is less than one–quarter of the total water pumped to irrigated acres (Buchanan et al., 2015; Lanning-Rush, 2016; McGuire, 2017; Steward et al., 2013). Extrapolation of the current depletion rate suggests that 35% of the southern High Plains will be unable to support irrigation within the next 30 years (Scanlon et al., 2012). The survival of the aquifer itself is linked to its use and climate change.[1] While climate change

[1] Irrigation intensity and expansion of irrigated acres due to improved technology and higher economic return. Climate change is change in average weather over long periods of time.

impacts on crop production have received substantial attention in the literature (Fischer et al., 2007; Howden et al., 2007; Nelson et al., 2009; Rosenberg et al., 1999; Schlenker and Roberts, 2009; Steward et al., 2013), the impact of climate change on irrigation withdrawals has received less attention. More than 40% of the crops produced come from irrigated acres (Döll, 2002), while more than 70% of freshwater use is for agriculture (?). Climate change affects water demand and use in two ways: (i) increasing temperatures increase the crop water requirement thus increasing pressure on irrigation resources (Döll, 2002; Gondim et al., 2012; Watson et al., 2017) and (ii) changing the amount of precipitation and the pattern of precipitation during the growing season (Luckey et al., 2000; Miller et al., 1997; Rosenberg et al., 1999; Trenberth, 2014).

I provide new evidence that shows how farmers react to increasing irrigation water demand when climate changes. As there are numerous studies on how irrigation water demand or requirement will increase as the temperature becomes warmer (Döll, 2002; Fischer et al., 2007), there are limited studies on how farmers will respond to these irrigation demands. I show that farmers are less responsive to changing irrigation water use than an irrigation schedule would predict due to changes in the weather. Gondim et al. (2012), Döll (2002) and Fischer et al. (2007) all projected an increase in irrigation water requirement. Woznicki et al. (2015) projected a decrease in irrigation demand as there will likely be less water available during the growing season in the future, or evapotranspiration will be hindered due to temperature stress in peak development periods for corn. De Silva et al. (2007) shows that a 3.5% increase in potential evapotranspiration will increase irrigation water use by 23% due to rain ending earlier. Nkemdirim and Purves (1994) predict an increase in precipitation and temperature with the predicted increases in precipitation not enough to compensate for increased evaporation and evapotranspiration.

Majority of the existing water–related economic studies focus mainly on the economic impacts of price elasticity of water demand, pumping cost, and energy price on irrigation water use (Hendricks and Peterson, 2012; Mieno, 2014; Pfeiffer and Lin, 2014b; Schoengold et al., 2006) while the few climate–related studies are limited due to incomplete weather information (Irmak et al., 2012) or use of crop growth models (Elliott et al., 2013; Steduto et al., 2009; Williams et al., 1989). Models of irrigation water demand can be divided into two broad groups; crop growth model and econometric based analysis. Crop growth models are limited due to many reasons ranging from the inability to incorporate the actual farmer's behavior, to under or overestimation of irrigation water use (Fischer et al., 2007; Guerra et al., 2005; Mieno, 2014; Wriedt et al., 2009). The econometric analysis is different from a model–based approach as econometric analysis uses observed irrigation use data and implicitly embeds farmer's behavior into the model (Mieno, 2014).

I use an econometric approach that exploits variability in weather variables to explain how precipitation variability and warming effects of temperature impacts irrigation water use. Water use by a crop is through evapotranspiration, which is the combination of evaporation and transpiration occurring simultaneously (Allen et al., 1998). The rate of evapotranspiration depends on the weather (Allen et al., 1998; Hess, 1998; Snyder, 1985; Yu et al., 2002), crop type and growth stages (Salter et al., 1967), and irrigation system used (Savva and Frenken, 2002). I use crop evapotranspiration ($ET^c$) instead of reference evapotranspiration ($ET^r$) (Hendricks and Peterson, 2012; Pfeiffer and Lin, 2014a,b) or temperature (Mieno and Brozović, 2016; Schoengold et al., 2006) to measure atmospheric water demand. Hendricks and Peterson (2012) find that a 1 inch per acre increase in atmospheric water demand will increase irrigation water use by 0.07 inches per acre.

There are two problems with using Hendricks and Peterson (2012) to project the impacts of climate change on irrigation water use. First, Hendricks and Peterson (2012) use weather at the nearest weather station, inducing measurement error bias. In contrast, I use a high resolution gridded weather data, and secondly, Hendricks and Peterson include year fixed effects which absorb much of the variation in weather over time and may bias the coefficients on $ET^r$ and precipitation. Mieno (2014) use a non-parametric method to analyze the impact of climate change on irrigation water use in Nebraska, comparing farmer's actual response with that of a hypothetical farmer using Aquacrop (Steduto et al., 2009). This study differs from Mieno (2014) as Mieno (2014) only covers three counties in Nebraska while this study covers the major groundwater management districts in Kansas. I use different global circulation models to project irrigation water use by mid–century and how this projected changes in irrigation water use will affect the rate of aquifer depletion.

Like most previous studies (Mieno, 2014; Ortiz-Bobea and Just, 2013; Schlenker and Roberts, 2009; Tack et al., 2015), I assume that temperature and precipitation are additively separable. I incorporate time separability through corn stages of growth to explore the sensitivity of irrigation water use and timing of precipitation at different stages of growth to changes in weather variables (Mieno, 2014). Ortiz-Bobea and Just (2013) and Tack et al. (2015) implemented time separability using crop yields and degree days to explain weather effects at different periods during production. I implement time separability by dividing corn stages of growth into three based on Kranz et al. (2008). An initial contribution by Robins and Domingo (1953), Shipley and Regier (1976) and recently by Peterson and Ding (2005) find that crop yield is more sensitive to changes in $ET^c$ at certain times in the growing season.

Crop meets its water requirement through precipitation, irrigation and soil water. I interact available water storage (AWS) with atmospheric water demand and precipitation for two main reasons. First, soil moisture is a function of precipitation and evapotranspiration, and secondly, it reflects the impact of soil properties that may affect soil water holding capacity, root depth, percolation and water runoff (Wehner et al., 2017). The decision to irrigate are commonly driven by target soil moisture levels during the growing season that minimizes crop yield losses (Jones, 2004). Climate change impacts soil moisture available by lowering soil water content through increased evaporation and lower water input. Savva and Frenken (2002) and NRCS (1997) included available water storage in their water balance model while Foster et al. (2014) used soil moisture management to formulate different irrigation strategies in response to total seasonal irrigation.

I also include an irrigation system and its interaction with atmospheric water demand as irrigation system used can alter the micro-climate, affect the crop characteristics, and the wetting of the soil and crop surface (Savva and Frenken, 2002). According to Kisekka et al. (2017), the use of low energy spray irrigation reduces evaporation loss. There has been a shift in the adoption of more efficient irrigation systems in Kansas over the years (Pfeiffer and Lin, 2014a). Over 32% of the farms in this study use standard center pivot, while less than 9% still use furrow irrigation. Application efficiency of each irrigation system use differs as it affects the net amount of irrigation water applied (Amosson et al., 2002).

As reported by Wehner et al. (2017), climate change is projected to further increase the duration and intensity of drought over the Southern Great Plains, impacting the way water is used and demanded. I project how precipitation variability and increasing temperature through evapotranspiration will affect irrigation water use by using 18 different climate models by mid–century (2034-2065) under Representative Concentration Pathways (RCPs) 4.5 and 8.5. I combine my estimates from my historical estimation with the climate change models to project how irrigation water use will change by mid-century by assuming that the short–run response from weather variations are representative of how farmers will respond to climate change in the future (Burke and Emerick, 2016). Temperature is expected to rise in the Southern Great Plains between 2$^o$C (3.6$^o$F) and 2.83$^o$C (5.1$^o$F) by the mid–21st century and by 2.4$^o$C (4.4$^o$F) and 4.67$^o$C (8.4$^o$F) by the late 21st century, with the occurrence of temperature similar to that of 2011 (Reidmiller et al., 2018). According to Wuebbles et al. (2017), the Southern Great Plains is projected to experience an additional 30–60 days per year above 100$^o$F than it does now by late 21st century if there are no reductions in emissions. Projected changes in summer and fall precipitation are small.

I simulate the proportion of water that will be saved if the authorized water quantity is fully enforced by assuming that authorized water quantity is binding. A water right's authorized quantity is how much water is appropriated annually. Water use during drought is different from the normal year as farmers tend to use more than usual during drought. Kansas has a prior appropriation water right system where maximum authorized annual quantity is set after farmers apply for a water right and have perfected their water right. Water right groups are water rights grouped together based on point of diversion or place of use, and the total water use by the group is summarized and compared to the total authorized quantity (KGS, 2000). During dry years, the number of water right groups exceeding their limit are higher as there are different programs that allow farmers to borrow water from next year to complete current year production.

I assess the impact of climate change on change in the rate of depletion of the HPA for the major Groundwater Management Districts in Kansas (GMDs). According to McGuire (2017), water–level has changed from the predevelopment level to 2015, by well, ranging from a rise of 84 feet to a decline of 234 feet. Since water depletion and recharge is localized, I use the percentage change in water use by GMD and the linearized model by Butler et al. (2016) to estimate the change in the rate of depletion for each GMD by mid–century. Butler et al. (2016) used the regional correlations between average annual water level change and annual water use to determine how water use affects the water level in the High Plains aquifer in Kansas. For example, water use and depletion rate in GMD 5 is different from GMD 3 which is semi-arid and directly underlying the aquifer in term of depletion rate and water use (Whittemore et al., 2016).

My key result is that farmers are less responsive to increasing irrigation water demand when the temperature becomes warmer than is predicted by the change in $ET^c$ demand. A 1–inch increase in atmospheric water demand will increase irrigation water use by 0.29 inches per acre. I also find that precipitation is not a perfect substitute for irrigation. Uncertainty in determining the level of irrigation water that will maximize yield for a given year due to weather variability, limits on the authorized water use, runoff and deep percolation are some of the reasons that can explain why farmers are less responsive to change in increasing $ET^c$ demand. Li and Zhao (2018) highlighted the desire to keep water rights as the reason farmers use a small amount of water even when irrigation is not profit–maximizing under the use or lose it policy. I also found that the adoption of improved technology and management practices over the past 24–years has saved over an inch per acre of irrigation water. Araya et al. (2017) found early planting to improve irrigation water productivity for grain compared to late or normal planting while, Zhao et al. (2018) found the adoption of drought–tolerant corn as an adaptation strategy under limiting water condition. The water saved is different from the water saved from the adoption of the efficient irrigation system.

Increasing temperature by 2$^o$C while holding other variables constant will increase irrigation water use by 4.8%. Using long–run projections, atmospheric water demand is expected to increase by ensemble average of 16.7% under RCP 4.5 and 22% under RCP8.5 annually by mid-century with an expected reduction in the amount of precipitation received by 6%.

Irrigation water use will increase by 9.62 and 12.65 % under RCP 4.5 and 8.5 respectively. Historically the average water rights that exceeded authorized limit is 9%, by mid 19.24% to 23.1% of the water rights will exceed their authorized quantity under RCP4.5 and 8.5 respectively. There is a huge degree of uncertainty in irrigation water use estimated with the climate change projections expected to increase for all climate models. The change in water use will have varying effects across GMDs. The water level decreases at the rate of 2.43 ft per year in GMD 3 compared to a historical rate of depletion of 1.69 ft. per year, while in GMD 5, the rate of deletion will increase to 1 ft/year compared to a historical rate of depletion of 0.19 ft/year. GMD 5 will be most affected in terms of depletion rate due to an increase in crop water demand and a reduction in precipitation.

## 3.2 Data

The objective of this study is to exploit variability in weather variables to explain irrigation water use. This analysis combines data from different sources.

### 3.2.1 Water Data

Data about water use on each irrigated field, type of crop grown and irrigated area, and the delivery system were obtained from the Water Information Management and Analysis System (WIMAS) of the Kansas Department of Agriculture from 1991–2014. The point of diversion represents wells for groundwater irrigation, henceforth, each point of diversion will be referred to as a field for the rest of this paper. A field is defined as the area irrigated by a single well. The dependent variable is the applied water per acre defined as the total amount of water pumped divided by the acres of corn irrigated. Only fields with corn are considered as I can only determine water use on corn if the entire field is planted to corn. Another important point is that I relate crop-specific evapotranspiration to the water on that crop. Extending the model to other crops is possible but would require evapotranspiration crop coefficients for those models. More than two–thirds of irrigated acres in Kansas is used to produce irrigated corn. The corn fields used in this study are within the Groundwater Management Districts (GMDs) 1, 3, 4 and 5. Fields less than 40 acres or greater than 400 acres are excluded from the analysis.[2] The location of corn fields is shown in figure 3.1 with the majority of the fields located in the southwest region of Kansas. More than two-thirds of the irrigated acres in Kansas is located in the south-west region because the region has the largest groundwater reservoirs (Rogers and Aguilar, 2017).

### 3.2.2 Weather Information

I use the historical daily weather data from PRISM[3] to calculate the reference evapotranspiration based on grass using the Modified Penman equation (Bos et al., 2008; Doorenbos, 1977). The Modified Penman method was considered to offer the best results with a minimum possible error in relation to a living grass reference crop (Allen et al., 1998). Reference evapotranspiration was calculated between May and September. Crop–specific coefficient ($K_{cd}$) based on Kincaid and Heerman (1974) is used to adjust reference evapotranspiration at different stages of growth to crop evapotranspiration (figure 3.2). This study differs from previous studies like Oehninger et al. (2016) and Mieno and Brozović (2016) that use temperature and degree days instead of crop evapotranspiration ($ET^c_{it}$) to measure weather effects on water use. Crop evapotranspiration is defined by Equation 3.1. Estimation without crop coefficient will not be scaled and for corn $ET^c$, I expect $\beta < 1$ and the coefficient on $ET^r$ to be smaller. Since $K$ is just a scaling factor, the predicted impact of climate change may not be much different if $ET^r$ is used instead of $ET^c$.

$$ET^c_{it} = \sum_{d=1}^{149} (K_{cd} \times ET^r_{idt}) \tag{3.1}$$

Precipitation data received during the growing season (May–September) is used as the effective precipitation at each field. Both crop evapotranspiration and precipitation are in

[2] Hendricks and Peterson (2012) and Pfeiffer and Lin (2014a) limit the size of fields used in their estimation to prevent outliers from skewing their results. My sample size was reduced by 7%. [3] PRISM Climate Group, Oregon State University– http://prism.oregonstate.edu/. Note that PRISM was merged to the water use data at section level (roughly 1 mile by 1 mile).

inches.

Figure 3.3 shows the distribution of precipitation (inches), average temperature ($^oC$), atmospheric water demand (inches), and irrigation water applied (inches) for corn production across the study area over time in Kansas. Atmospheric water demand and irrigation water applied are high in years with low precipitation and increased average temperature. For example, the drought of 2011 and 2012 in Kansas show how an increase in average temperature and low precipitation resulted in an increase in atmospheric water demand and irrigation water applied.

### 3.2.3 Irrigation system Information

The information about the irrigation system use is obtained together with the water information WIMAS. The three most common irrigation systems used are furrow, standard center pivot and center pivot with low nozzles as more than 96% of the fields in this study are irrigated by these systems. Furrow irrigation uses gravity to deliver water to the crops through ditches in the field rows. Furrow irrigation has low application efficiency when compared to other methods of irrigation like a center pivot with a low nozzle that has 88% application efficiency (Amosson et al., 2002). I divide the irrigation systems into three based on their application efficiency and create discrete variables representing each of the systems.[4]

### 3.2.4 Soil and Price information

I use information from the Web Soil Survey of the USDA Natural Resources Conservation Service about root zone available water storage. Root zone available water storage is the volume of plant available water that the soil can store within the root zone based on all map unit earthy major components. I use root zone available water storage as a proxy for available water storage (AWS). I use the Chicago Mercantile Exchange (CME) expected price for corn futures which is the average daily settled price in April and May for the December CME Group corn contract.

[4] Less than 0.43% of the fields use drip irrigation. Other fields are irrigated by the combination of one or two of the systems.

### 3.2.5 Descriptive Statistics

The summary statistics for the different variables used in the analysis are presented in table 3.1. The average irrigation water use is 16.17 inches. This could be as high as 20 inches during dry years. The average atmospheric water demand and precipitation are 28.10 and 13.62 inches respectively. There is a spatial variation in atmospheric water demand and precipitation across the groundwater management districts in Kansas. There is an increase in precipitation as I move from Southwest and Northwest to the Southcentral part of Kansas. GMD 3 receives less precipitation when compare with GMD 5. As shown in table 3.1, 60% of the irrigated fields are irrigated by a center pivot with low nozzles and less than 9% of the fields apply water through furrow irrigation. The average expected price for corn futures is \$3.34/bushel.

