THREE ESSAYS ON FEDERAL CROP INSURANCE

A Dissertation

by

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Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

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December 2016

Major Subject: Agricultural Economics

ABSTRACT

This dissertation evaluates the demand for crop insurance and designs and demonstrates a methodology to estimate the impacts of climate change on the federal crop insurance program (FCIP). An empirical model is built to estimate the demand for corn yield and revenue insurance and wheat yield insurance at each coverage level for the major production regions. Original Least Square regression is used. The results show that the elasticities of demand for federal crop insurance with respect to net premiums are significantly different across crops, coverage levels, insurance plans, and regions. At the 75% coverage level, the elasticity of demand for corn yield and revenue insurance with respect to net premium is -0.654 and -0.670, respectively, in the Southern Plains. The absolute values of the elasticities of demand for corn insurance (0.654 and 0.670) are much higher than the elasticities reported in the majority of the previous studies which do not separate coverage levels and regions in the crop insurance demand analysis. At the 80% coverage level, the elasticity of demand for corn yield insurance with respect to net premium is -0.230, -0.158, and -0.259 in the Corn Belt, Lake States, and Northern Plains, respectively, which are much smaller than the elasticity at the 75% coverage level in the Southern Plains (based on absolute values).

For wheat yield insurance, the elasticity of demand with respect to net premium is -0.264 and -0.145 at the 75% coverage level in the Southern Plains and Northern Plains, respectively. In the Northern Plains, wheat producers would reduce their demand for federal yield insurance by 2.610%, 4.800%, and 7.211% at the 70%, 75%, 80% coverage level, respectively, given a 10 percentage points reduction. Producers in the Southern Plains are expected to reduce their demand for federal wheat yield insurance by 3.153% and 2.636% at the 70% and 75% coverage level, respectively, given a 10 percentage points cut in the subsidy rates.

A methodology is built and demonstrated to evaluate the impats of climate change on the FCIP for a representative grain sorghum farm. Different user interfaces of the APEX model are use to simulate crop yields for a representative farm. The simulated yields are further used to calculate the representative farm's insurance premiums, indemnities, and loss ratios. The results indicate that the approved APH yields and federal yield protection insurance premiums would decrease as the grain sorghum yields trend to decrease as climate change continues. Federal crop insurance loss ratios are statistically different in year 2020, 2030, and 2040 for each climate change scenario. Therefore, which climate change scenario is assumed for analyses of the impacts of climate change on the FCIC would result in statistically different conclusions. The study also shows that the efficiency of the current APH formula will not be negated by climate change since no extreme yield change occurs during 2020 – 2040 based on the climate change forecasts.

DEDICATION

This dissertation is dedicated to Dr. James Richardson, Dr. Henry Bryant, Dr. Joe Outlaw, Dr. David Bessler, and Dr. Keli Xu.

I also dedicate this work to my family: Suying Wang, Lanlin Yi, Minxia Zhang, Jianguo Xu, and Harper Xu.

ACKNOWLEDGEMENTS

Special thanks to my committee chairs: Dr. James Richardson and Dr. Henry Bryant. This dissertation could not have been done without their in-depth involvement and patience. They always took time to help me, and were always available for me. I sincerely appreciate their guidance, immense knowledge and endless encouragement.

Extra thanks to Dr. Joe Outlaw and Dr. David Bessler for their great support and help. They served as committee members during their busy schedule and were always supportive. My thanks also extend to Dr. Abeyou Worqlul, Dr. Luca Doro, and Dr. Javier M. Osorio Leyton from the Blackland Research and extension Center for their help on the APEX model.

My special appreciation extends to my daughter Harper Xu for being such a wonderful baby. Thanks for giving me the sweetest smile and forgiving my absence.

NOMENCLATURE

AFPC	Agricultural Food and Policy Center
APEX	Agricultural Policy Environmental eXtender
APH	Actual Production History
ARPA	Agricultural Risk Protection Act
CAT	Catastrophic Level of Coverage
CDF	Cumulative distribution functions
CFSR	Climate Forecast System Reanalysis
CMIP3	Coupled Model Intercomparison Projection Phase 3
CMIP5	Coupled Model Intercomparison Projection Phase 5
CRC	Revenue Insurance Policy
DCHP	Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections
EPIC	Environmental Policy Integrated Climate
ERS	Economic Research Service
FCIP	Federal Crop Insurance Program
FCIRA	Federal Crop Insurance Reform Act
GIS	Geographic Information System
GDP	Gross Domestic Product
GRP	Group Risk Plan
GWDS	Global Weather Data for SWAT
HRU	Hydrologic Response Unit

HWSD	Harmonized World Soil Database
NASS	National Agricultural statistics Service
NetCDF	Network Common Data Form
NOAA	National Centers for Environmental Information
RCPs	Representative Concentration Pathways
RMA	Risk Management Agency
SWAT	Soil and Water Assessment Tool
T-yield	Transitional Yield
USDA	U.S. Department of Agriculture
USGS	U.S. Geological Survey
VBA	Visual Basic for Applications
YP	Yield Protection

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CHAPTER I

INTRODUCTION

Federal crop insurance has been an important tool for agricultural risk management with a long history. It was first authorized in the 1930s to protect farmers against low yields and to reduce producers' risk. In its first 50 years, the program developed very slowly. Only few counties and crops were eligible for crop insurance. To encourage participation, the 1980 Federal Crop Insurance Act (FCIA) included many more regions and crops in the Federal Crop Insurance Program (FCIP) and initialized federal premium subsidies (Coble and Knight 2002). Although the participation rate (enrolled acres/eligible acres) increased from 16% in 1981 to 25% in 1988, the 25% participation rate was still significantly lower than the 50% participation rate envisioned by Congress (Glauber 2013). Economists suggested that crop insurance premium subsidies had to be greatly increased to deliver the 50% participation in the FCIP (Glauber 2013). To further expand participation, crop insurance premium subsidies were increased through several policies. Figure 1 shows the total insured acres and the federal premium subsidies in 1981 to 2013.