## 3.3 Empirical Method

I expressed irrigation water use "$W_{it}$" for a field $i$ at year $t$ as

$$W_{it} = \mathbf{X_{it}}\beta + c_i + \tau(t) + \gamma Cprice_t + \rho_0 CP + \rho_1 CPN + \varepsilon_{it} \tag{3.2}$$

where $X_{it}$ is the vector of $ET^c_{it}$, and precipitation, $\beta$ is the vector of parameters to be estimated, $c_i$ is the county fixed effects used to control for time-invariant heterogeneity like soil quality, $\tau(t)$ is the time trend which can be specified as linear or quadratic depending on the functional form, $\gamma$ is the coefficient of corn price, $\rho_0$ and $\rho_1$ are the coefficients of the standard center pivot and the center pivot with nozzle respectively,and $\varepsilon_{it}$ is the error term. I cluster the standard errors in all the analyses by the county to allow the error to be spatially correlated within each county. In some of the alternate specifications, I interact $ET^c_{it}$ and precipitation with available water storage and irrigation systems. Although AWS is a time–invariant variable controlled for using field level fixed effects, its interaction with precipitation and $ET^c_{it}$ account for spatial variation in available water storage within each county. This reflects soil properties and how it may affect soil water holding capacity, root depth, and amount of water available to crop. I also estimate a model including a quadratic term of precipitation and trend to control for technological change.

Time separability is incorporated by dividing the duration of growth into 3 periods based on corn growth physiological stages (Kranz et al., 2008): (i) vegetative, (ii) reproductive, and (ii) maturity. The reproductive stage begins when the corn tassels and ends when the corn is in full dent. In the last stage, the crop has reached full maturity and crop water requirements are minimal. Different studies have shown how corn response to water requirement during different phenological stages. Water deficit during the reproductive period (after tasseling) can delay silking, the interval between silking to pollen shed (Herrero and Johnson, 1981) and shorten the grain filling period (Kefale and Ranamukhaarachchi, 2004; Westgate, 1994), therefore resulting in reduced yield. I explore the sensitivity of atmospheric water demand at different stages of growth to changes in weather variables. The corn growing season is fixed to the month of May through September. The variables are similar to equation 3.2 except that the subscripts $s$ represents the stages of growth.

$$W_{it} = \sum_{\mathbf{s=1}}^{\mathbf{3}} \mathbf{X_{ist}} \beta_{\mathbf{s}} + c_i + \tau(t) + \gamma Cprice_t + \rho_0 CP_i + \rho_1 CPN_i + \varepsilon_{it} \tag{3.3}$$

### 3.3.1 Warming Scenarios

The marginal impact of warming on irrigated water use is simulated for each $1^oC$ increase in temperature up to $5^oC$ by increasing the observed daily maximum and minimum temperatures and then recalculating the appropriate weather variables for the whole growing season. Simulated impacts are obtained by predicting the change in water use due to the change in $ET_{it}^c$ while other factors are held constant.

### 3.3.2 Climate Change Projection

I use 18 different global climate models (GCMs) to project change in atmospheric water demand, precipitation by mid–century (2034–2065), and use these changes in atmospheric water demand and precipitation to simulate how irrigation water use will change. I use the downscaled Coupled Model Intercomparison Project (CMIP5) daily climate projections for two main reasons. Downscaled CMIP5 was used to inform the IPCC (Intergovernmental Panel on Climate Change) Fifth Assessment and secondly, the data are downscaled. The use of downscaled data resolve the issues of aggregation bias raised by Auffhammer et al. (2013). I make a bias correction to the GCM projections to correct for possible error in relation to the historical information. Bias–corrected projections are obtained by using the mean difference between variables constructed from historical simulated data through climate models and the observed data from the PRISM (equation 3.4) to adjust the future data projections (equation 3.5) (Hawkins et al., 2013). Data between 1991–2005 are used to estimate the bias:

$$Bias_c = \frac{1}{T}\sum_t (ET^{MH}_{ct} - ET^{O}_{ct}) \tag{3.4}$$

$Bias_c$ is the mean difference between historical–climate constructed variables ($H$) from climate model $M$ and the actual observed climate variables *(O)* at the county level *(c)*. Climate projections are adjusted by using $Bias_c$ to shift the projection. Climate $\text{Projection}^{'}_{mct}$ is the uncorrected climate projection.

$$\text{Climate Projection}_{mct} = \text{Climate Projection}^{'}_{mct} - Bias_c \tag{3.5}$$

Other challenges involved with the use of a single projection of future climate is resolved by using an ensemble average from 18 different models (Auffhammer et al., 2013; Burke et al., 2015). I report a simulation with an ensemble average by averaging the predicted change in each variable across all models. I also report simulation results for each climate change models to show the level of uncertainty across different climate models under RCP 4.5 and RCP 8.5 respectively. The list of the 18 climate models and institutions are listed in table A. The use of ensemble average smooths out the uncertainty and extreme projections from different models.

The ensemble average bias for the atmospheric water demand is ±0.09 inches while the ensemble average of precipitation is ±3.4 inches. Atmospheric water demand is expected to increase annually by 5 inches under RCP 4.5 and 7 inches under RCP8.5 by mid-century with an expected reduction of 0.6 inches in the amount of precipitation received (figure 3.4). Under both scenarios, the ACCESS1-0 climate model simulated the largest change in atmospheric water demand, 34.97% and 45.4% under RCP 4.5 and 8.5 respectively, and MRI-CGCM3 indicates the smallest changes in atmospheric water demand, 7.6% and 12.9% under RCP 4.5 and 8.5 respectively (figure 3.13). The projected change in precipitation range between -25.6% and 9.6% under RCP 4.5 and -33.3% and 9.8% under RCP 8.5. ACCESS1-0 model projects the largest decrease in precipitation while MRI-CGCM3 projects an increase in precipitation under both RCP4.5 and RCP8.5 respectively (figure 3.14).

### 3.3.3 Climate Change Impact on the Aquifer through Water Use

I use the aquifer balance model from Butler et al. (2016)[5] to calculate how an increase in irrigation water use will change the rate of depletion of the Ogallala aquifer. The model is based on the relationship between water–level changes and reported pumping for each of the GMDs (Whittemore et al., 2016). Butler et al. (2016) fitted a line between the average annual water–level change and the annual water use for each of the groundwater districts using well measurements between 1996–2013[6] and the reported total water pumped. To adopt this model, I assume the same rate of increase in water use for all irrigated crops in each GMD as my model predicts for corn, no change in irrigated acres as my model predicts for corn, and there is no switching of crops from high water use to low water use and climate change has no effect on aquifer recharge. or vice versa. I use equation 3.6 to calculate the rate of depletion of the aquifer for each of the GMD by mid-century.

$$\triangle WL_i = \alpha_i - \rho_i Q_i \qquad \text{where } i \text{ is GMDs} = 1, 3, 4, 5 \tag{3.6}$$

$\triangle$WL$_i$ is the average water level change over an aquifer area in GMD $i$ for a given time interval and $Q_i$ is the total water pumped from the aquifer area for the given time interval.

[5] See Butler et al. (2016) for more details about the model. [6] 2006 and 2007 were not included as heavy snows delayed the 2007 water-level measurements in northwest Kansas, which affected the 2006 and 2007 water–level change values.

$\alpha$, $\rho$ and the average historical water $Q_i$ are estimated as an inverse of product between the specific yield and the area of the aquifer used in normalizing the net inflow, and the total water pumped from the aquifer for each of the GMDs respectively. I multiplied the average water used for each GMD between 1996–2017 with the predicted change in water use between 2034–2065 from my econometric projections to calculate the rate of depletion.

## 3.4 Results

The parameter estimates from equation 3.2 are shown in table 3.2 column (1). The second and third column of table 3.2 shows the results of interactions between $ET_{it}^c$ and precipitation with available soil water and irrigation system. The fourth column shows the result of the estimation that includes the quadratic precipitation and trend terms. The signs and the significant effects of $ET_{it}^c$ and precipitation on irrigation water use are robust across all specifications and the coefficients are all significant at 1%. Using the linear specification in table 3.2, column (1), an additional 1–inch increase in atmospheric water demand will increase irrigation water use by 0.29 inches per acre. Irrigation water use is more responsive to $ET_{it}^c$ than precipitation. This shows farmers are more responsive to increasing irrigation water use when atmospheric water demand increases than when less precipitation is received. This means $ET_{it}^c$ has a larger impact on irrigation water use than precipitation.

The coefficients of precipitation in all the specifications are less than one in absolute value. This shows that precipitation is not a perfect substitute for irrigation water use. From the second column in table 3.2, the coefficients of interaction between precipitation and $ET_{it}^c$ with AWS are not significantly different from zero. In the nonlinear model, the coefficients of precipitation are both negative. This indicates an inverted U-shaped effect on the relationship between precipitation and irrigation. At sample mean using model 4, a 1–inch increase in precipitation will reduce irrigation water use by 0.23 inches per acre.

A plausible explanation for the farmer's less responsiveness to the use of irrigation water could be attributed to uncertainty in determining the level of irrigation water that will maximize yield for a given year due to weather variability and policy limitations on water use.

The limitation may be due to policy constraints like limits on authorized water quantity, use it or lose it policy, and reductions in well yield due to declining water tables. Precipitation is less responsive to irrigation due to possible high variability in the frequency of precipitation, and the amount of water lost from surface runoff and deep percolation. There is also a possibility of measurement error when calculating effective precipitation and soil water condition, and atmospheric water demand that goes into irrigation scheduling (**?**). The measurement error of $ET^c_{it}$ is likely minimal because the temperature does not vary sharply over the study region. Measurement error in precipitation is more likely due to isolated storms causing highly variable precipitation. Mun et al. (2015) highlighted that accurate measurement of irrigation and rainfall are critical to minimizing errors when using irrigation scheduling tools.

The coefficients of the irrigation systems in column (1) of table 3.2 show the effect of using an efficient irrigation system. The amount of water saved is larger when furrow irrigation is converted to more efficient systems. Converting from furrow irrigation to standard center pivot (CP) will reduce water applied by 2.63 inches per acre. This result is consistent with the result of Hendricks and Peterson (2012). Converting standard center pivot to center pivot with drop nozzles will only reduce an additional 0.19 inches per acre. This result is consistent with (Pfeiffer and Lin, 2014a) about the adoption of more efficient irrigation technology. The interaction between atmospheric water demand and irrigation system is significant for both the standard center pivot and standard center pivot with low nozzles (column (3) of table 3.2). This means that a one–inch increase in atmospheric water demand will increase water use by 0.16 for furrow irrigation, 0.33 inches for the standard center pivot and 0.29 inches for the center pivot with drop nozzles. The result shows that farmers using an efficient irrigation system are more responsive to changes in atmospheric water demand than when furrow irrigation is used as it gives the farmer better control of water use.

The coefficient of corn price is significant and positive but not robust in all specifications especially in the nonlinear model where I added the quadratic time trend and precipitation to the model. In the nonlinear model (column (4)), the size of the corn price coefficient drops substantially to almost half of the coefficient from other specifications. An increase in expected corn price will result in an increase in irrigation water use. Using the coefficient from the linear estimation, a \$1 increase in the expected corn price will increase irrigation water use by 0.28 inches per acre.

The coefficient of the trend which captures technological advancement is negative, statistically significant and robust in all specifications. Even after controlling for the irrigation system, technological progress has reduced water use by 0.05 inches per acre per year (column (1)). These changes could be from the adoption of improved seed and improved management practices that save water. This is an addition to the water saved from the adoption of the more efficient irrigation systems.

I incorporate time separability by dividing growth periods into three stages. The result of the estimation using equation 3.3 is shown in table 3.3. Using the linear specification (column (1)), the F–statistic (41.78 & 8.43) against the null hypotheses that the atmospheric water demand and precipitation effects from all the three stages are the same are rejected. This is different when the nonlinear model is used as I fail to reject the null hypothesis for precipitation with or without stage 3. The coefficient estimates of atmospheric water demand from column (1) of table 3.3 for stage 1 and stage 2 are both positive and significant with irrigation water more responsive to atmospheric water demand from stage 1 than stage 2.

The reverse is the case with precipitation as irrigation water use is more responsive to precipitation in stage 2 than stage 1. The difference in irrigation water use between these two stages can be attributed to the minimal development of canopy to reduce water evaporation from soil and not fully developed root systems in stage 1 to extract of water from the soil for plant use when compared to stage 2.

The third stage is different from the other two stages (column (1) and (3)) as an increase in atmospheric water demand does not transform into an increase in irrigation water use. The coefficient of $ET^c_{it}$ for stage 3 has a negative sign, the standard error larger than the first two stages, and the coefficient on precipitation in stage 3 in the linear model is not significant. In reality, irrigation water use at this stage is almost zero as the crop would have reached maturity at this stage. I found no statistical difference in the results in term of coefficient size and R-squared when I used the first two stages (column (2) and (4)) alone.

### 3.4.1 Warming Scenarios

I used equation 3.2 to simulate the impact of an increase in temperature through $ET_{it}^{c}$ on irrigation water use while holding precipitation and other variables constant. Atmospheric water demand was recalculated under each warming scenario. Simulated impacts are obtained by multiplying estimated parameters from the preferred specification (model I in table 3.2) by the projected mean change on the $ET_{it}^{c}$. A $2^{o}$C increase temperature will increase atmospheric water demand by 10.4% and irrigation water use by 4.8% (figure 3.5). This result is consistent when reference evapotranspiration is used instead of crop evapotranspiration. Table 3.4 shows the result when reference evapotranspiration is used instead of crop evapotranspiration. The coefficient of $ET_{it}^{r}$ is downward biased toward zero.

### 3.4.2 Climate Change Projections

I simulate the relative change in irrigation water use by pairing the climate projections with my preferred econometric model (Equation 3.2). Since the climate projections output is at the county level, I predict the irrigation water use at the county level by using the projected climate data from the 18 different climate models and scenarios using 2014 technology. The ensemble average which is the average of all climate model projections of irrigation water use under different scenarios is compared with the average historical irrigation water use. The ensemble average of irrigation water use under both RCP scenarios is projected to exceed the historical average water use by mid–century above the historical average water use (figure 3.6). The yearly variation in the projected irrigation water use reflects the impact of variability in weather conditions by mid–century. The ensemble average of irrigation water use is expected to increase by 1.56 (9.62%) and 2.04 (12.65%) inches per acre by mid–century under RCP 4.5 and 8.5 respectively from the historical average water use (figure 3.7). Figure 3.12 shows the prediction from each of the 18 climate models.

Next, I decompose the source of change in irrigation water use: precipitation, and temperature through atmospheric water demand. To estimate the source of change, I simulate by using the ensemble average of the projected atmospheric water demand alone to project irrigation water use while holding precipitation and other variables in the model constant. I repeat the same procedure for precipitation. The middle dot from the error bar represents the mean estimates and the bars represent the 95% confidence interval generated using 1500 bootstrap replications. Summing the relative change in irrigation water use across sources equal the total effect. 93% of the change in irrigation water use is due to the change in atmospheric water demand arising from an increase in temperature while the remaining percent can be attributed to the reduction in precipitation (figure 3.7).

There is large uncertainty in the projected irrigation water use across the climate models. The projected change in irrigation water use ranges between 0.8% to 20.7% under RCP 4.5 and between 3.1% to 27.1% under RCP8.5 (figure 3.8). Under both scenarios, the ACCESS1-0 climate model indicates the biggest change in irrigation water use, and CESM1.0-BGC indicates the smallest changes in irrigation water use (see table A.1 for the list of climate models).

I combine the water use projections with the authorized water quantity to determine the proportion of water right groups that will probably use more than their annual authorized quantity. Figure 3.9 illustrates the proportion of groups that used more than the authorized water quality between 1991–2014 and 2034–2065. According to certain climate models in figure 3.9, close to 40% of water rights will violate their authorized quantity in some years by mid–century. Historically, on average, about 9.8% of water rights exceeded their authorized quantity while by mid–century this will increase to 19.3% and 23.1% under RCP 4.5 and 8.5 respectively.

Next, I calculate the projected water use if I assume that the authorized quantity is binding and farmers are not allowed to use more than their authorized water quantity. I assume that there is no drought-relief program that will allow farmers to borrow water. I used the authorized water quantity to constraint water use for groups that exceed their authorized quantity, assuming no change in irrigated area and no switch in crops cultivated. I used the maximum allowable water to replace the projected water use if the predicted water use exceeds what is allowed per acre. Historical, enforcing the authorized water quantity on average would have saved almost 13% of the irrigation water used for corn. If the authorized quality is fully enforced by mid–century, the irrigation water use on average would be reduced by 13.2% and 15.5% under RCP 4.5 and 8.5 respectively. This means farmers will be using on average less than what is needed at the expense of corn yield.

### 3.4.3 Climate Change Impact on Water Level

I used the percent change in water use in each of the GMD (Table 3.5) to calculate the rate at which the aquifer will decline by mid–century assuming no constraint in authorized quantity. The result shows how a change in water level and spatial impact from an increase in total water pumped varies across all the GMDs. GMD 3 has the highest change in water level at 2.43 ft per year under RCP 4.5. GMD 5 which has the smallest change in water level historically will have the biggest change in the rate of depletion by mid-century at the rate of 412.9 and 518.4% under RCP 4.5 and 8.5 respectively. GMD 5 has a higher rate of aquifer recharge so depletion has been slowest in GMD 5 historically. However, my projections indicate that by mid-century GMD 5 will have the second-fastest rate of depletion across the four GMDs.[7]

## 3.5 Conclusion

I examine how climate change will affect groundwater extraction by exploiting variability in weather variables to explain change in irrigation water use. The result shows that farmers are less responsive in increasing irrigation water use than irrigation schedule would predict when atmospheric water demand increases. One of the possible explanation for the less responsiveness can be attributed to risk and uncertainty associated with farmer's behavior in making decision about irrigation water use. I also incorporate the stages of growth into the model by looking at how the timing of precipitation and warming can impact irrigation water use. The result shows that corn is more responsive to irrigation water use during the first stage and least responsive to precipitation in comparison to other stages. Although the

[7] The average water use per acre for GMD 1, 3, 4,5 between 1991-2014 for corn is 15.58, 18.89,15.08, and 13.92 inches respectively

coefficient on reference evapotranspiration is biased toward zero, there is no significant difference in impact when reference evapotranspiration is used instead of crop evapotranspiration to model climate change impacts on irrigation water use.

I find that irrigation water use for corn will increase by an average of 1.5 and 1.9 inches per acre by mid-century under RCP 4.5 and 8.5 respectively. I also found that 93% of the increase in irrigation water use is attributed to an increase in atmospheric water demand through temperature. More water right groups will exceed their allowable limit by 18.1% by mid–century under RCP 4.5. The spatial impacts from an increase in irrigation water use vary across all the GMDs. GMD 3 will deplete at an average of 2.43 ft per year, while GMD 5 will have the second-fastest rate of depletion across the four GMDs.

My results provide key implications for policymakers. Policymakers and districts managers have to decide on the best ways to slow the rate of depletion of the aquifer through the way water resources are being allocated and used. One of the ways to lower water use and save for the future is by enforcing already existing policies to reduce the current rate of water use. Enforcing the authorized water quantity policy may have the potential of reducing water use for corn by 13.2% under RCP 4.5 by mid–century. I also find that increasing temperature is the main driver of an increase in irrigation water use through evapotranspiration. Increasing investment in the development of heat–tolerant corn varieties that can maximize yield under limited irrigation may be another way of reducing water usage. Only 40% of corn planted in Kansas in 2019 are drought–tolerant (McFadden et al., 2019). Investment in water–related research and crop water management practices, development and adoption of more efficient irrigation technology. The use of improved technology like seed and management practices has already saved almost an inch of water per acre over the last 24 years.

There are several important limitations to my analysis. My projection estimates ignore any potential adaptation through the adoption of improved technology and change in management practices. I may overestimate the projected irrigation water use if there is an adoption of improved technology or management practices that may adapt to the impact of temperature increases. My estimates do not consider the effect of $CO_2$ fertilization on corn.

**?** shows that young corn plants use water more efficiently at elevated $CO_2$.

There are many important areas for future research. One important area of research is to examine the impact of enforcing the authorized water quantity policy in term of water saved, the difference in return as a result of the policy and water saved when farmers switch crops. Another area of research is to estimate the effectiveness of these conservation policies to determine if these policies actually reduce water use, and if they do reduce water, along which margins could these reductions come from?

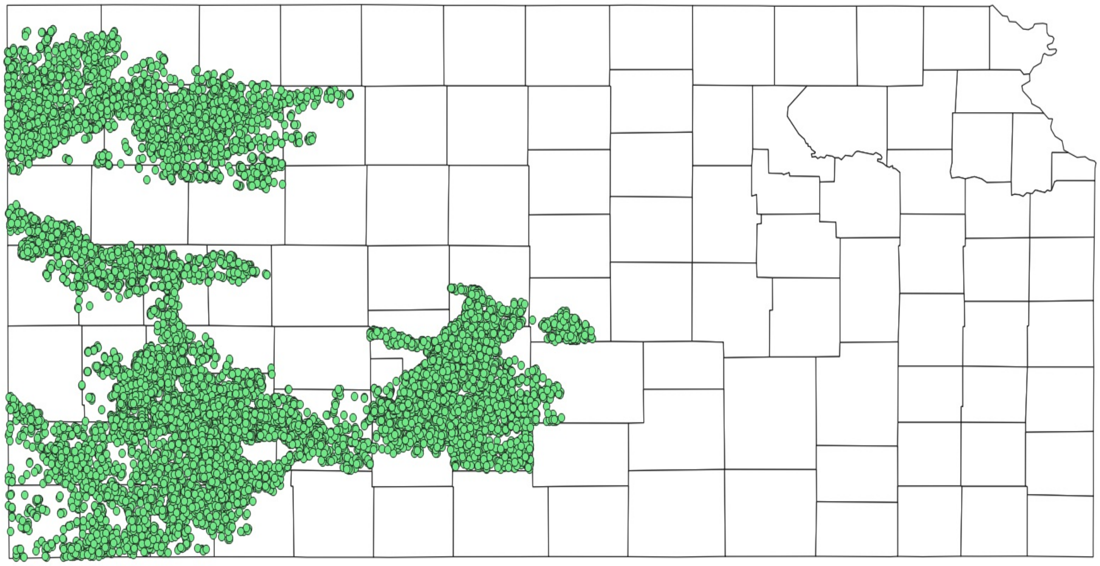

**Figure 3.1**: *Location of wells in the study region*

**Table 3.1**: *Summary Statistics of all Variables*

| Variables | Mean | Std Dev. | Min. | Max. |
|---|---|---|---|---|
| Applied water per acre (Inches) | 16.17 | 5.89 | 1.00 | 39.97 |
| Area Irrigated (acres) | 132.95 | 47.81 | 40.00 | 400.00 |
| Rootznaws (Inches) | 9.85 | 2.22 | 1.54 | 13.19 |
| Precipitation (Inches) | 13.62 | 4.58 | 2.46 | 32.17 |
| Crop Evapotranspiration (Inches) | 28.10 | 3.47 | 19.75 | 39.40 |
| Reference Evapotranspiration (Inches) | 40.66 | 4.83 | 28.61 | 56.30 |
| Corn price ($) | 3.34 | 1.55 | 1.97 | 7.52 |
| Proportion of Furrow | .084 | 0.28 | 0 | 1 |
| Proportion of Standard Center Pivot (CP) | 0.32 | 0.47 | 0 | 1 |
| Proportion of CP low nozzles | 0.60 | 0.49 | 0 | 1 |

The weather variables are calculated between May and August of each year.

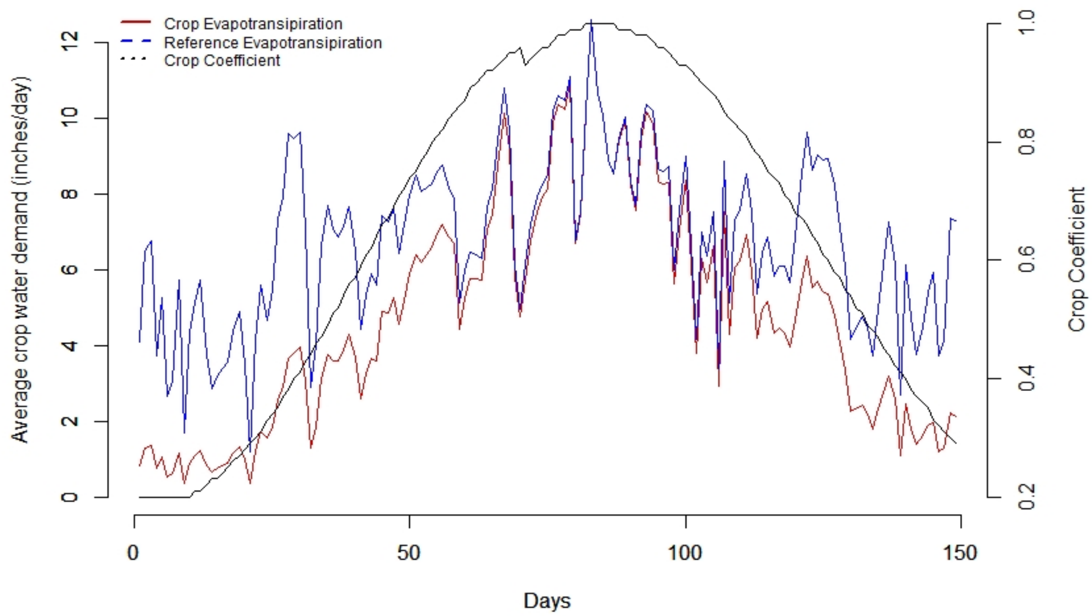


**Figure 3.2**: *Corn water demand and the corn coefficient*

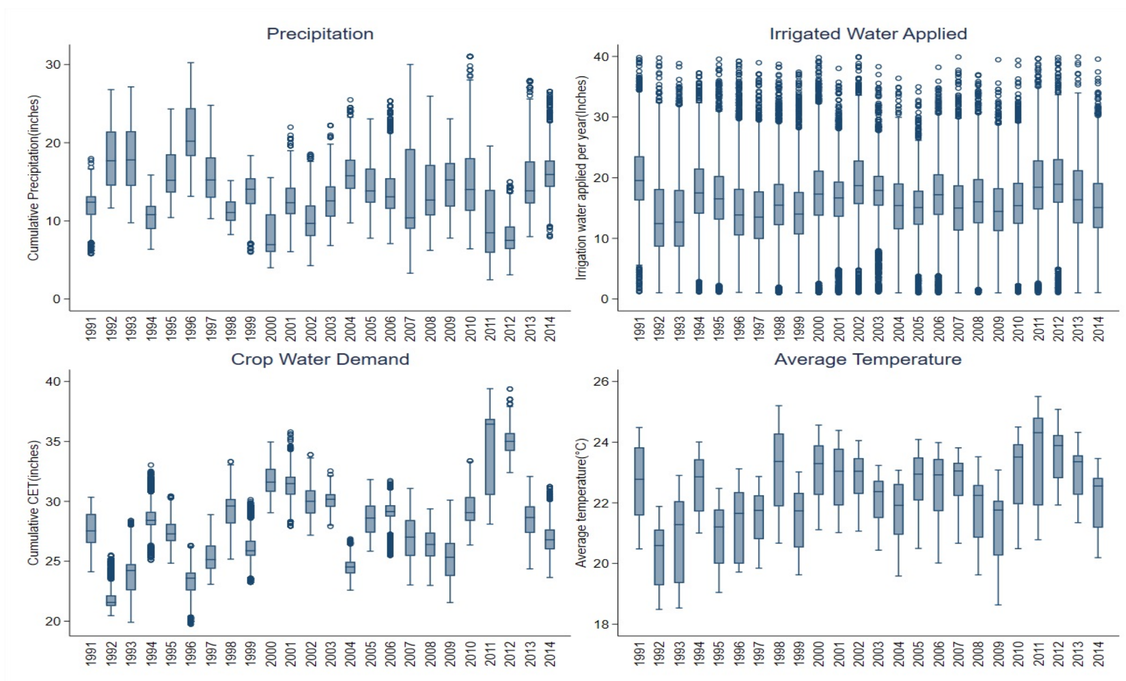


**Figure 3.3**: *Annual box-plots showing distribution and variability of water and weather variables over time. The county and field measures were used to construct boxplots for each year. Each box is defined by the upper and lower quartile, with the median depicted as a horizontal line within the box. The endpoints for the whiskers are the upper and lower adjacent values, which are defined as the relevant quartile +/- three-halves of the interquartile range, and circles represent data points outside of the adjacent values.*

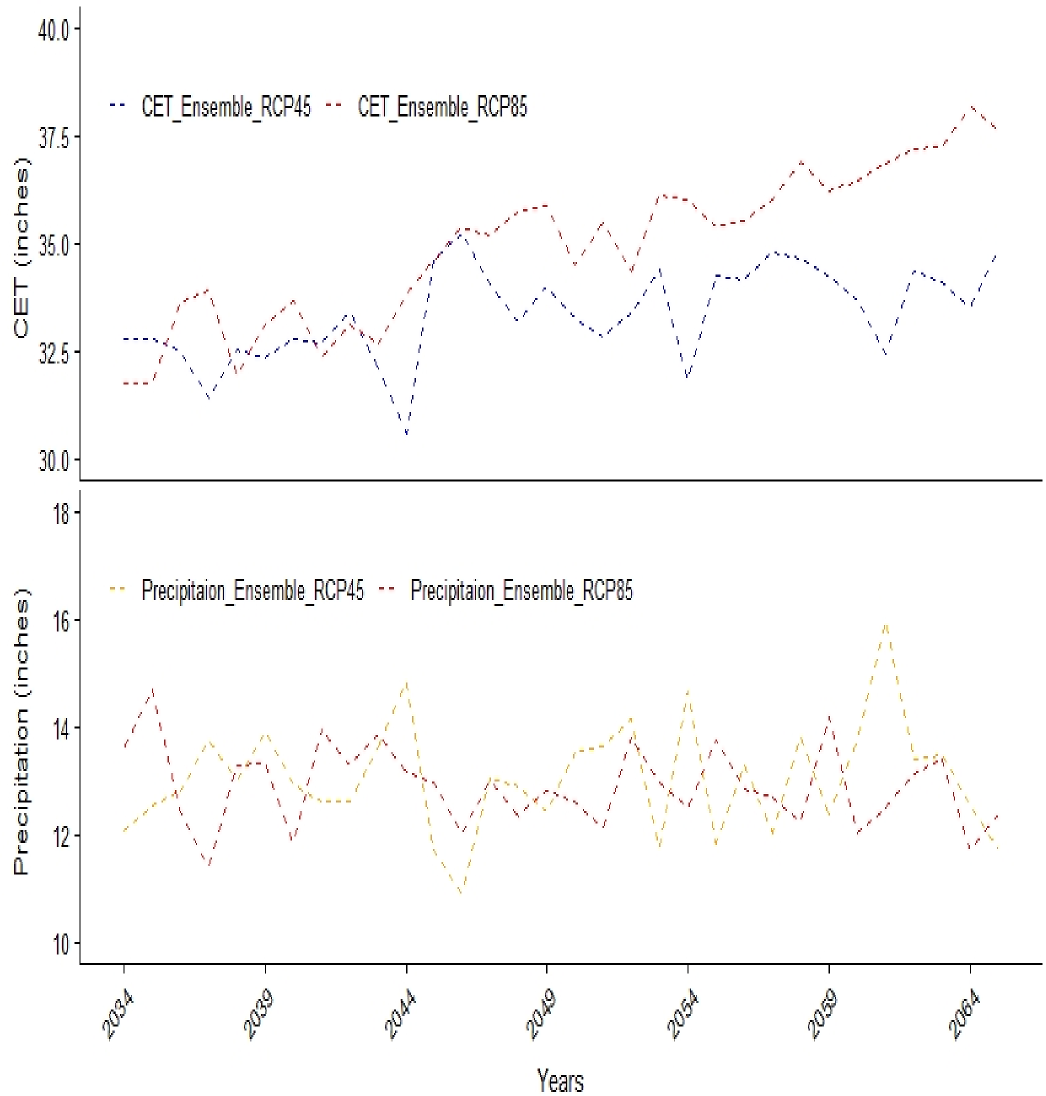


**Figure 3.4**: *The projected precipitation and crop evapotranspiration for Kansas by mid–century. The crop* $ET^c$ *and precipitation are an ensemble average from the 18 different climate models.*

**Table 3.2**: *Parameter Estimates for Water Use Using Different Specifications*

| Estimates | (1) Model I | (2) Model II | (3) Model III | (4) Model IV |
|---|---|---|---|---|
| Trend | -0.055*** | -0.057*** | -0.059*** | -0.219*** |
| | (0.016) | (0.016) | (0.015) | (0.013) |
| Trend$^2$ | — | — | — | 0.004*** |
| | | | | (0.000) |
| Precipitation | -0.232*** | -0.153* | -0.257*** | -0.106*** |
| | (0.022) | (0.081) | (0.040) | (0.016) |
| Precipitation$^2$ | — | — | — | -0.004*** |
| | | | | (0.000) |
| $ET_{it}^c$ | 0.288*** | 0.238* | 0.161** | 0.305*** |
| | (0.019) | (0.119) | (0.064) | (0.006) |
| Corn price | 0.281*** | 0.290*** | 0.291*** | 0.175*** |
| | (0.059) | (0.061) | (0.052) | (0.016) |
| Standard CP | -2.629*** | -2.669*** | -7.398*** | -2.536*** |
| | (0.264) | (0.254) | (2.021) | (0.143) |
| CP with Nozzle | -2.815*** | -2.845*** | -6.764** | -2.579*** |
| | (0.255) | (0.252) | (2.782) | (0.147) |
| $ET_{it}^c$×AWS | — | 0.005 | — | — |
| | | (0.012) | | |
| Precipitation×AWS | — | -0.009 | — | — |
| | | (0.010) | | |
| $ET_{it}^c$×Standard CP | — | — | 0.170*** | — |
| | | | (0.061) | |
| $ET_{it}^c$×CP with Nozzle | — | — | 0.130* | — |
| | | | (0.077) | |
| Precipitation×Standard CP | — | — | 0.020 | — |
| | | | (0.036) | |
| Precipitation×CP with Nozzle | — | — | 0.039 | — |
| | | | (0.056) | |
| $N$ | 116,273 | 116,273 | 116,273 | 116,273 |
| $R^2$ | 0.152 | 0.152 | 0.152 | 0.155 |
| Fixed effect | Yes | Yes | Yes | Yes |

Note: The dependent variable is the water applied per acre. Figures in the parenthesis are standard errors clustered by county. *, ** and *** indicate significance at 10, 5, and 1 percent levels.