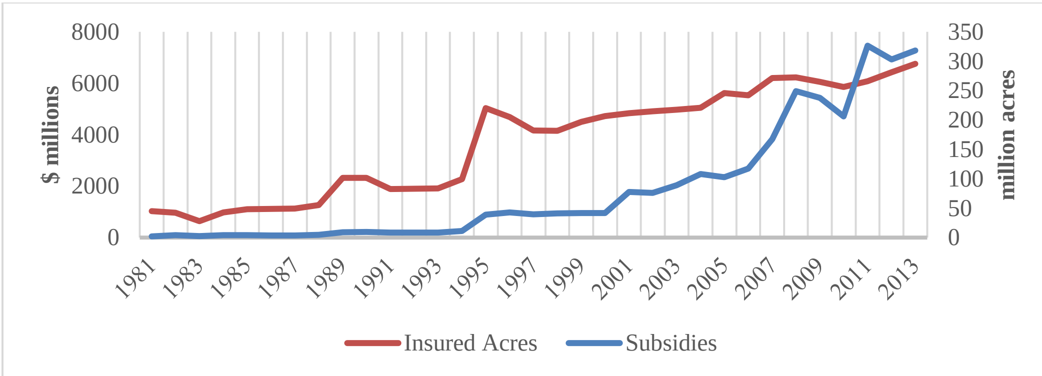

Figure 1. Total Insured Acres and Federal Premium Subsidies for the FCIP

Source: USDA, Risk Management Agency, Summary of Business files; Glauber (2004).

With government support, the crop insurance program has made considerable progress and has been one of the most important tools for farmers to manage agricultural risks. In 2015, 298,718,502 acres were enrolled in the FCIP, and the participation rate of eligible acres was 86%. However, there are questions about the federal crop insurance program.

First of all, there are questions about the efficiency of government spending on crop insurance premium subsidies. With increases in crop insurance participation and premium subsidy rates, the federal subsidized crop insurance has become more expensive than the Title I programs in the 2014 Farm Bill. The heavily subsidized crop insurance program was singled out for an $18 billion reduction in the Obama administration's 2017 budget proposal. If subsidies for crop insurance are reduced, the current coverage levels that farmers are buying will become more costly. Therefore, there are questions as to the likely change in the types of coverage and levels of protection farmers would purchase in the absence of subsidies.

Secondly, there are questions about the accuracy of the current premium ratemaking process under the impacts of climate change. Farming is risky due to the impacts of climate conditions, especially in rain-fed agricultural regions. In the U.S., floods and droughts have resulted in sever crop damage and large crop insurance losses. Figure 2 displays the national crop insurance loss ratios for all crops, all plans and all coverages. Relatively large losses and loss ratios occurred in 1988 at 2.45, 1993 at 2.19, 2002 at 1.39 and 2012 at 1.58. The large losses were mainly due to weather extremes (figure 2). Moreover, these historical loss ratios were constructed based on gross premium, which are the ratios of crop insurance indemnities to gross premium. If we look at the net loss ratios, which are the rates of crop insurance indemnities to net premium (gross premium - government subsidies), the losses of crop insurance were even higher when extreme weather happened. For example, the national net loss ratios were 3.25, 2.98, 3.46, and 4.22 in 1988, 1993, 2002 and 2012, respectively.

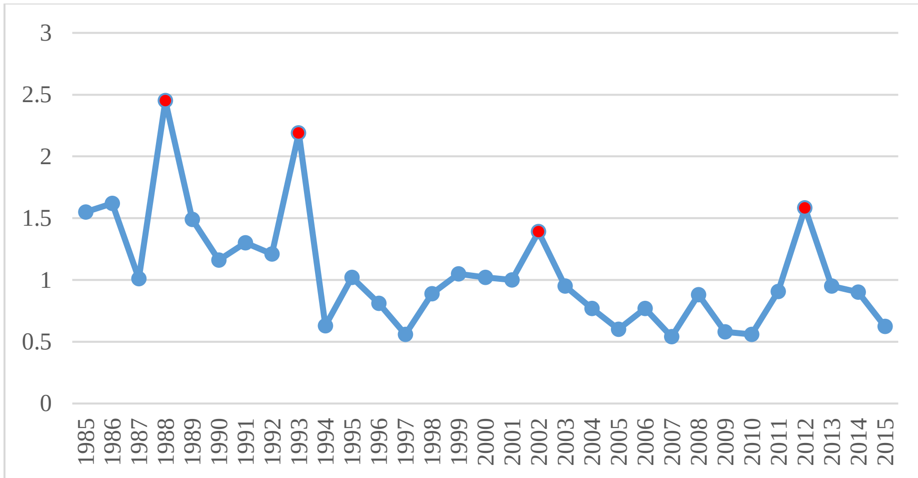

Figure 2. National Crop Insurance Gross Loss Ratios

Source: USDA, RMA, Summary of Business Reports.

Studies show that climate change is inevitable and climate variability would increase with global warming (e.g., Thornton et al. 2014). So farming would be more risky and historical patterns of yield would be less reliable in the estimation of future production. Therefore, how to adjust the current premium ratemaking process has become an important issue.

The purpose of this dissertation is to partially address these questions. In particular, the first two chapters estimate the elasticities of demand for corn and wheat insurance at each coverage level across major agricultural production regions. The third chapter examines how the impacts of climate change affect RMA's ratemaking process by using grain sorghum as an example. This study is the first one that explicitly discusses the regional demand for federal corn as well as wheat insurance at each coverage level, and it is the first study that explicitly presents the possible impacts of climate changes on crop insurance premiums. Considering that federal subsidy rates are specified for each coverage level, the detailed demand analysis at each coverage level could provide critical information for policy makers and private insurance companies.

CHAPTER II

HOW DO PREMIUM SUBSIDIES AFFECT CROP INSURANCE DEMAND AT DIFFERENT COVERAGE LEVELS: THE CASE OF CORN

Introduction

The U.S. federal crop insurance program plays a critical part in providing farmers protection against agricultural risk. Despite the higher participation with higher premium subsidies (figure 1), this program has been criticized as inefficient because of the massive government spending and poor actuarial performance (Glauber 2004). On average, the adjusted loss ratio is 2.07 over 2000 – 2013 (figure 2), which means producers tend to collect \$2.07 in indemnity payments for each dollar of their premium payment. Therefore, understanding the effects of subsidies on demand is essential for policy makers and the private sectors.