**Table 3.3**: *Water Use Estimation Result–Time separability*

| Estimates | (1)<br>linear<br>With Stage 3 | (2)<br>Quadratic<br>With Stage 3 | (3)<br>linear<br>Without Stage 3 | (4)<br>Quadratic<br>Without Stage 3 |
|---|---|---|---|---|
| Trend | -0.071*** | -0.291*** | -0.084*** | -0.281*** |
| | (0.021) | (0.048) | (0.020) | (0.046) |
| Trend$^2$ | — | 0.008*** | — | 0.009*** |
| | | (0.002) | | (0.002) |
| Precipitation (Stage 1) | -0.143*** | -0.289*** | -0.126*** | -0.179*** |
| | (0.024) | (0.058) | (0.024) | (0.056) |
| Precipitation$^2$ (Stage 1) | — | 0.008** | — | 0.002 |
| | | (0.003) | | (0.003) |
| Precipitation (Stage 2) | -0.016*** | -0.102 | -0.374*** | -0.168* |
| | (0.041) | (0.081) | (0.040) | (0.087) |
| Precipitation$^2$ (Stage 2) | — | -0.016*** | — | -0.012*** |
| | | (0.003) | | (0.004) |
| Precipitation (Stage 3) | -0.082 | -0.126 | | — |
| | (0.053) | (0.094) | | |
| Precipitation$^2$ (Stage 3) | — | 0.025 | — | — |
| | | (0.016) | | |
| $ET^c_{it}$ (Stage 1) | 0.893*** | 0.792*** | 0.802*** | 0.734*** |
| | (0.070) | (0.057) | (0.061) | (0.054) |
| $ET^c_{it}$ (Stage 2) | 0.197*** | 0.239*** | 0.210*** | 0.237*** |
| | (0.030) | (0.030) | (0.032) | (0.033) |
| $ET^c_{it}$ (Stage 3) | -0.690*** | -0.834*** | — | — |
| | (0.156) | (0.151) | | |
| corn price | 0.110 | -0.096 | 0.206*** | 0.050 |
| | (0.083) | (0.091) | (0.071) | (0.077) |
| Standard CP | -2.710*** | -2.661*** | -2.703*** | -2.632*** |
| | (0.255) | (0.250) | (0.256) | (0.249) |
| CP with Nozzle | -2.798*** | -2.543*** | -2.801*** | -2.560*** |
| | (0.252) | (0.250) | (0.254) | (0.248) |
| $N$ | 116,273 | 116,273 | 116,273 | 116,273 |
| $R^2$ | 0.171 | 0.177 | 0.168 | 0.172 |
| Fixed effect | Yes | Yes | Yes | Yes |

Note: The dependent variable is the water applied per acre. Figures in the parenthesis are standard errors clustered by county. *, ** and *** indicate significance at 10, 5, and 1 percent levels.

**Table 3.4**: *Water Use Estimation Result Using Reference Evapotranspiration*

| Estimates | (1) linear |
|---|---|
| Trend | –0.045*** |
| | (0.016) |
| Precipitation | –0.252*** |
| | (0.022) |
| $ET^r_{it}$ | 0.175*** |
| | (0.011) |
| Corn price | 0.232*** |
| | (0.058) |
| Standard CP | –2.624*** |
| | (0.267) |
| CP with Nozzle | –2.812*** |
| | (0.256) |
| $N$ | 116,273 |
| R-squared | 0.148 |
| Fixed effect | Yes |

Note: The dependent variable is the water applied per acre. Figures in the parenthesis are standard errors clustered by county. *, ** and *** indicate significance at 10, 5, and 1 percent levels.

**Table 3.5**: *Impact of Climate Change on the High Plain Aquifer through Increase in Water Use*

| | (1) Historical | (2) RCP 4.5 | | | (3) RCP 8.5 | | |
|---|---|---|---|---|---|---|---|
| | 1996–2017 | | 2034–2065 | Depletion | | 2034–2065 | Depletion |
| GMD | △WL(ft.) | △Q | △WL(ft) | Rate | △Q | △WL(ft) | Rate |
| 1 | -0.598 | 9.09% | -0.771 | 28.8% | 12.20% | -0.830 | 38.7% |
| 3 | -2.047 | 6.14% | -2.431 | 18.79% | 8.57% | -2.583 | 26.2% |
| 4 | -0.592 | 10.60% | -0.864 | 46.1% | 13.83% | -0.947 | 60.0% |
| 5 | -0.194 | 12.30% | -0.996 | 412.9% | 15.44% | -1.201 | 518.4% |

Note: △WL is the change in water level. △Q is the percentage change in water use from 1991–2014 to 2034–2065 for each GMD. GMD 1, 3, 4 and 5 is located in West Central, Southwest, Northwest and South Central respectively.

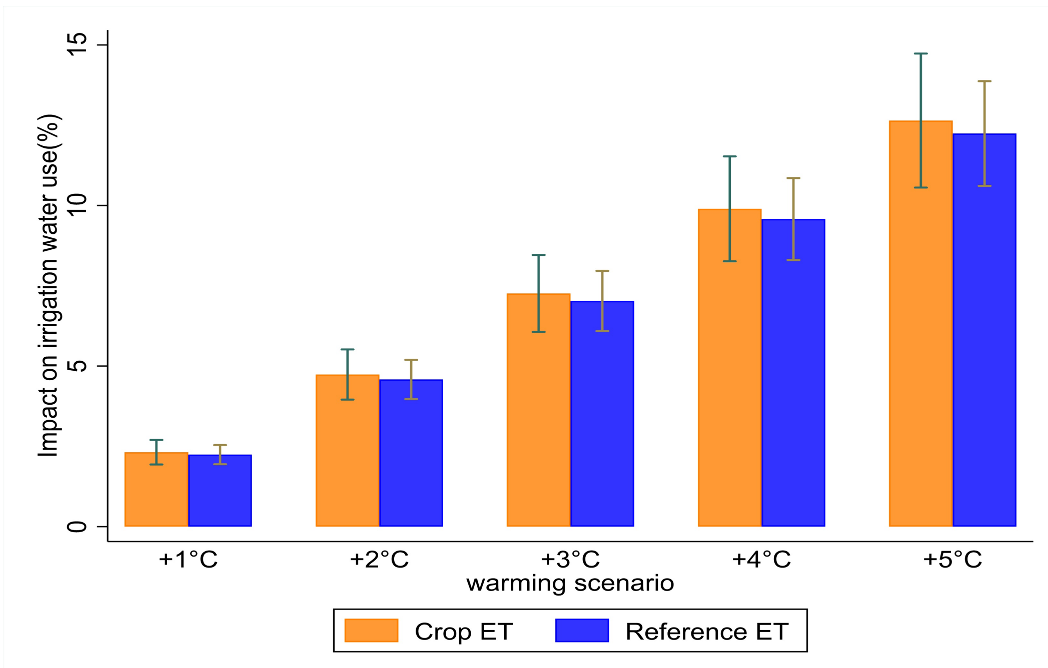


**Figure 3.5**: *The figure shows the predicted impact of an increase in temperature through atmospheric water demand on irrigation water use while precipitation and other variables are held constant. Atmospheric water demand was recalculated under each scenario to model the effect of temperature increase on irrigation water use. The bars show the warming impact on irrigation water use for each of the scenarios. Bars show 95% confidence intervals using the standard error clustered by county.*

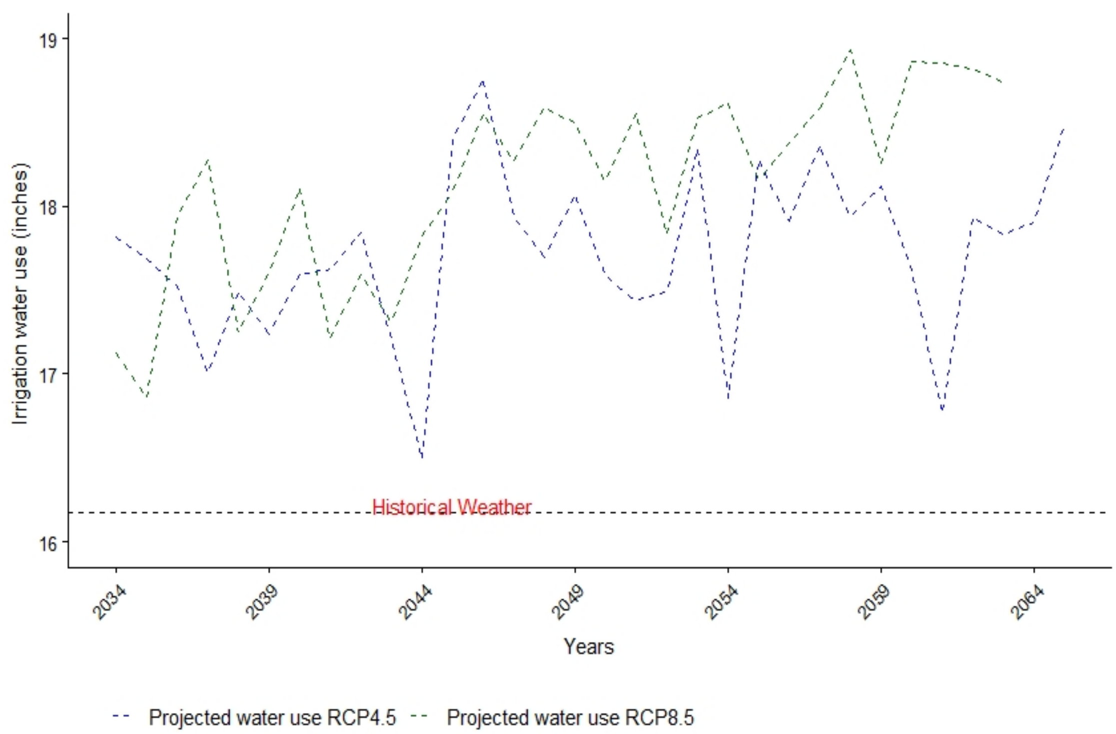


**Figure 3.6**: *The figure shows the ensemble average of the projected irrigation water use between 2034–2065 under RCP 4.5 and 8.5 respectively. The black dashed horizontal line that indicates the average water use between 1991-2014 weather and 2014 technology.*

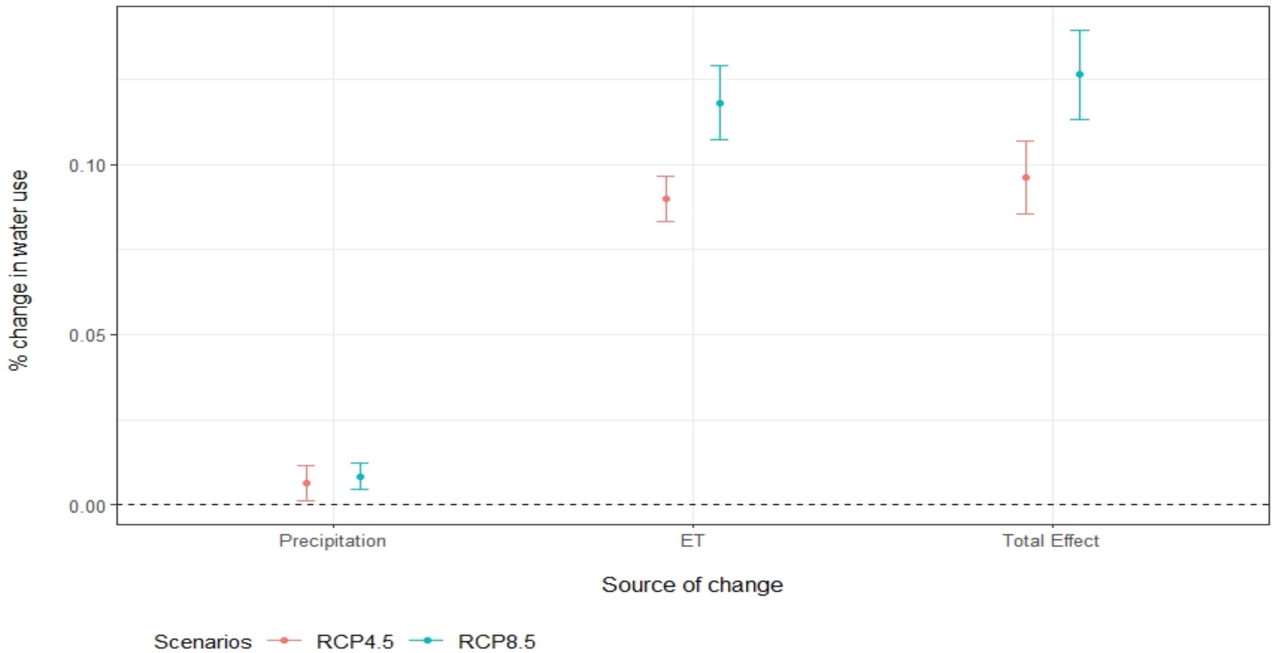


**Figure 3.7**: *The figure shows the percent change in irrigation water use and the sources of change under RCP 4.5 and 8.5. The dot represents the point estimates and the bar represents the 95% confidence interval obtained by 1500 bootstraps.*

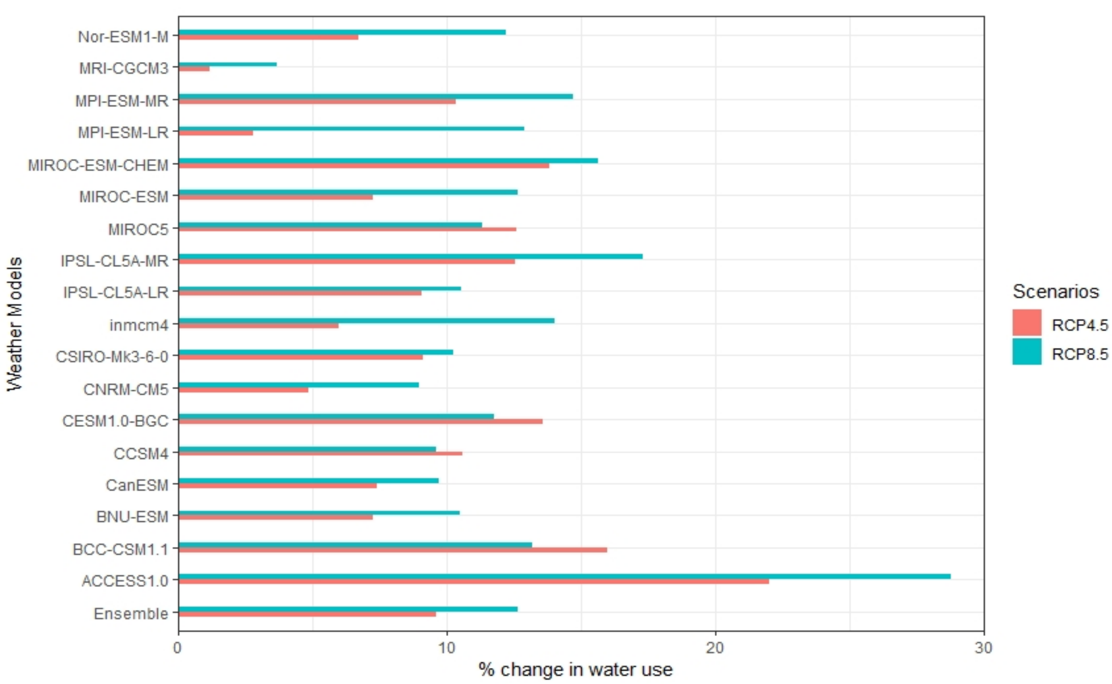


**Figure 3.8**: *The figure shows the percent change in irrigation water use from the baseline. The baseline is the average irrigation water use between 1991-2014.*

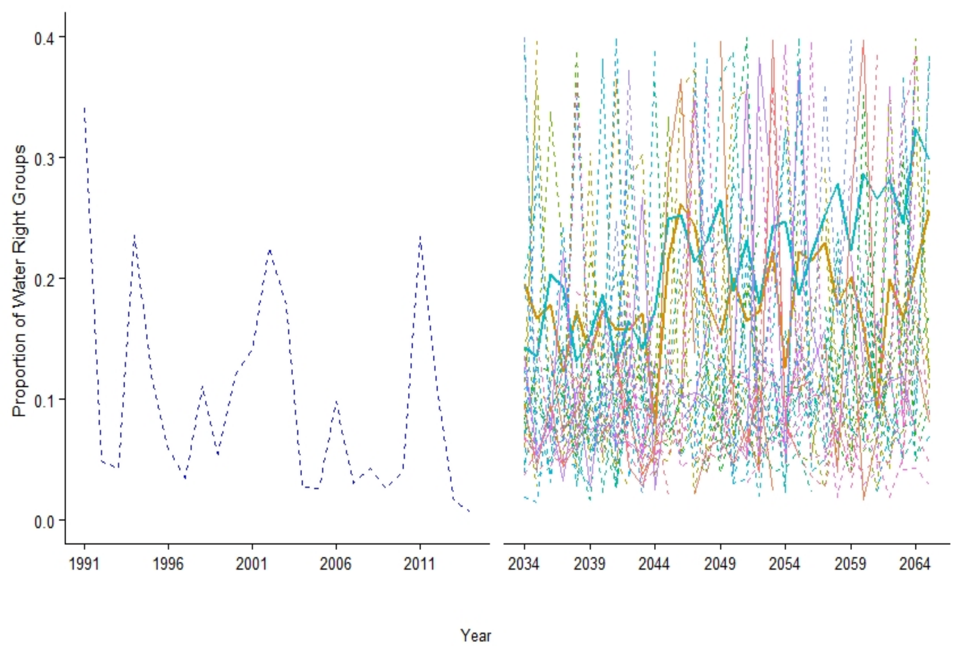


**Figure 3.9**: *The figure shows the proportion of water right groups that will exceed their authorized water quantity by mid–century. The left portion of the graph shows the proportion of water rights that exceeded their authorized limit between 1991–2014 and the right side shows the projected number of groups that will exceed their authorized quantity by mid–century. Each line represents a different climate model.*

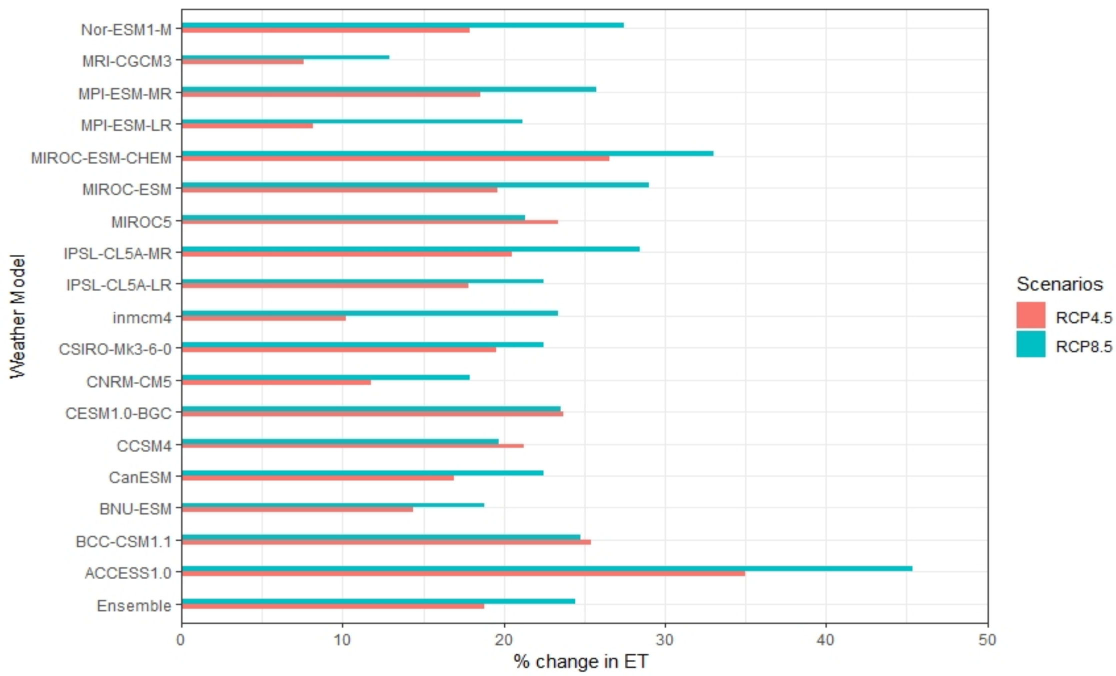


**Figure 3.10**: *The figure shows the percent change in atmospheric water use from the baseline. The baseline is the average irrigation water use between 1991-2014. The ensemble average is the projected average of crop water requirement from 18 different climate models.*

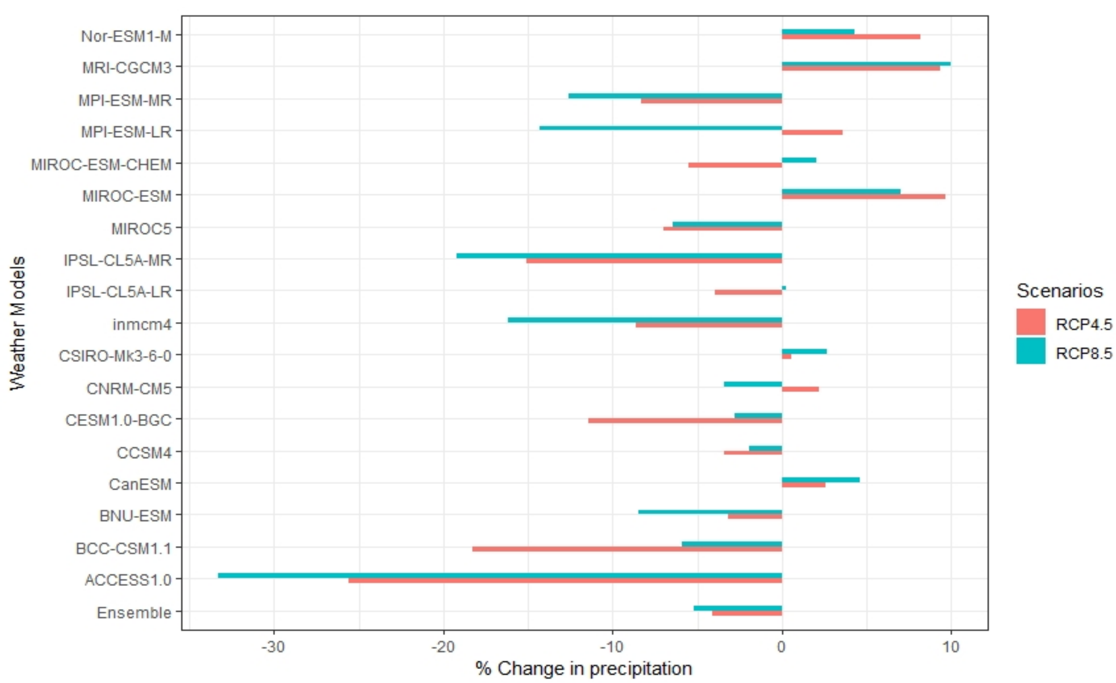


**Figure 3.11**: *The figure shows the percent change in average precipitation between 2034–2065 and 1991-2014 from 18 different climate models using 1991–2014 as the baseline. The ensemble average is the projected average of precipitation from 18 different climate models.*

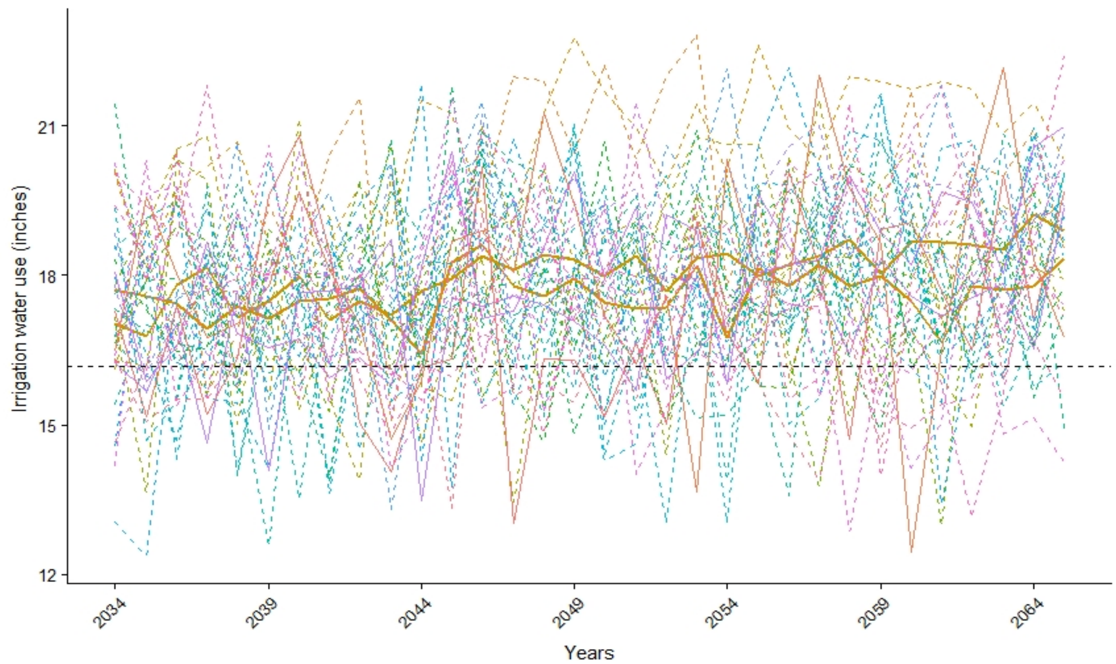


**Figure 3.12**: *The figure shows the projected irrigation water use between 2034–2065 under RCP 4.5 and 8.5 respectively by the 18 different climate models. The black dashed horizontal line indicates the average water use between 1991-2014 weather.*

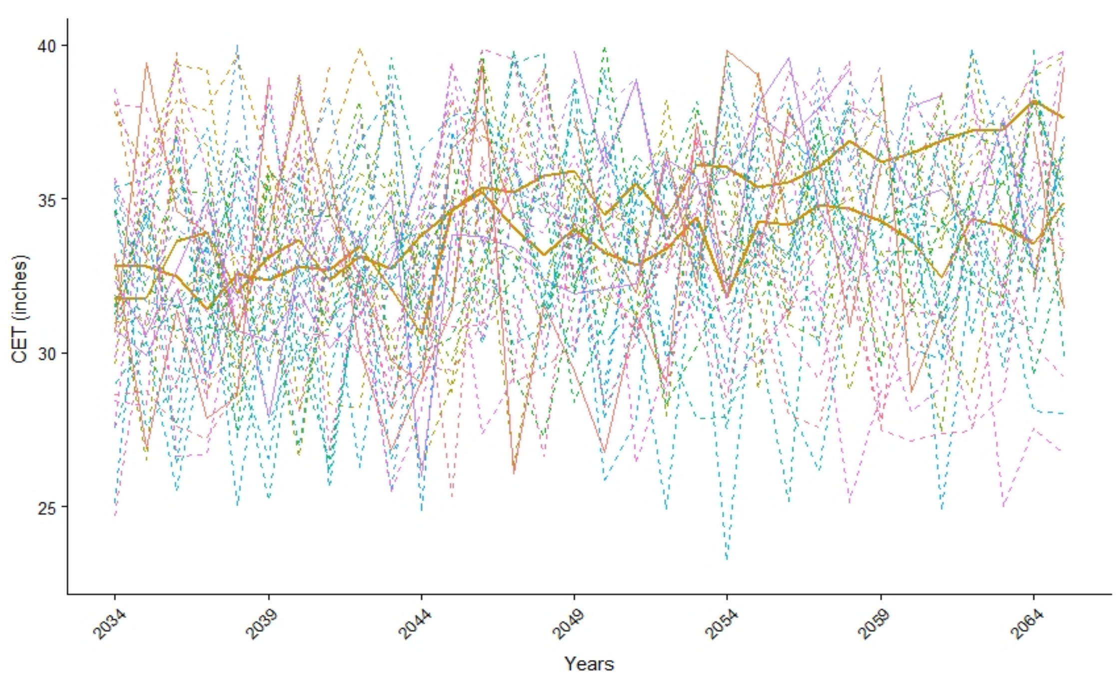


**Figure 3.13**: *The figure shows the projected crop evapotranspiration between 2034–2065 under RCP 4.5 and 8.5 respectively by the 18 different climate models.*

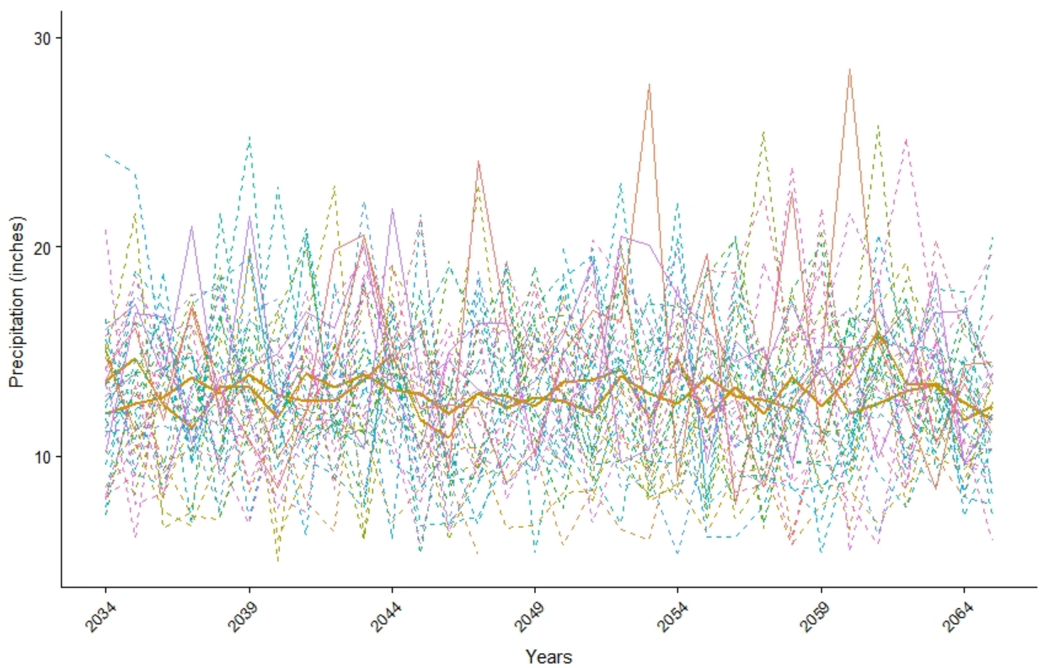


**Figure 3.14**: *Figure shows the projected precipitation between 2034–2065 under RCP 4.5 and 8.5 respectively by the 18 different climate models.*

# Chapter 4

# Marginal Cost of Carbon Sequestration through Forest Restoration of Agricultural Land in the Southeast United States

## 4.1 Introduction

There are numerous reasons for land use change in the last century as the world population and economy continue to grow rapidly. These changes continue to lead to more deforestation on forestland [1] and demand for more cropland as the world population is expected to reach 9 billion by 2050 (Alig et al., 2010; Byerlee et al., 2014; Colby and Ortman, 2017; Mu et al., 2017). These changes come with more emission of greenhouse gases (GHGs) from fossil burning, deforestation, and change in land use. Greenhouse gases cause climate change and the impact of climate change on the environment has been well documented especially in agriculture (Deschenes and Greenstone, 2007; IPCC, 2013; Mendelsohn et al., 1994; Schlenker and Roberts, 2009). Following the Kyoto protocol, there have been numerous programs

[1] Deforestation will take place on more than 50 million acres as U.S. by 2051 as the population reaches 400 million

and studies on how afforestation and forest restoration of agricultural land can be used to sequester $CO_2$ (Alig et al., 2010; Lubowski et al., 2006; Newell and Stavins, 2000; Plantinga et al., 1999; Stavins, 1999). Enticing private landowners to plant trees on their retired and marginal lands may be a cost–effective way to offset carbon emission.

I examine the impact of the increase in the Conservation Reserve Program (CRP) payments on land use change. The Conservation Reserve Program (CRP), one of the USDA programs established by the Food Security Act of 1985, provides annual rental payments to farmers and landowners to voluntarily retire environmentally sensitive land from agricultural production for the duration of 10 to 15 year. CRP pays farmers to implement practices designed to perform different functions such as the establishment of permanent grasses and legumes or planting trees. CRP payments generate land use change and corresponding flows of carbon from terrestrial sinks and sources by incentivizing farmers to convert land from cropland into CRP in order to receive the payment. Apart from carbon sequestration, reforestation of CRP land has a potential of reducing carbon emission, soil erosion and improving water quality (Goodwin and Smith, 2003; Gorte, 2009). I examine how cost–effective is the use of tree–planting on CRP parcels in reducing carbon emission through sequestration.

Agricultural activities play both roles in emitting carbon and reducing it by trapping carbon soil and plant biomass (Birdsey, 1992; Canadell et al., 2007; Dale, 1997; Guo and Gifford, 2002; Karl and Trenberth, 2003; Lal, 2004). Major land use change in agriculture involves the conversion of land from its initial use to another. The transition of land and its use is dynamic. Between 2007 and 2012, cropland is expanded by 4.7 million acres from the CRP land, while cropland abandonment for pastureland increased by 200,000 acres. In 2015, agriculture was directly responsible for 8.5% of the total GHG emitted in the USA while land conversion to cropland release 23.2 MMT $CO_2$e.[2] While the abandonment of CRP could result in loss of benefits accrue to the land (Wu, 2000), the conversion of cropland to CRP has been attributed with improved water quality (Frisvold, 2004; Osborn et al., 1990; Ribaudo and Hellerstein, 1992), reduction in erosion (Gilley et al., 1997; Goodwin and

[2] Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2016 at https://www.epa.gov/sites/production/files/2018-01/documents/2018_complete_report.pdf.