Previous studies examined the demand for crop insurance, however, the majority of the existing studies did not report the effects of premium at each coverage level. Consequently, it is not clear whether there are differences among the price elasticities of crop insurance demand across coverage levels. The only two known studies which account for the differences show that the demand for grape insurance in eleven California counties is price-elastic at the catastrophic (CAT) level of insurance. However, at higher coverage levels, the demand for grape insurance is price-inelastic (Knox and Richards 1999; Richards 2000). Although the majority of existing studies find that the aggregated demand for the federal crop insurance is price-inelastic, the elasticities of demand for crop insurance at different coverage levels could be significantly different. Moreover, since the federal premium subsidy rates are specified at each coverage level, understanding the elasticities across coverage levels is critical for future policy making.

The major objective of this chapter is to analyze the demand for federal corn insurance across different coverage levels and regions. This chapter is the first one that differentiates the demand for corn insurance policies for each coverage level and insurance plans (APH and CRC). Since federal subsidy rates are specified for coverage levels, detailed information at each coverage level could provide more reliable information for policy makers and private sectors.

Background

The FCIP is an important safety net for agricultural producers. To encourage greater participation, crop insurance premium subsidies were increased through the Federal Crop Insurance Reform Act (FCIRA) of 1994 (Nickerson et al. 2011). The FCIRA also authorized a catastrophic risk protection (CAT), which guaranteed 50% of a producer's approved yields at 60% of projected market prices (Glauber 2004). The premium for basic CAT insurance was subsidized by the federal government, and $50 administrative fee per crop per county was paid by enrolled producers (Just and Pope 2013). Participation in the FCIP was required under the 1994 Act for producers to be eligible for government payments, such as deficiency payments (Glauber 2007). In 1996, the mandatory require for crop insurance participation were eliminated (Glauber 2004), resulting in a significant decline of the enrollment in CAT insurance (Figure 3).

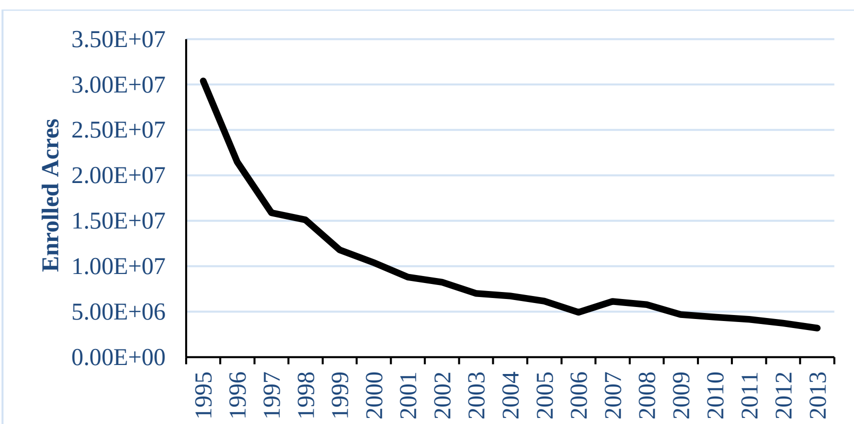

Figure 3. Acres Enrolled in CAT Coverage Level

Source: USDA, Risk Management Agency, Summary of Business files, 1989-2013.

To further increase the participation rate, crop insurance premium subsidies were increased by the Agricultural Risk Protection Act (ARPA) of 2000 (Babcock, Hart, and Hayes 2004; Coble and Barnett 2013). According to Babcock and Hart (2005), "One of the policy objectives of the ARPA was to induce producers to buy more insurance coverage in which one measure of 'more insurance' is the proportion of acres insured at levels greater than 65%." Table 1 provides a comparison between the percentages of the premium paid by the Federal Crop Insurance Corporation (FCIC) at various coverage levels at 100% of price coverage pre- and post- ARPA. For corn insurance, coverage is available in 5% increments from 50% to 85%. Before the ARPA, the dollar amount of subsidies were the same among coverage levels higher than or equal to 65%. The dollar amount of subsidies was accomplished by setting different subsidy rates at each coverage level (Babcock and Hart 2005). Under the ARPA, the subsidy level was increased by 12 percentage points at the 50% coverage level in the Actual Production History (APH) policy, while it increased by 37 percentage points at the 75% level under the Crop Revenue Coverage (CRC) policy. Moreover, under the ARPA, the increase in the insurance premium at higher coverage levels is generally less than the associated increase in subsidy rates. Therefore, producers would benefit more from purchasing higher coverage levels (Babcock, Hart, and Hayes 2004). Another significant change is that the subsidy level, as a percentage of the full premium, is now the same for both the yield insurance program (APH) and the revenue polices (CRC). Besides, the administrative fee for CAT insurance was increased from $50 to $100 per crop per county.

Table 1. Basic Unit Subsidy Levels Pre- and Post-ARPA

Coverage Level	Pre-ARPA		Post-ARPA
	APH	CRC	
50/100	55%	42%	67%
65/100	42%	32%	59%
70/100	32%	25%	59%
75/100	24%	18%	55%
85/100	13%	10%	38%

Source: Kelly 2001

Not surprisingly, the changes in quantity demanded differed among coverage levels with the uneven changes on subsidies. Thirty percent of total insured acres were enrolled in the CAT coverage level in 1998, while less than 15% of total insured acres enrolled in the CAT in 2002. Less than 15% of total demand was enrolled in the high-coverage category (coverage levels higher than 65%) in 1998, while the percentage participation increased to 62% in 2002 (Figure 4). Comparing the percentage of insured acres in each category pre- and post- ARPA, the purchase shares (insured acres devided by the total insured acres) for the CAT and low coverage categories decreased, while the purchase shares for the high coverage category increased.