Smith, 2003; Pimentel et al., 1995), increased carbon sink (Gebhart et al., 1994; ?), and land value (Wu and Lin, 2010; Young and Osborn, 1990).

I estimate the correlated random effects probit model using a repeated point–level data on land use change, land quality and returns to alternative land use from 2000 to 2012 in the Southeast region of the United States. The use of the correlated random effects probit model (CRE) allows the use of panel data and controls for time–invariant variables by including the mean returns of the point as additional controls (Wooldridge, 2010). Parcels may have unobserved characteristics that can influence land use decisions, and be correlated spatially. Ignoring unobserved heterogeneity results in biased estimates—counties with smaller CRP rental rates are likely to be counties with lower returns to crop production and higher rates of enrollment in CRP. Fixed effects estimates can also correct the omitted variable bias, but the use of the fixed effect in nonlinear estimations gives rise to the incidental parameter problem (Wooldridge, 2010). The use of the CRE model allows us to exploit changes in returns over time rather than the pure cross-sectional variation in returns in most of the existing literature.

Rashford et al. (2011) used a pooled National Reserve Inventory (NRI) data between 1979–1997 and failed to control for unobserved effects that may influence grassland conversion to cropland. Lubowski et al. (2006) also using NRI data did not control for unobserved heterogeneity, but reduced the concern for spatial dependence in the random error term by removing observations close to one another. Claassen et al. (2005) examining changes in land use due to an increase in crop insurance premium subsidies controlled for the unobserved heterogeneity by using a spatial polynomial surface trend estimated from longitudes and latitudes. Alig et al. (2010) used U.S. Geological Survey Land Cover Trends to control for between block and not within block spatially correlated unobserved characteristics by including landscape block random effects in their random parameters logit.

I consider the historical crop rotation and carbon level of a parcel transitioning to CRP or abandoning tree–planting for cropland when calculating the net carbon sequestered. This research is different from Plantinga et al. (1999) as this study takes into consideration the carbon storage of cropland transitioning to CRP and the amount of carbon that can be emitted when CRP parcel is abandoned. Plantinga et al. (1999) assume the absence of afforestation of cropland, net carbon sequestered on cropland transiting to afforested CRP is zero. Accounting for carbon storage during transition and loss during abandonment impacts marginal cost as it matters on the amount paid to sequester carbon. Historical land management practices and crop rotations have been shown to impact the amount of carbon sequestered and emitted on a land parcel (Peterson et al., 1998). Popp et al. (2011) showed that there are differences in carbon sequestered/emitted from different crop production system. Rice production emits around 4.92 tons carbon equivalent, while corn can sequester around 1 ton per acre (Popp et al., 2011).

I calculate the transition probabilities of a parcel moving from cropland to tree–planting, and the abandonment of tree–planting for cropland. I express land use choice as a function of returns to crop production, returns to CRP, and land quality. Lubowski et al. (2008) identify return to land use and land quality as the drivers of land use change. I use the transition probabilities to calculate the net land gained by the tree–planting program. I converted the land transition to carbon units by using the annualized carbon sequestered per acre estimated from Stavins (1999). I estimate the marginal cost of abatement of atmospheric $CO_2$ from the return and carbon sequestered in tree-planting acres.

Richards et al. (1993) used a bottom-up-engineering approach to estimate the marginal cost of sequestration through tree–planting and modified forest services. Bottom–up–engineering involves the construction of carbon fixation cost from revenue and cost associated with an alternate land use or type, and sorting these in ascending order of cost. The marginal cost for Delta states ranges between from \$10 and to \$21.8 per ton. They found that tree–planting and management programs can reduce carbon emission by 56.4%. Newell and Stavins (2000) developed an econometric model that is derived based on the shares of land devoted to forestry and agriculture. The land use share model is estimated as a function of agricultural rents, farm production costs, the average cost of conversion per acre, and net returns to forestry. The result shows that the marginal costs of carbon increase monotonically as crop prices increase.

I compare my estimated marginal cost function with various social costs in the literature to estimate how much additional carbon can be sequestered if CRP rent is matched up to these social costs. There is no general social cost for carbon due to differences in the discount factor used in discounting damage, the type of Integrated Assessment Model use and joint agreement on the atmospheric lifetime of greenhouse gases. Nordhaus (2011) using Rice (2011) estimated the social cost of carbon to be $44 per ton for the year 2015, while Auffhammer (2018) mentioned $42 as the central and the most cited social cost of carbon in 2007 dollars. Nordhaus (2017) revisited the social cost of carbon using the DICE model[3] and the result shows that the social cost of carbon is $31 per ton of CO2 in dollars.

## 4.2 Econometric Model

I assume that a profit maximizing farmer is faced with a choice of allocating parcel $i$ among $Q$ alternatives. Assuming land use decisions are made by landowner by comparing returns from an alternate land use, a farmer will choose a land use that maximizes the present discounted value of an infinite stream of net returns less conversion costs. Suppose a landowner can allocate parcel $i$ to $Q$ potential land uses $\{j, k = 1, 2...Q\}$, then a landowner will choose a condition that satisfies the allocation of parcel $i$ to land use $k$ from $j$ at time $t$ if

$$\arg\max_k (R_{kt} - rC_{jkt}) \geqslant R_{jt}$$

$R_{kt}$ represents the expected net return to parcel $i$ on land use $k$ at time $t$, $r$ is the interest rate and $C_{jkt}$ is the one time expected marginal conversion cost of transitioning from land use $j$ to $k$. The marginal conversion cost of transitioning is zero if there is no transition from one land use to another. Based on Train (2009), landowner utility can be specified as $U_{ijk}$ for the allocation of parcel $i$ initially in land use $j$ to $k$ at time $t$, $\beta_{jk}$ is the vector of the coefficient returns of the landowners and $\varepsilon_{ijkt}$ is specified as the unobserved error component (idiosyncratic error). Then:

$$U_{ijk} = \beta_{\mathbf{jk}} X_{ijkt} + \varepsilon_{ijkt} \tag{4.1}$$

[3] The Dynamic Integrated Climate-Economy

A landowner will choose to transition from alternative cropland($j$) to tree–planting $k$ if $U_{ijkt} > U_{ikjt} \; \forall \; j \neq k$. The probability that a landowner will transition parcel $i$ from cropland ($k$) to tree–planting ($j$) at time $t$ is

$$Pr_{ijkt} = P(\beta_{jk} X_{ijkt} - \beta_{kj} X_{ikjt} > \varepsilon_{ikjt} - \varepsilon_{ijkt}) \tag{4.2}$$

If $\varepsilon_{ikjt}$ is normally distributed, the probability can be estimated using a probit model. The notation $\Phi(.)$ denotes the cumulative normal distribution. $Pr_{ijkt}$ measures the probability that a parcel $i$ with given characteristics would transition to alternative use $k$ from $j$ at time $t$. The transition probability is defined as a function of returns to crop production, returns to CRP, and land quality.

$$Pr_{ijkt} = \Phi(\alpha^0_{jk} + \alpha_{jk} Lcc_i + \beta_r R_{rct} + \beta_{qr} Lcc_i R_{rct} + \delta_i) \tag{4.3}$$

$\alpha^0_{jk}$ is the alternative specific intercept, $\alpha^q_{jk}$, $\beta_r$, and $\beta_{qr}$ are vectors, $R_{rct}$ is the county–level return to each land use in county $c$ given $r$=$j$, $k$, and $Lcc^q_i$ represents the land quality $q$ of parcel $i$. I estimate equation 4.3 for each transition. $\beta_r$ can be estimated consistently with a standard probit model if $R_{rct}$ is strictly exogenous conditional on unobserved heterogeneity ($\delta_i$) (Wooldridge, 2010). If $R_{rct}$ is not strictly exogenous conditional on $\delta_i$, estimating equation 4.3 without controlling for $\delta_i$ leads to omitted variable bias.

I control for $\delta_i$ by adding the average return ($\overline{R^r_i} \equiv T^{-1} \sum_{t=1}^{T} R_{rct}$) of each the land use. This specification is called correlated random effects probit (CRE) model and I allow for correlation between $\delta_i$ and $R_{rct}$ by assuming a conditional normal distribution with linear expectation and constant variance (Chamberlain, 1980; Wooldridge, 2010). Adding $\overline{R^r_i}$ means I can consistently estimate $\beta_r$ as well as the average partial effects (APEs). I can only exploit changes in $R_{rct}$ on land use choice over time. The transition probability of tree-planting from cropland is estimated as

$$Prob(lu_{it} = \text{Tree–Planting}|lu_{i,t-1} = cropland)$$
$$= \Phi(\alpha_0 + \varrho_0 Lcc_{12} + \beta_0^{CRP} R_{ct}^{CRP} + \theta_0^{crop} R_{ct}^{crop} + \gamma_0 Lcc_{12} R_{ct}^{CRP} + \gamma_0 Lcc_{12} R_{ct}^{crop} + \rho_0^{crop} \overline{R_i}^{crop} + \rho_0^{CRP} \overline{R_i}^{CRP})$$
$$\text{if } t \in \text{General signup} \quad (4.4)$$

where $Prob(lu_{nt} = \text{Tree–Planting}|lu_{n,t-1} = cropland)$ is defined as the probability that an NRI point $n$ has a land use of cropland in $t-1$ and this probability is a function of returns to cropland ($R_{ct}^{crop}$) in county $c$, returns to CRP ($R_{ct}^{CRP}$) and $Lcc_{12}$. $Lcc_{12}$ is the land capacity class 1 and 2 and $\rho_0^{CRP}$ and $\rho_0^{CRP}$ are added as controls for average returns to control for unobserved heterogeneity and should not be interpreted as causal parameters.

The probability of abandonment of tree–planting program to cropland is estimated similarly as

$$Prob(lu_{nt} = cropland|lu_{n,t-1} = \text{Tree–Planting})$$
$$= \Phi(\alpha_1 + \rho_1 Lcc_{12} + \beta_1^{CRP} R_{ct}^{CRP} + \theta_1^{crop} R_{ct}^{crop} + \gamma_1 Lcc_{12} R_{ct}^{CRP} + \gamma_1 Lcc_{12} R_{ct}^{crop} + \rho_1 \overline{R_i^{crop}} + \rho_1 \overline{R_i^{CRP}})$$
$$\text{if } nt \in \text{Contract expires.} \quad (4.5)$$

where $nt$ is the year that contract expires for each specific field.

I compare my APEs from CRE model with marginal effects from fixed effects linear probability model and pool probit model. The pooled probit assumes the returns are exogenous from the unobserved heterogeneity. According to Wooldridge (2010), first differencing or the use of fixed effects with linear probability model can control for $\delta_i$. I use Equations (4.4) and (4.5) to model the land use transition or abandonment of parcels to tree–planting or out of under tree–planting. The results from this fixed effect and pool probit are compared with the CRE model

### 4.2.1 Simulation of CRP Payments

I use the acres of land that transition to and abandon tree–planting as the basis for simulating carbon sequestered/emitted, and the marginal cost of carbon abatement as CRP payment increases. A uniform percent increase and decrease in CRP rent are used to simulate land transition from cropland to tree–planting and retention of parcels under tree–planting program. Increase in the net return to tree-planting increases conversion to tree-planting and retention of tree-planting acres. Existing acres rents are increased to discourage exit from the program and to prevent loss of benefits accrue to the land when their contract expires. This is different from Lubowski et al. (2006) and Stavins (1999) that paid a subsidy to newly transition parcels to forestry and tax on landowners trying to exist and renter to benefit from the subsidy payments. I simulate land use change for a uniform percent increase in CRP return between -30% to +70%.

I predict the transition probability using eqs. (4.4) and (4.5) at each point under different CRP payments. Acres of land that transitions to and from tree–planting is estimated by multiplying the transition probability at each point by the number of acres the point represents. I limit exit to 10% of the land under contract based on an assumption of a 10-year contract. This means a parcel can only exit the program after 10 years. I simulate the differences in the tree–planting acres under each percent change in payment by taking the difference between acres of land that transitions to and from tree–planting. Each payment level is associated with a change in carbon stored, measured by the carbon sequestered following the conversion to tree–planting. I used Equation (4.6) to calculate the net land gained. Net change in CRP is the difference between the acres transitioning to and acres abandoning tree–planting.

$$\text{Net change in CRP } = \text{Transition to CRP } + \text{Abandon CRP} \tag{4.6}$$

I consider the carbon level of the land transition or abandoning tree-planting into consideration when estimating the total carbon sequestered. If a land transitioning to tree–planting from cropland has a positive carbon storage, the carbon is subtracted from the expected annualized carbon sequestered. The same thing is done for a parcel abandoning tree–planting by subtracting carbon stored from the expected carbon storage of the expected cropland parcel. More carbon is sequestered when a parcel with deficit carbon emissions transitions to CRP tree–planting than when a land with positive carbon storage transitions.

I use 1.5 ton as the annualized carbon sequestered per acre which I adjusted by using the net carbon sequestered/emitted on the land transitioning from cropland or abandoning tree-planting (Stavins, 1999). I used the carbon sequestration and emission information from Popp et al. (2011) to calculate the net carbon sequestrated on cropland as the carbon storage of a parcel under different crop rotation that abandons cropland or transitions into cropland. I used Equation (4.7) to calculate the net carbon sequestrated in a tree–planting program as the product of net lands under tree–planting and carbon sequestered on these lands.

$$\begin{aligned}\text{Net amount of carbon sequestered} &= \\ &\sum_i \text{Net change in CRP } \times (1.5 - \text{Net carbon sequestered on } \textit{cropland}_i) \\ &+ \text{current lands under CRP contract} \times 1.5 \qquad (4.7)\end{aligned}$$

The most common crop rotation practice in the study area is corn-soybean-cotton and rice-soybean rotations. A land transitioning to tree–planting comes from either rotation, and a land retiring from tree–planting returns to either of the rotations. I use the carbon information from Popp et al. (2011) to calculate the average carbon storage on each possible rotation. Corn, wheat and sorghum sequester 1, 0.49, 0.73 tons of carbon per acre while rice, cotton and soybean emit 4.92, 0.71 and 0.01 tons per acre of carbon (Popp et al., 2011).

I calculate the marginal cost of carbon sequestered as the cost of CRP payments divided by the net amount of carbon sequestered for the payments, where all changes are calculated relative to a 2011 baseline (Equation 4.8).

$$\text{Marginal cost} = \frac{\text{CRP payment} \times (\text{Net change in CRP} + \text{current land under CRP contract})}{\text{Net amount of carbon sequestered}} \tag{4.8}$$

I also tested the sensitivity of carbon sequestered by increasing crop prices between 10 and 100% between 2000 and 2012. This helps to gauge the sensitivity of carbon sequestration to crop price increases.

## 4.3 Data and Variable Construction

The study area is restricted to the land resource regions area (LRRs) O, N, and P which cover many states along the South–East region of the USA. While only 4.9% of the total CRP acres are used for tree–planting, more than 78% of these acres are located in LRRs O, N, and P (Figure 4.1). More than 55% of CRP acres in these LRRs are used for tree–planting.

I combined parcel–level data on land use choice and quality from (NRI) with the county–level estimates of annual net returns (per acre) for six major crops and CRP returns. I restrict the analysis between 2000 and 2012 after the 1996 Farm Bill since farm bills prior to 1996 had acreage set–aside programs that substantially distorted cropland area from year to year. I estimate the model using a repeated annual parcel–level data of the NRI between 2000 and 2012.

Two major land use decisions take place during CRP general sign–up. The transition of other land use (cropland) to CRP programs, and exit of expiring CRP acres back to other land use. For a land to be eligible for CRP sign–up, the land must be under cropland production at time $t$ prior to CRP general sign–up at time $t+1$. During general sign–up, landowners can enroll the whole field or whole farm for a period of 10–15 years. Between 2000 and 2012, more than 80% of the land enrolled in CRP is through general sign–up (USDA-FSA, 2009). The general CRP sign–ups are for land use transitions in the years 2001, 2004–2007, and 2011. NRI data does not have information about the continuous sign–up CRP acres, therefore, I only model the decision for general CRP. For tree–planting abandonment for cropland, only lands initially in tree–planting that were previously enrolled during general sign–up, and with possible expiration between 2000 and 2012 are considered. I don't know when these acres expired, but I know the sign-up year for each CRP parcel and I tabulate how often land exited CRP for each sign–up year to determine the most common exit years between 2000 and 2012. I only estimate the probability of a parcel exiting CRP in the years with significant exits for the respective sign-up year.

The NRI data have information on the general sign–up and the type of CRP program a land is enrolled. I create two different dummy variables to represent possible sign–up and exit years. The sign–up/exiting variable is set to equal one or zero otherwise if a year is a general sign–up year, or the year a CRP contract will possibly expire. I defined my dependent variable for each parcel to equal one at time *t+1* if it was initially in alternate land use at time $t$ when sign–up or exiting equals one. My dependent variables are explained as a function of land quality and expected return to these land use at time $t$.