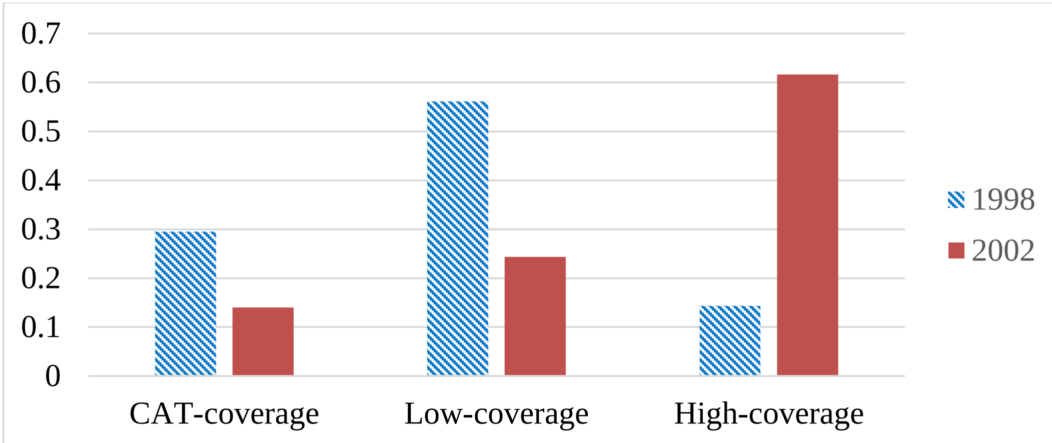

Figure 4. Percentage of Enrolled Acres in Each Category

Source: USDA's RMA, Summary of Business Reports.

The changes not only varied among different coverage levels, but also among different insurance plans. APH and CRC are the two most popular crop insurance policies during this time period (Babcock, Hart, and Hayes 2004). Figure 5 shows the total enrolled acres in different categories under APH policies and CRC polices. Compared with 1998, the total insured acres enrolled in APH medium coverage category decreased, while the total insured acres enrolled in CRC medium coverage category increased. Before ARPA, the per acre dollar amounts of CRC premium subsidies cannot be higher than the subsidy amounts of APH (Babcock and Hart 2005). After ARPA, the subsidy rates for APH and CRC were the same. Because the CRC premium was greater than APH premium, the per acre subsidies under CRC were also greater.

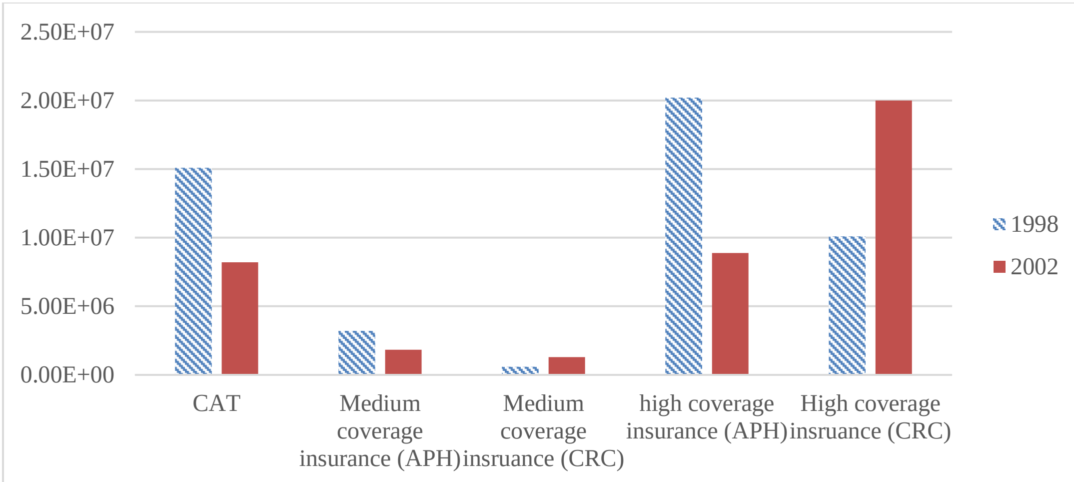

Figure 5. Total Insured Acres under APH and CRC in 1998 and 2002.

Source: USDA's RMA, Summary of Business Reports.

Although ARPA was implemented in 2000, it remains the most recent and broadest reform in premium (O'Donoghue 2014). Furthermore, there are very few studies which explore the impacts of subsidy adjustments on crop insurance demand and none of them differentiated coverage levels and plans. Therefore, this study examines the effects of increased subsidies among coverage levels and insurance plans.

Literature Review

A number of papers examined the demand for crop insurance, but the potential differences in crop insurance demand among coverage levels and policy plans received limited empirical attention. Table 2 shows the elasticities reported in the literature. Among all the available studies, the crop insurance demand is price-inelastic if coverage levels are not specified. Only two known studies which differentiate coverage levels show that the demand for grape insurance is price-elastic at the 50% coverage level, while the demand is price-inelastic among higher coverage levels.

Table 2. Estimated Price Elasticities of Crop Insurance Demand in Literature

Crop	Estimated price elasticity of demand	Coverage Level	Location	Years examined	Journal publication date	Author(s)
Corn	-0.32 (acreage)	-	IA	1985-1990	1993	Goodwin
	-0.73 (liability)	-				
	-0.28 (liability)	-	Heartland	1985-1993	2004	Goodwin et al.
	-0.24 (liability)	-	IL, IN, IA	1996-1998	2001	Goodwin
	-0.27 (acreage)	-	IL, IN, IA, OH	1997, 2002	2014	O'Donoghue
	-0.13 (liability)	-				
	-0.24 (liability)	-	MI, MN, WI			
	-0.25 (liability)	-	KS, NE, SD			
Soybeans	-0.33 (liability)	-	Heartland	1985-1993	2004	Goodwin et al.
	-0.20 (liability)	-	IL, IN, IA	1996-1998	2001	Goodwin
	-0.26 (liability)	-	MI, MN, WI	1997, 2002	2014	O'Donoghue
	-0.17 (liability)	-	KS, NE, SD			

Table 2. Continued.

Crop	Estimated price elasticity of demand	Coverage Level	Location	Years examined	Journal publication date	Author(s)
Grape	-1.25 (proportion of acreage)	50%	CA	1986-1996	1999	Knox and Richards
	-0.28 (proportion of acreage)	65%				
	-0.49 (proportion of acreage)	75%				
	-1.68 (liability)	50%	CA	1986-1996	2000	Richards
	-1.42 (proportion of acreage) -0.67 (liability)	65%				
	-0.44 (proportion of acreage) -0.50(liability) -0.41 (proportion of acreage)	75%				

Table 2. Continued.