I used the land capability class (LCC) from the NRI data to create dummy variables that measure soil suitability to produce a crop. LCC is time–invariant and ranges between 1 and 8. Land in LCC class 1 and 2 have few limitations for crop production but still suitable for agriculture while land in classes between 3 to 8 have different limitations to crop production. I divided the LCC into two binary variables: classes 1 and 2, and classes 3 and above. The dummy variable with LCC 3 and above is used as the base to avoid perfect multicollinearity. These dummy variables are interacted with expected returns to capture the possibility that different types of land may respond differently to changes in returns. The coefficient of $\beta_r$ in equation 4.4 measures the effect of return when LCC is between 3 to 8.

The estimated cropland return is constructed as an acre–weighted county gross revenue less variable cost of corn, rice, winter and spring wheat, cotton, soybean, and sorghum. Figure 4.2 shows the average cropland return for the LLR O, N, and P which fall under the Mississippi portal, Southern Seaboard, Eastern Uplands and Heartland of the farm resource regions. The revenue is a product of future expected price from the Chicago Mercantile Exchange (CME) contract and county level trend yield. For corn, I use the average of the daily settled price between January and February for the December corn contract. For wheat, the expected price is the average daily settled price between January and March for December contract. For the soybean and rice, I used the average settled price between January and March for the contract ending in November. For Cotton, I used the average settled price between January and March for the contract ending in October. State marketing year price is used as the price for sorghum. The trend yields are estimated from county-specific linear trend regressions using the National Agricultural Statistics Service (NASS) data from 2000 to 2012.

The return to cotton is calculated using the return from cotton lint and cottonseed. The revenue for cotton lint is calculated in the same way as revenue for other crops. The revenue to cottonseed is calculated as the product of trend cotton yield, an adjustment factor of 1.62 and state level marketing year price. The total return to cotton is the sum of return to cotton lint and cottonseed. The acreage weight for crop $i$ at time $t$ is derived by using the rolling average of county acreage in the four most recent years. The use of a rolling average reduces the impact of temporary departures from a typical mix of crops on expected returns (Claassen et al., 2017). The variable cost information is obtained from the Economic Research Service (ERS) cost estimates for Farm Resource Regions. I include the cost of seed, fertilizer, chemicals and custom operation expenses for each crop.

CRP returns data are obtained through a Freedom of Information Act request. CRP returns are the county level average rental rate for the newly enrolled contracts which differs from the CRP rental rate available online as the online data represent the rental rate for an average enrolled acre. The missing rental information is replaced by the predicted rental rate where the rental rate for the newly enrolled acres is expressed as a function of the average CRP rent for all enrolled acres per county for a given year. The predicted value from this regression is used to replace the missing data. The average CRP rental rate in LRRs O, N, and P is shown in figure 4.3.

## 4.4 Result and Discussion

The results of the estimation are shown in tables 4.1 and 4.2. Table 4.1 shows the parameters for land use transition from cropland to CRP while table 4.2 shows the parameter estimates of land use abandonment of CRP for cropland.

### 4.4.1 Marginal Effects of the Preferred Model

Table 4.1 shows the result for land use transition from cropland to tree–planting under CRP. The coefficients on economic returns and land quality are all statistically significant with the expected sign (Table 4.1, column (1)). The average partial effects (APE) of CRP return is positive and significant while the coefficient of cropland return is significant and negative. The APE of CRP return is very small but shows that a \$10/acre change in CRP rental rate will increase the probability of cropland moving to tree-planting by 0.028 percentage points. A \$10 acre increase in cropland return will decrease the probability of cropland moving to tree-planting by 0.001 percentage points. The average transition probability of a parcel moving from cropland to tree–planting is 0.097%. Even though the average partial effects look small, the number of lands transiting is small and returns have a significant impact on the number of transitions.

Also, in table 4.1, the coefficients of average CRP and cropland returns indicate that counties with lower CRP rent and larger cropland returns are less likely to enroll in CRP. This is likely because higher productive land is less likely to enroll in CRP and this cross–sectional variation is not the type of variation we want to exploit to estimate the causal impact of changes in returns.

The coefficient of land quality of class 1 and 2 is significant and parcels within these classes are less likely to transition to tree–planting as cropland return increases. LCC 1 and 2 are more suitable for agriculture than those with land quality ranging between 3 to 8. The interaction between land quality and returns reflects how a return to a parcel varies with land quality, and the parcel's degree of responsiveness to transition when returns to these parcel changes. The coefficients are significant, but the APEs are not. Parcels with LCC 1 and 2 are more responsive to CRP return than the other land quality classes. With cropland return, parcels with land quality 1 and 2 are more responsive to changes in cropland returns, and more likely to stay in cropland as cropland return increases. Therefore, a higher quality land (LCC 1 and 2) is less likely to transition to CRP on average but is more responsive to changes in returns.

Table 4.2 shows the result for land use transition from tree planting under CRP to cropland. The coefficient of returns to CRP has the right sign but is not significant. Therefore, Increasing return to CRP has a stronger impact on the decision to enroll in CRP than the decision to exit CRP. Increasing CRP rental rate by $10/acre will reduce the probability of tree-planting moving to cropland by 0.44 percentage points. The coefficient of returns to crop is significant and with a positive sign. The probability that a parcel abandons tree–planting program increases as returns to cropland increases. The average transition probability of abandoning tree–planting is 0.62%. Higher quality land is not significantly more or less likely to exit CRP and is not significantly different in the response to changes in returns.

### 4.4.2 Comparison to Alternative Methods

Next, I compare the parameter estimates from the CRE model, linear probability model (LPM) and pooled probit model. The CRE model allows the control of unobserved heterogeneity and inclusion of time–invariant variable like land quality in the model and avoids any problem related to the incidental parameters problem of the linear fixed effects model. The statistical significance of the coefficients of average returns is the evidence that ignoring the unobserved heterogeneity results in biased coefficients (table 4.1). The marginal effects of the fixed effects linear probability model (LPM) are similar to the average partial effects (APEs) from the CRE model. This is different for the pooled probit model as the sign and size of the APEs are different from the other two models. Using the pooled probit, the APE for CRP return in table 4.1 is significant with the wrong sign. In table 4.2, although with the APE of cropland return having the right sign as that of CRE, the APE of cropland return is biased downwards toward zero. The difference can be attributed to the uncontrolled unobserved heterogeneity in the pooled model.

### 4.4.3 Simulations

Using the transition probabilities estimated in tables 4.1 and 4.2, I simulate the additional land gained for tree–planting by increasing payment to the CRP (Figure 4.4). Figure 4.4 illustrates the different number of acres converted and abandoned at different levels of CRP payments. The average CRP rental rate paid between 2000 and 2012 is $71.21 per acre, and Panel A and B of figure 4.4 show how a 10% increase in CRP payment will expand tree-planting by 37,400 acres and reduces exit by 450 acres while Panel C shows a net gain of 41,000 acres to tree–planting program. The increase in tree–planting acres is due to higher return induced by increased CRP rent. When CRP rent is reduced at a percent rate, more tree–planting acres are abandoned, and net acres added to tree–planting is less. At 30% reduction in CRP rent, 4,300 acres of tree–planting acres is gained by cropland (Panel C of Figure 4.4). Land transition to tree–planting program increases at an increasing rate as the CRP rent increases. At 30%, tree–planting acres will be expanded by 277,782 which is around 13% of acres under tree–planting in LLRs O, N, P.

I combine both the tree–planting parcels and carbon flow to produce a marginal cost function for tree–planting which is summarized in figure 4.5. The marginal cost function is concave and more elastic at higher carbon prices. Carbon flow increases as the CRP return increases. At the average CRP rental rate of $71.20, 2.1 million tons of carbon is sequestered at a marginal cost of $24.47 per year. A 30% increase in CRP rent will increase the marginal cost of carbon to $33.52 with an additional 0.24 million tons of carbon sequestered per year. This is equivalent to emissions from 460,000 typical passenger vehicles per year. For the same amount of carbon sequestered, the marginal cost of sequestration is roughly 93% larger if I ignore the carbon emissions from crop production before transitioning to CRP or when a parcel leaves CRP.

I compare the amount of carbon sequestered to the equivalent emissions from an average passenger travel car. A typical passenger vehicle emits about 4.6 metric tons of carbon dioxide per year (EPA, 2018). [4] A 30% increase in CRP rent will sequester emissions from about 460,000 typical passenger vehicles per year.

I compare my estimated marginal cost function with various social costs in the literature to estimate how much additional carbon can be sequestered if CRP rent is increased to these social costs. Figure 4.5 illustrates the different levels of additional carbon sequestered at different social costs. Using \$42, the common social cost of carbon (Auffhammer, 2018), an additional 0.65 million tons of carbon is sequestered per year, a 31.23% increase above the carbon sequestered at the average CRP rental rate. I also compare my marginal cost with the social cost estimated by Nordhaus (2011) using the RICE model. At \$44, an additional 0.78 million tons of carbon is sequestered per year.

I simulate the impact of crop prices increase on cropland and tree–planting program by increasing crop prices between 10 and 100%. Increase in crop prices do not only increase conversions to cropland from CRP but also reduces the amount of land transitioning to the tree–planting program. If the crop prices are increased by 50%, the number of parcels transition to CRP tree–planting program at the baseline will reduce by 22,000 acres, while the number of parcels abandoning the program will increase by 9000 acres. At 50% increase in crop prices, the amount of carbon sequester decreases by 27%. Increase in crop prices lead to increased deforestation and loss of carbon on CRP acres as these parcels exit tree–planting. A 100% increase in crop prices result in an expansion of cropland by 43,000 acres and sequestration of 0.05 million tons of carbon per year (Panel D of Figure 4.6).

## 4.5 Conclusion

In this study, I estimate the marginal cost of sequestering $CO_2$ through forest restoration using the CRP. I used the correlated random probit model that allows us to control for unobserved heterogeneity that may be correlated with land use return. Estimation without the control of unobserved heterogeneity produces a biased estimate. The marginal cost

[4] This assumes the average gasoline vehicle on the road today has a fuel economy of about 22.0 miles per gallon and drives around 11,500 miles per year. Every gallon of gasoline burned creates about 8,887 grams of $CO_2$. https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P100U8YT.pdf

function is concave and more elastic at higher carbon prices. Carbon flow increases as the CRP return increases. At the average CRP return between 2000–2011, 2.1 million tons of carbon is sequestered per year at a marginal cost of $24.6. Increasing CRP rent by 30% expands tree–planting acres by 277,782, sequestrating 2.3 million tons of carbon. Increasing CRP rent to the social cost of carbon to $42 will increase the amount of carbon sequestered by 0.385 million tons. This provides further evidence that afforestation of CRP acres is a cost–effective method of reducing carbon emission. Increase in crop prices increases crop abandonment and emission of carbon sequestered on CRP parcels. There are fewer transitions to CRP and an increase in abandonment of CRP as crop prices increase. More than 0.5 million tons of carbon is emitted at a 50% increase in crop prices.

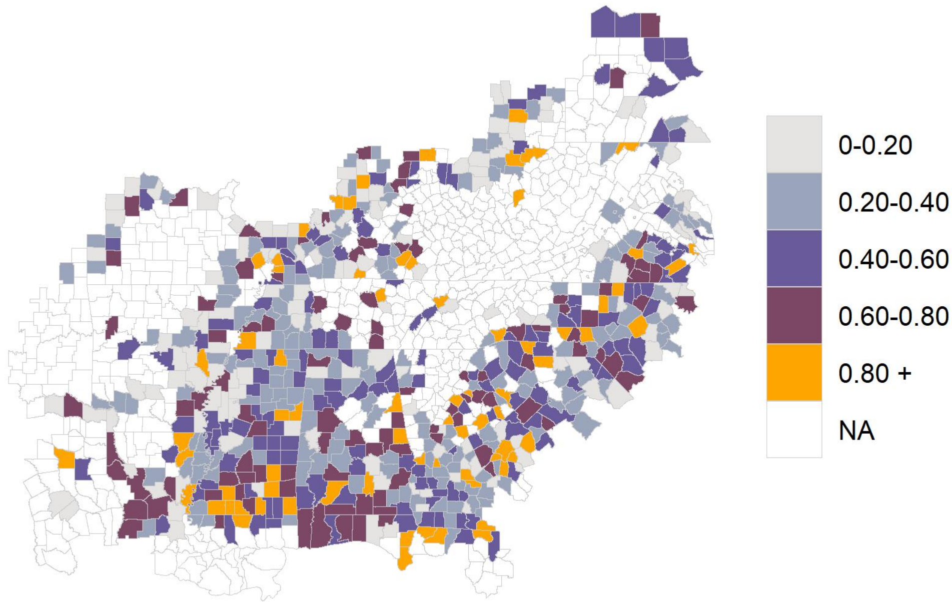


**Figure 4.1**: *Share of the CRP that is afforested per county in 2017. Data source: USDA-FSA (2015)*

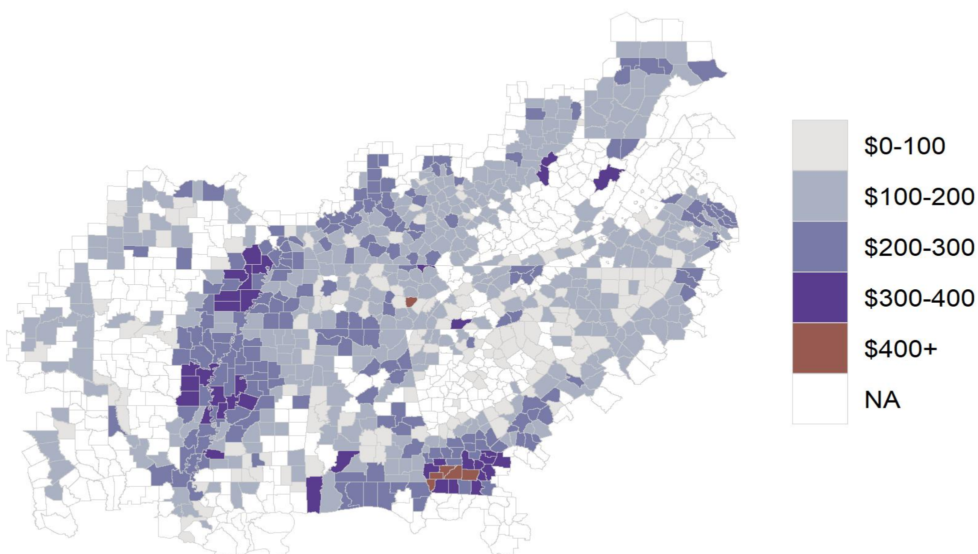


**Figure 4.2**: *Average Cropland Return per County in LRRs O, N, P (2000–2012)*

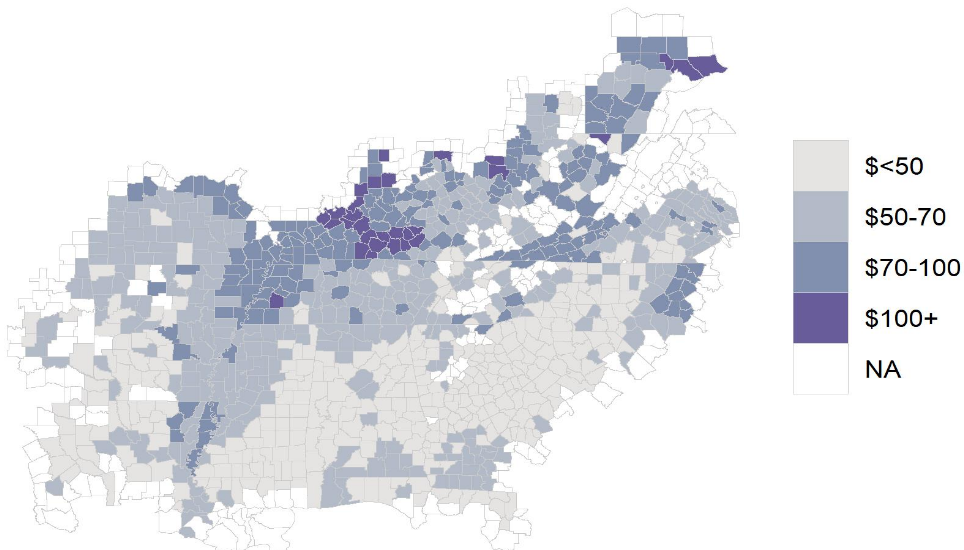


**Figure 4.3**: *Average CRP Rent per County in LRRs O, N, P (2000–2012)*

**Table 4.1**: *Parameter Estimates for Land use Transition from Cropland to CRP Tree*

| Estimation Methods | (1) Chamberlain's CRE Probit Pooled MLE | | (2) Linear Fixed Effects | (3) Probit Pooled MLE | |
|---|---|---|---|---|---|
| Variables | Coefficient | APE | Coefficient | Coefficient | APE |
| $R^{CRP}$ | 0.009703*** | 0.000028*** | 0.000021*** | -0.008886*** | -0.000028** |
| | (0.002706) | (0.000009) | (0.000008) | (0.003059) | (0.000011) |
| $R^{cropland}$ | -0.000417* | -0.000001 | -0.000001** | -0.001315*** | -0.000004*** |
| | (0.000248) | (0.000001) | (0.000001) | (0.000368) | (0.000001) |
| $Lcc_{12}$ | -0.349300* | -0.001011* | | -0.198631 | -0.000619 |
| | (0.194490) | (0.000611) | | (0.329011) | (0.001051) |
| $Lcc_{12}R^{CRP}$ | 0.005460* | 0.000016 | 0.000028 | 0.006159 | 0.000019 |
| | (0.003076) | (0.000010) | (0.000023) | (0.004457) | (0.000015) |
| $Lcc_{12}R^{cropland}$ | -0.000173 | -0.000001 | -0.000001 | -0.000463 | -0.000001 |
| | (0.000486) | (0.000001) | (0.000001) | (0.000781) | (0.000002) |
| $\overline{R^{CRP}}$ | -0.025304*** | | | | |
| | (0.003555) | | | | |
| $\overline{R^{cropland}}$ | -0.004261*** | | | | |
| | (0.000550) | | | | |

Standard error are in the parenthesis below all coefficients or average partial effects (APE). Note: .
*, ** and *** indicate significance at 10, 5, and 1 percent levels.