Crop	Estimated price elasticity of demand	Coverage Level	Location	Years examined	Journal publication date	Author(s)
Soybeans, cotton, wheat, tobacco, peanuts	-0.92 (acreage)	-	U.S.	1979	1986	Gardner and Kramer
Wheat, corn, sorghum, soybeans	-0.21 (proportion of acreage)	-	KS	1993-2000	2003	Serra, Goodwin, and Featherstone

Source: O'Donoghue 2014 plus additional update from the list.

To empirically estimate the demand for crop insurance, Gardner and Kramer (1986) sampled 57 counties in 1979 over soybeans, cotton, wheat, tobacco, and peanuts across 13 states. The percentage of insured acres was used as the dependent variable to measure the quantity of insurance. The ratio of expected indemnities less premium to liability (expected rate of return) was used as the price variable. The results suggest that the participation rate would increase by 18.5% with a 1% increase in the rate of return. Therefore, Gardner and Kramer suggested that the subsidy rate should be greater than 50% to achieve a majority of farmers' participation.

Knox and Richards (1999) and Richards (2000) applied a two-stage selection approach to estimate grape insurance demand in California. In the first stage, they estimated the probability that growers choose each coverage level. Then the fitted probability was used in the second stage, with linear models used to estimate the amount of insurance bought at each coverage level. The major difference between these two studies is that they used different models in the first stage. Multinomial logit model and ordered probit model were used by Knox and Richards (1999) and Richards (2000), respectively. Their procedures were similar to the Heckman correction approach, but the selection process was multinomial rather than binomial. The proportion of insured acres was used as the dependent variables and the expected net premium was used to measure the price of insurance in both studies. Furthermore, in Richards' (2000) study, he also estimated the elasticities of demand for grape insurance with the liability per acre as the dependent variable. The county-level panel data used in the analysis consisted of 11 years (1986-1996) for the eleven largest grape-growing counties in California. With the dependent variable defined as the proportion of eligible acres insured in each county, the estimated price elasticities were -1.252, -0.276, and -0.492 at the 50%, 65%, and 75% coverage levels, respectively, in Knox and Richards' (1999) study. The elasticities were reported as -1.420, -0.436, and -0.408 at the 50%, 65%, and 75% coverage levels, respectively, in the Richards' (2000) study. Overall, these studies find that the demand for 50% coverage level is price-elastic, while the demand is price-inelastic for higher coverage levels (65% and 75%). These studies also find that expected net premium, the variance of returns, and the first two moments of the expected market returns influenced producers' choices of coverage levels. In addition, the mean and variance of indemnities, and farm income effected the producers' quantity purchases in the second stage.

Goodwin (1993) utilized county-level corn data for 99 Iowa counties during 1985 to 1990 to estimate the demand for crop insurance. Purchases of insurance were measured by both the ratio of insured to planted corn acres and the liability per planted acre of corn. The average price per insured acre was used as the relevant price variable in the first equation, and the dollars per hundred dollars of liability (premium rate) was used as the correspondence in the second equation. Fixed effect regression was applied to the models. The estimated elasticities were -0.32 and -0.73 in the acreage equation and the liability equation, respectively.

Smith and Baquet (1996) was the first study which used the Heckman two-stage approach to model the wheat producer's participation and coverage-level decisions separately. The probit model was applied in the first stage to estimate the probability of purchasing MPCI. Then the estimated inverse Mills ratio was fitted in the second stage to adjust for the sample selection problem. Maximum likelihood procedures were utilized in the models. The cross-sectional data consisted of 370 individual wheat farms in Montana. They conclude that premium rates do not have significant impacts on crop insurance participation, while the premium rates have influence on producers' decisions on coverage level. They refer to this as "lead to a decision to use multiple peril crop insurance (MPCI) more intensively." In addition, the results suggest that operator age and farm size didn't have a statistically significant effect either on producers' decisions of participation or on coverage-level selection.

Serra, Goodwin, and Featherstone (2003) used farm-level data in Kansas from 1993 to 2000 to analyze the demand for insurance during the 1990s. The ratio of county average net premium over the total liability across all crops and insurance plans (county average premium rate) was used as the price of insurance. The likelihood of a farm's participation in crop insurance is considered in the two-stage model. The two-stage model used in the study was proposed by Nelson and Olson (1978) but it did not yield reliable estimates of the variance of parameters. To address this problem, Serra, Goodwin, and Featherstone (2003) used Monte Carlo bootstrapping procedures to obtain consistent variance covariance estimates for the parameters in the model. Their results show that the absolute values of elasticities of the demand for crop insurance decreased from 1993 to 2000 with the exception of 1996. The price elasticity is -0.57 and -0.13 in 1993 and 2000, respectively. They suggest that it is hard to increase crop insurance participation through premium subsidies or premium discounts.

Studies done by Babcock, Hart, and Hayes (2004) and Just, Calvin, and Quiggin (1999) imply that increasing net income instead of reducing risk is the major reason for crop insurance participation. Babcock, Hart, and Hayes also attribute the increase in crop insurance participation in high coverage levels in 2000 and 2001 to the decreased crop insurance premiums in the ARPA.

Babcock and Hart (2005) examined the impacts of increased subsidies on producers' coverage level decisions. County-level crop insurance participation data in 1998 and 2002 were used in their analysis. Crop insurance coverage levels at or greater than 65% are referred as buy-up insurance. The percentage subsidy was used as an independent variable in the model to estimate how the percentage subsidy influences the proportion of insured acres above 65% in the total buy-up insured acres. The study implies that the demand for buy-up crop insurance policies would be increased by four times across corn, soybenas, and wheat if actuarially fair premiums are adopted. Since the proportions are used as the dependent variables, a two-limit Tobit model is constructed in their study due to the censoring in the data. The study also find that producers who participate in revenue insurance policies prefer high coverage levels. Babcock and Hart's (2005) study implies that crop insurance subsidies have an effect on producers' purchasing decisions and selections

Most recently, O'Donoghue (2014) used county-level data in 1997 and 2002 to examine the impacts of crop insurance premium subsidies on the demand for crop. First differencing is applied in this analysis to control for time-invariant effects. Results show that the increases in subsidy rates under ARPA induced producers to participate in high coverage levels and the influence varies across regions and crops. The elasticities of demand for corn liabilities with respect to subsidies are 0.13, 0.24, 0.25 in the Midwest (IL, IN, IA, OH), Lake (MI, MN, WI), and Northern Plains (KS, NE, SD), respectively. The elasticity of demand for wheat liabilities with respect to subsidies are 0.27 in the Northern Plains (KS, NE, ND, SD). The elasticities of demand for soybeans are 0.26 and 0.17 in the Lake (IL, IN, IA, OH) and Northern Plains (KS, NE, ND, SD).

Many of the existing studies find that the demand for crop insurance is price-inelastic. Table 2 shows the elasticities reported by existing studies. The demand for crop insurance is price-inelastic if coverage levels are not differentiated. The only two studies which differentiate coverage levels show that demand for grape insurance is price-elastic at the 50% coverage level.

Overall, coverage levels have received limited research efforts regarding the demand for crop insurance. Although the majority of the existing studies show that the demand for crop insurance is price-inelastic, elasticities may be different across levels of coverage.

Empirical Modeling Framework

Expected utility maximization is usually the theoretical framework in which the determinants of insurance purchases are examined. A representative producer is subject to constraints imposed by characteristics of marketing and production environment, such as commodity prices. Following Goodwin (1993), the maximization of the expected utility yields a linear equation, which is a function of the representative producer's risk attitudes, and the production and marketing characteristics. The demand for corn insurance is given by

$$y_i = \alpha + X_i \beta + \varepsilon_i$$

y_i is the insurance purchase decision made by the producer under the utility maximization problem. X_i is a vector of factors that influence the expected utility of insurance and ε_{1k} is a random error term.

Following Gardner and Kramer (1986) and Goodwin (1993), each county is treated as a representative farm. Although the utilization of county-level data could reduce the variation, compared to farm-level data, given the data availability, the county-level dataset is the best one which can be used for estimation of crop insurance demand. Since insurance premium and agricultural practice vary across crops, focusing on one crop could provide more reliable estimation results compared to mixed crops.

The measure defined to quantify the crop insurance demand varies in previous studies, such as the percentage of insured acres used in Gardner and Kramer (1986), and premium less expected indemnities per dollar of liability in Cannon and Barnett (1995).

In this study, the quantity variable is constructed as the per dollar liabilities (liabilities divided by projected prices) per enrolled acre. Liabilities are the amount of indemnities if all losses occur, and are determined by the production conditions of insured acres, the product of insured acres, the projected price of the product. As Goodwin (1993) mentioned, the liability should be the true measure as the level of insurance. In Goodwin (1993), the dependent variable is the liability per planted acre of corn. However, insured acres should be preferred to the planted acres at the county-level to adjust liabilities as liabilities are determined by the characteristics of the insured acres, not the total planted acres, and the total corn planted acres are also controlled in the model. Moreover, the liabilities per enrolled acres are divided by the corn projected price in each county to estimate the per dollar purchases.

The definitions of the price variable in the analysis of crop insurance demand are as diverse as the measure for the quantity. The premium rate per acre (liabilities times the premium rate) is the commonly used term to measure the cost of insurance, such as in Smith and Baquet (1996). In this study, the normalized net premium (gross premium less subsidies) per insured acre divided by the projected price is used to estimate the cost of insurance per insured dollar. The premium per acre is the acre unit price, while the net premium per acre per (insured) dollar is the dollar unit price. So the normalized net premium per insured acre per insured dollar should be the true dollar unit price faced by producers. The net premium is calculated by subtracting the subsidies from the premium. All monetary variables in this study are normalized using the Consumer Price Index (CPI).

Following Babock and Hart (2005), insurance participation data in 1998 and 2002 are selected for the present analysis based on the following reasons. The ARPA was authorized in June of 2000 and the implementation would be even later. Corn producers already made their decisions on insurance selection in 2000 before the application of ARPA (Appendix 1 for corn usual planting and harvesting dates, by states). Since the industry needs time to accommodate the changes, the participation data in 2001 is not as reflective of the changes in subsidies in crop demand as it is in later years. Therefore, 2002 crop year data would be more reasonable to be used in the analysis.

An ad hoc premium reduction program was introduced both in 1998 and 1999. In 1999, some producers might have not been aware of the premium reduction program. So the insurance participation data in the 1999 crop year may not fully reflect producers' decisions with respect to premiums. Although the program also exited in 1998, it was introduced after producers made their participation decisions (Babcock and Halt 2005). Therefore, we could assume that producers made their participation decisions based on full information in 1998.

In the literature, different estimation approaches were used. For example, a two-stage model was used in Richards (1999) and Serra, Goodwin, and Featherstone (2003) to adjust the non-participation problem. However, county-level data are used in this study and there is no server non-participation problem at the county level. The fixed effect model was used by Goodwin (1993) to estimate the demand for corn insurance by using panel data during 1985-1990. Since cross-sectional data (consisted of data for 1998 and 2002) are used to analyze the effects of subsidies in the ARPA in this study, fixed effects and random effects are not considered in the present study. Therefore, OLS regression is used for the estimation of the demand for corn insurance in this study.

In this study, APH and CRC are the focus because they were the two most popular insurance policies in 1998 and 2002. Considering the APH insurance plan provides yield protection for corn producers, while the CRC insurance plan provides revenue protection, instead of using the aggregate data, an improvement is that the two insurance plans are separated into different equations.