**Table 4.2**: *Parameter Estimates for Land use Transition from CRP Tree to Cropland*

| Estimation Methods | (1) Chamberlain's CRE Probit Pooled MLE | | (2) Linear Fixed Effects | (3) Probit Pooled MLE | |
|---|---|---|---|---|---|
| Variables | Coefficient | APE | Coefficient | Coefficient | APE |
| $R^{CRP}$ | –0.026440 | –0.000436 | –0.000683 | –0.005994 | –0.000103 |
| | (0.017128) | (0.000326) | (0.000685) | (0.003698) | (0.000064) |
| $R^{cropland}$ | 0.004234*** | 0.000070* | 0.000053 | 0.001095*** | 0.000019*** |
| | (0.001340) | (0.000038) | (0.000053) | (0.000345) | (0.000006) |
| $Lcc_{12}$ | 0.789710 | 0.013024 | | 0.743791** | 0.012832** |
| | (1.171717) | (0.021634) | | (0.295275) | (0.005221) |
| $Lcc_{12}R^{CRP}$ | 0.000987 | 0.000016 | 0.000680 | 0.002901 | 0.000050 |
| | (0.010587) | (0.000172) | (0.000685) | (0.005074) | (0.000088) |
| $Lcc_{12}R^{cropland}$ | –0.002640 | –0.000044 | –0.000036 | –0.002792*** | –0.000048*** |
| | (0.002279) | (0.000044) | (0.000055) | (0.000552) | (0.000010) |
| $\overline{R^{CRP}}$ | –0.005141*** | | | | |
| | (0.001366) | | | | |
| $\overline{R^{cropland}}$ | 0.028910 | | | | |
| | (0.018929) | | | | |

Note: . *, ** and *** indicate significance at 10, 5, and 1 percent levels.

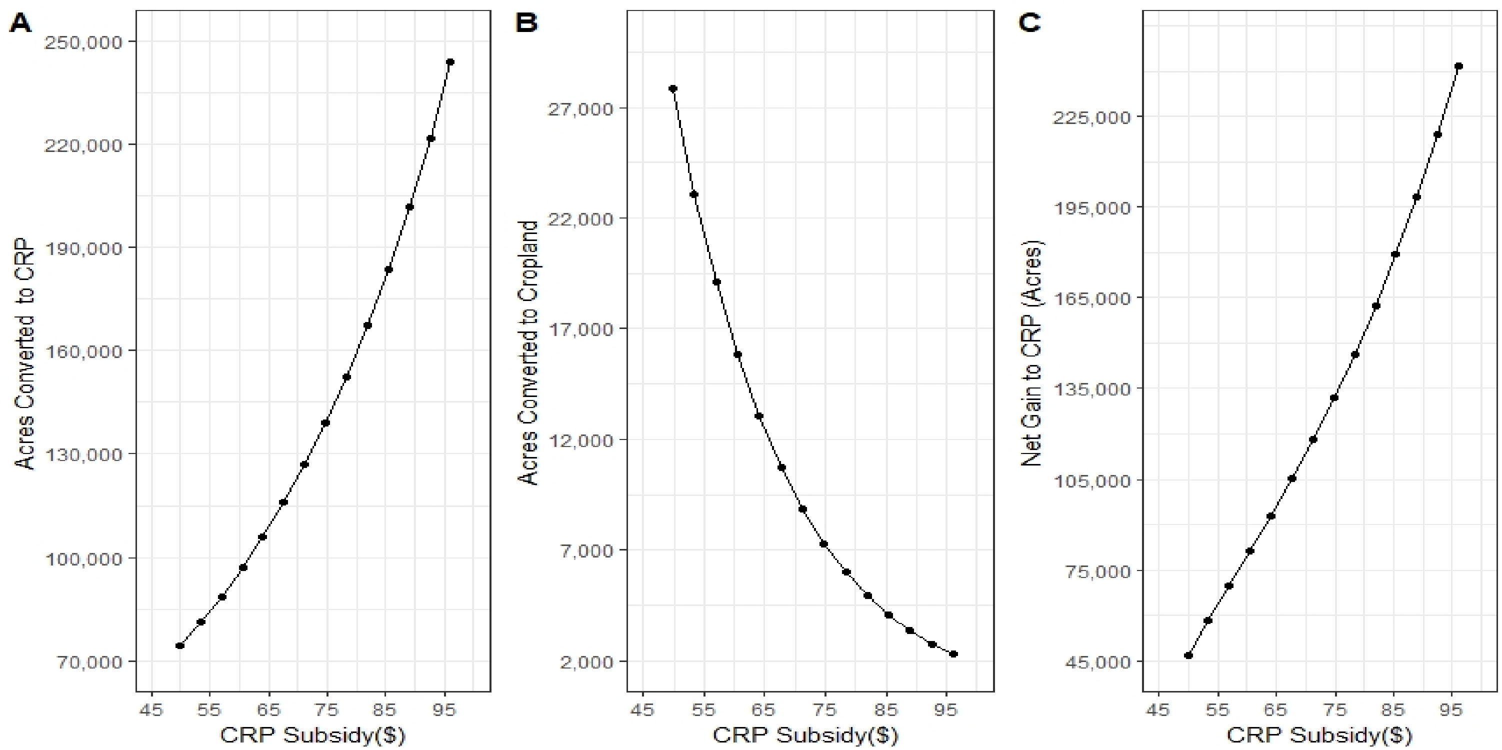


**Figure 4.4**: *The figures show the impact of an increase in CRP rent on land use. Panel A shows the acres of land that transition to tree planting acres. Panel B shows the acres of land converting to cropland from tree planting. Panel C shows the net gained in land to tree planting CRP. I limit exit to 10% of the land under contract based on an assumption of a 10 year contract.*

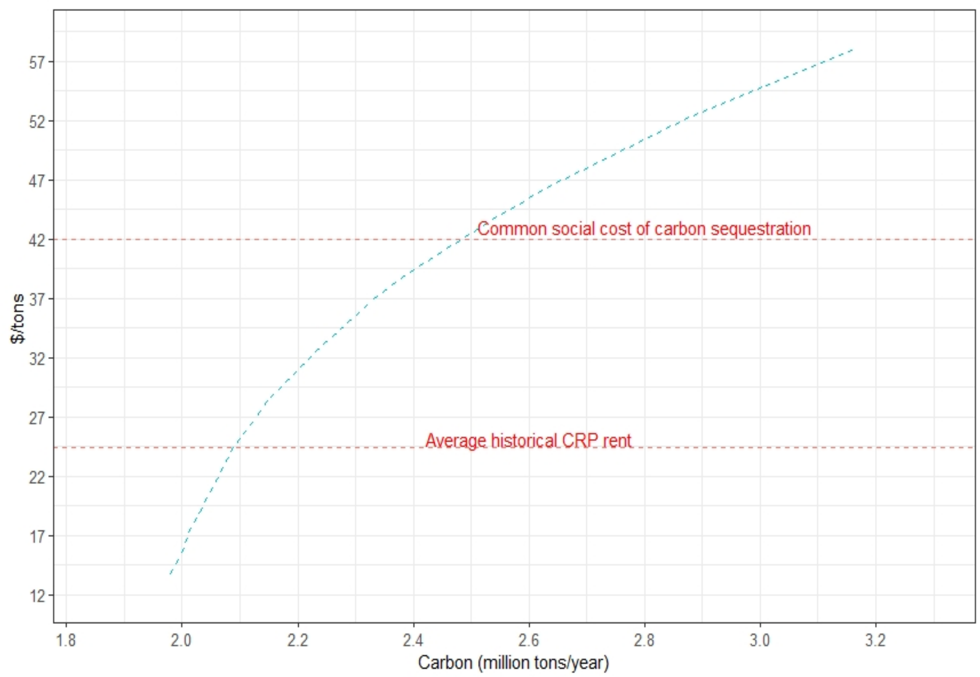


**Figure 4.5**: *Marginal costs of carbon from tree planting program when the subsidy is increased at a percent rate. The figure shows how much carbon is sequestered at a marginal cost*

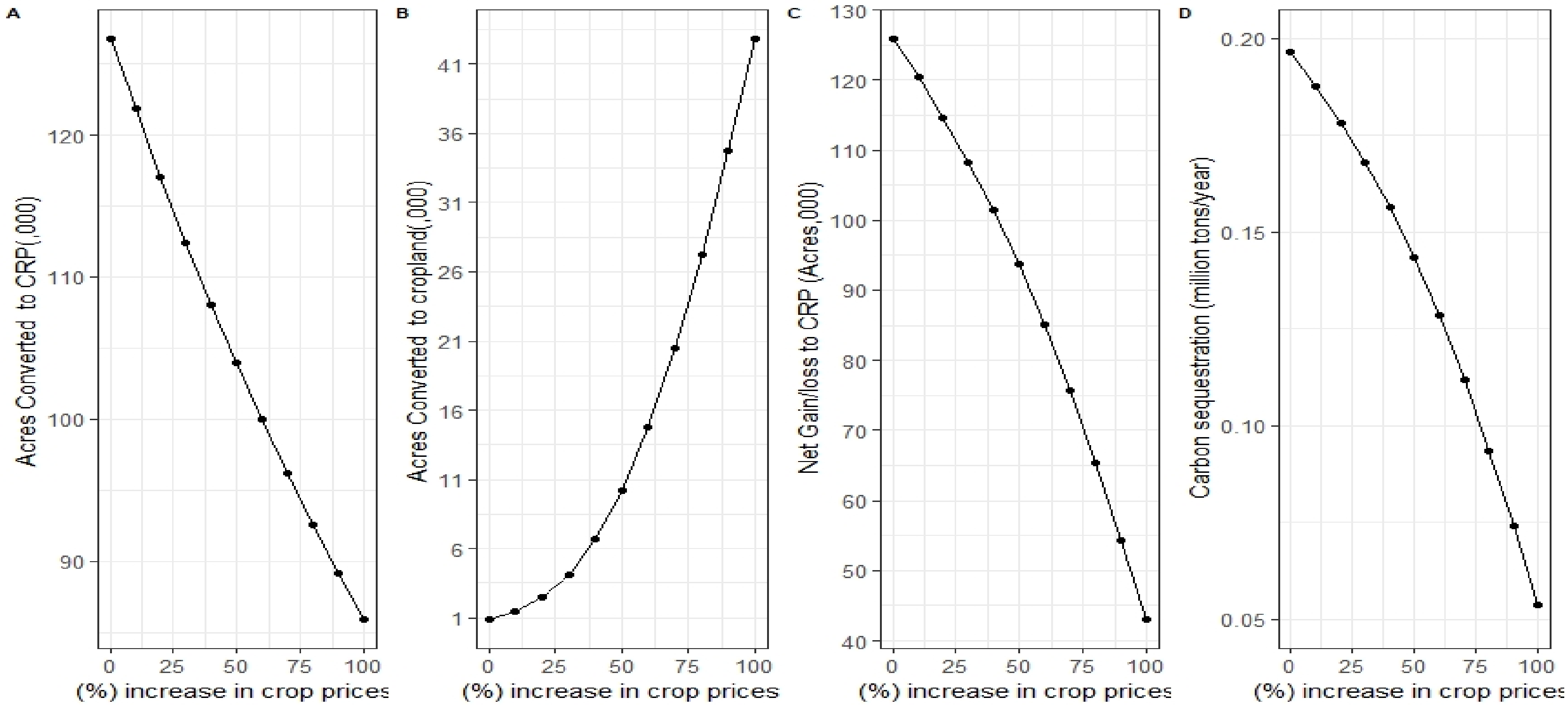


**Figure 4.6**: *The figures show the impact of an increase in crop prices on land use. Panel A shows the acres of land that transition to tree planting program. Panel B shows the acres of land converting to cropland from tree planting. Panel C is showing the net gain to the tree planting program. Panel D shows the number of carbon sequestered at each level of price increase. I limit exit to 10% of the land under contract based on an assumption of a 10 year contract.*

# Chapter 5

# Conclusion

Climate change and agriculture are both connected. Climate change impacts agriculture by lowering yield, area of the planted field harvested and crop water use. In another direction, agriculture plays both roles in emission and sequestration of greenhouse gases. The general objectives of this dissertation are to examine the impact of climate change on yield, land and water use and, how land use change can be used to mitigate some of these effects.

In the first essay, I show that yield variability is not the same as production variability. I find that the use of yield variability for a crop like winter wheat will underestimate impacts from weather. The results show that the main driver of change in production by mid–century is temperature. By mid–century, production is projected to decrease by 16.3% under RCP 4.5 with crop abandonment accounting for 13.17% and yield reduction accounting for 86.72% of the change in production.

In the second essay, I estimate the impact of weather variability on irrigation water use for corn. I provide new evidence that shows how farmers react to increasing irrigation water demand when climate changes. My result shows that farmers are less responsive to increasing irrigation water demand when the temperature becomes warmer than is predicted by the change in $ET^c$ demand. A 1–inch increase in atmospheric water demand will increase irrigation water use by 0.29 inches per acre. I also find that precipitation is not a perfect substitute for irrigation. Uncertainty in determining the level of irrigation water that will maximize yield for a given year due to weather variability, limits on the authorized water use are some of the reasons explains why farmers are less responsive to change in increasing $ET^c$ demand. By mid–century, Irrigation water use will increase by 9 and 12 % under RCP 4.5 and 8.5 respectively. Also, increasing water use by mid–century will have different spatial impacts across the GMDs.

The third essay shows the cost–effectiveness of using tree–planting program of the CRP to sequester carbon. I use a correlated random effects probit model (CRE) to estimate the impact of an increase in the Conservation Reserve Program (CRP) payments on land use change. The CRE model allows us to control for unobserved heterogeneity and exploit variation in returns to land over time. Estimation without control for unobserved heterogeneity produces biased estimates with coefficients of the wrong sign. Afforestation of CRP lands may be another cost–effective way to sequester carbon. Carbon flow increases as the CRP return increases. Increasing CRP rent to the social cost of carbon at $42 will increase the amount of carbon sequestered by 0.65 million tons.

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# Appendix A

# Climate Change Impacts on Wheat Production

**Table A.1**: *List of global climate models and their source*

| Models | Sources |
|---|---|
| ACCESS 1.0 | Common Wealth Scientific and Industrial Research Organization and Bureau of Meteorology, Australia |
| BCC-CSM1.1 | Beijing Climate Center, China Meteorological Administration, China |
| BNU-ESM | Beijing Normal University, China |
| CanESM | Canadian Center for climate modeling and analysis, Canada |
| CCSM4 | National Center for Atmospheric Research (NCAR), USA |
| CESM1.0-BGC | National Center for Atmospheric Research (NCAR), USA |
| CNRM-CM5 | Centre National de Recherches Mtorologiques, France |
| CISRO-MK3 | Australian Common Wealth Scientific and Industrial Research Organization |
| inmcm4 | Institute of Numerical Mathematics, Russian Academy of Sciences |
| IPSL-CL5A-LR | Institute Pierre-Simon Laplace, France |
| IPSL-CL5A-MR | Institute Pierre-Simon Laplace, France |
| MIROC5 | Japan Agency for Marin-Earth Science and Technology, Atmosphere and Ocean Research Institute |
| MIROC-ESM | Japan Agency for Marin-Earth Science and Technology, Atmosphere and Ocean Research Institute |
| MIROC-ESM-CHEM | Japan Agency for Marin-Earth Science and Technology, Atmosphere and Ocean Research Institute |
| MPI-ESM-LR | Max Plank Institute for Meteorology (MPI-M), Germany |
| MPI-ESM-MR | Max Plank Institute for Meteorology (MPI-M), Germany |
| MRI-CGCM3 | Meteorological Research Institute of Japan |
| Nor-ESM1-M | Norwegian Climate Center, Norway |