Table 3. Definition of Variables in the Models

Variables	Definition	Notation in this study
dependent variable	normalized liabilities per acre/projected price	liab_cpi_acre_price
price	normalized net premium per acre/projected price	netprem_cpi_acre_price
expected yield	average yield in the preceding three years	mean_lag_yd3
expected revenue	average revenue in the preceding three years	mean_lag_rev_cpi3
cv of yield	coefficient of variance for corn yield (1989-2013)	cv_yield
cv of revenue	coefficient of variance for revenue (1989-2013)	cv_rev
planted acres	planted acres	acreplt
enrolled acres in CRP	enrolled acres in CRP	crp
percentage of irrigated cropland	the ratio of acres of irrigated cropland to acres of total cropland in each county	irr_per
percentage of cropland operated by females	the ratio of acres operated by females to acres of total cropland in each county	fe_per

Table 3 provides a summary of the definition of each variable. The preceding three-year's average yield is incorporated in the model to estimate producer's expected yield (e.g., for 1998, the years 1997, 1996, and 1995 are used). One year lagged yield is a common term to estimate producer's expectation of yield in the literature (e.g. Wang et.

al. 1998), however, the preceding three-year's average yield should be preferable to the one year lagged term because agricultural production is quite variable and the preceding one year's yield does not fully reflect the producer's expectation of the yield and the variability of yield. Meanwhile, as the technology developments, the preceding three-year's average yield should be preferable to the mean of historical yield used in previous studies, such as the average yield in the preceding 10 years used by Goodwin, Vandeveer, and Deal (2004). Similarly, the preceding three-year's revenue is used to estimate producers' revenue expectation in the CRC equations.

O'Donoghue (2014) as well as Goodwin and Ker (1998) included the yield variance in the study of crop insurance. The coefficient of variance (CV) for yield is included in the current model to estimate the relative yield risk of the county. Using the CV for yield is better than the yield variance because the CV estimates the relative yield risk while the variance of yield reflects the absolute yield risk. Because of the significant difference in the mean yield in the four regions, relative yield risk is preferable to the absolute yield risk. In this study, historical corn yield data in 1989 through 2013 are used to compute the CV for each county.

The total corn planted acres are incorporated in the model since a potential correlation is expected between the planted acres and the insurance purchases. The enrolled acres of CRP are used as an independent variable because it is impossible to purchase insurance protection for acres enrolled in the CRP.

The percentage of irrigated cropland in each county is controlled in the model as this item could reflect the production environment and affect the distribution of yield.

Women tend to be more risk averse than men (Charness and Gneeze 2012), thus the percentage of cropland operated by females is also incorporated in the equations.

Data

The data utilized in this analysis were drawn from three major sources. The primary data source is USDA, Risk Management Agency (RMA) administrative data. The individual data are aggregated to the county-level by crop type and crop insurance policy at each coverage level. Information about insured acres, total premium, liabilities, and subsidies is available from RMA's Summary of Business Report (SBR) publications. The SBR publications report participation data from 1989 through 2014 and contain spatially identifying information. Thus the participation data can be combined with other datasets. There are about 2,000 observations for each year during the time period in the SBR publication. Among all the counties, the Corn Belt, Lake States, Northern Plains, and Southern Plains are the focus of this study. The states in each region are reported in table 4.

Table 4. Regional Division Definition

Regions	States Included
Corn Belt (CB)	Iowa, Illinois, Indiana, Missouri, and Ohio
Lake States (LS)	Michigan, Minnesota, and Wisconsin
Northern Plains (NP)	Kansas, and Nebraska, and South Dakoda
Southern Plains (SP)	New Mexico, Oklahoma and Texas

USDA, National Agricultural Statistics Service (NASS) surveys provide county-level data about crop yield and total planted acres in each crop. The Bureau of Labor Statistics (BLS) provides the annual Consumer Price Index (CPI). In this study, all monetary variables are normalized by deflating with the CPI. Data about irrigated cropland and acres operated by females and males are obtained from National Agricultural Statistics Services (NASS)'s 1997 and 2002 Censuses of Agriculture. County-level data on participation in Conservation Reserve Program (CRP) is collected from USDA, Farm Service Agency (FSA) to estimate the effect of CRP acreage on insurance demand.

Demand Estimation

Figure 6 shows the county average yield in 1989-2013. Figure 7 shows the coefficient of variation (CV) of yield at the county level. The CV is calculated as the ratio of the standard deviation of yield to the mean of yield. The standard deviation and the mean of yield are calculated using the historical data from 1989 to 2013. As shown in figures 6 and 7, agricultural crop production is concentrated by region. To target the estimation on moderately homogeneous regions, the empirical model was applied in the four following regions: Corn Belt, Lake States, Northern Plains, and Southern Plains (estimation results for other regions are also reported in the appendix). Table 4 lists the states included in each region. The four regions account for more than 80% of total corn planted acres both in 1998 and 2002. Detailed production information is presented in Table 5.

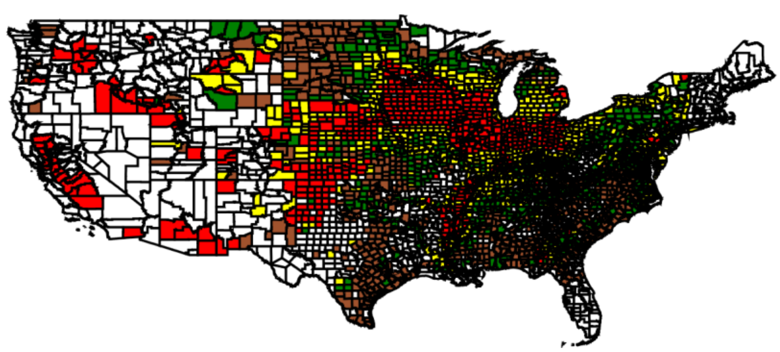

Figure 6. County Average Yield in 1989-2013 (irrigated and non-irrigated)

Source: USDA NASS.

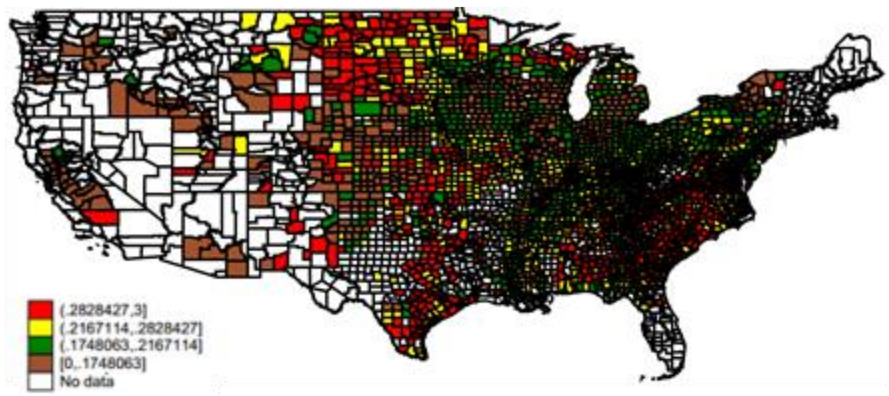

Figure 7. County Average Coefficients of Variation (CV) of Yield in 1989-2013

Source: USDA NASS.

Table 5. Corn Planted Acres in Each State

States	Planted Acres in 1998	Percentage of Total Planted Acres in 1998	Planted Acres in 2002	Percentage of Total Planted Acres in 2002
IL	10,600,000	13.22%	11,100,000	14.07%
IN	5,800,000	7.24%	5,400,000	6.84%
IA	12,500,000	15.59%	12,200,000	15.46%
MS	2,650,000	3.31%	2,800,000	3.55%
OH	3,550,000	4.43%	3,250,000	4.12%
MI	2,300,000	2.87%	2,250,000	2.85%
MN	7,300,000	9.11%	7,200,000	9.13%
WI	3,700,000	4.62%	3,650,000	4.63%
KS	3,000,000	3.74%	3,250,000	4.12%
NE	8,800,000	10.98%	8,400,000	10.65%
SD	3,900,000	4.86%	4,450,000	5.64%
NM	140,000	0.17%	140,000	0.18%
OK	270,000	0.34%	240,000	0.30%
TX	2,400,000	2.99%	2,050,000	2.60%
SUM		83.47%		84.14%

Source: USDA NASS.

Figure 8 shows the total planted acres in the four regions. The Corn Belt is the major corn production region in the U.S., and the average planted acres in this region is more than 80 million acres in 1980-2014. On average, the planted acres in the Corn Belt account for more than 40% of the total corn planted acres in the U.S. during this period. The Lake States was the second largest corn production area, but it has been surpassed by the Northern Plains since 1996. The planted acres in the Lake States account for 17% of the total planted acres in the country. The Northern Plains is also a major corn production area. On average, it accounts for 19% of total corn planted acres in 1980-2014. Planted acres in the Southern Plains is stable, and it only accounts for 3% of the total planted acres in the U.S. on average.

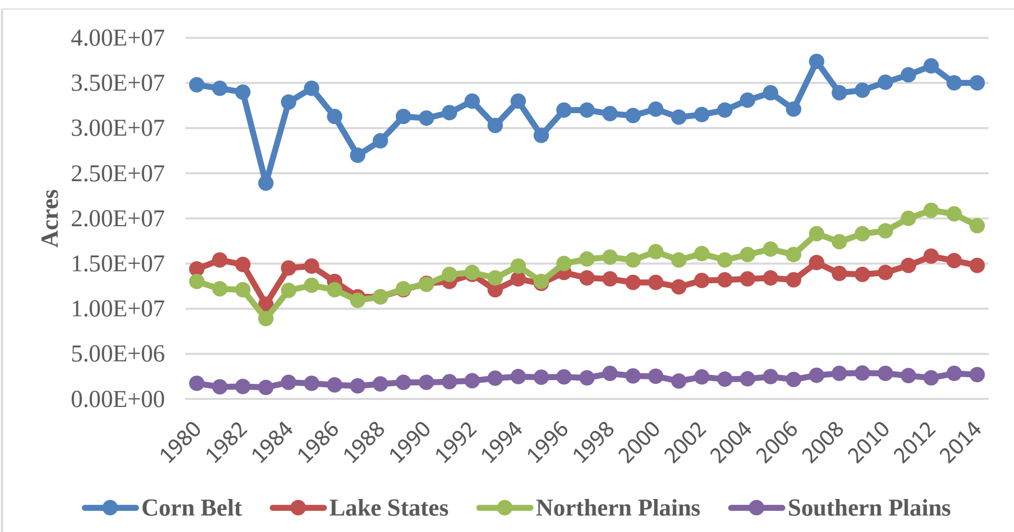

Figure 8. Corn Planted Acre in 1980-2014

Source: USDA, NASS.

Figure 9 shows the mean yield in the four regions in 1989-2013. The average yield in the Corn Belt is the highest (132 bu/acre). The average yield in the Lake States is 119 bu/acre, which is slightly higher than it is in the Northern Plains. The yield in the Southern Plains is the lowest (94 bu/acre).

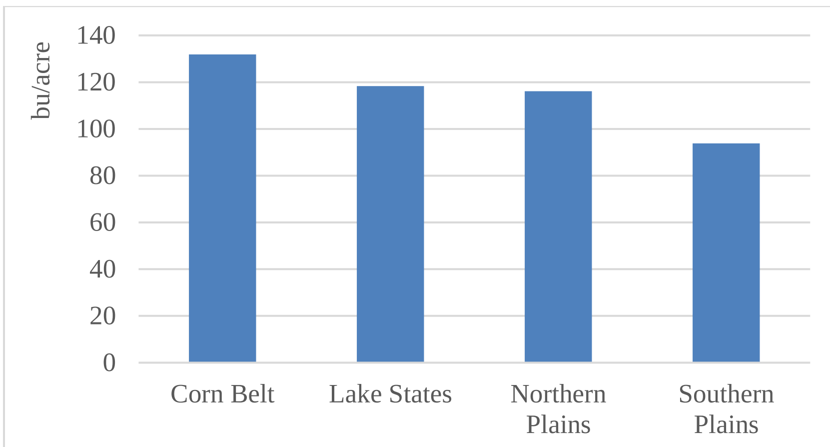

Figure 9. Average Corn Yield (average over 1989-2013)

Source: USDA, NASS.

Not only the mean yield varies across the regions, the coefficient of variation (CV) of yield also differs. Figure 10 shows the values of the CV of yield in each region. Although the Corn Belt has the highest yield, it has the lowest CV among the four regions, while the Sourthern Plains has the highest relative risk.

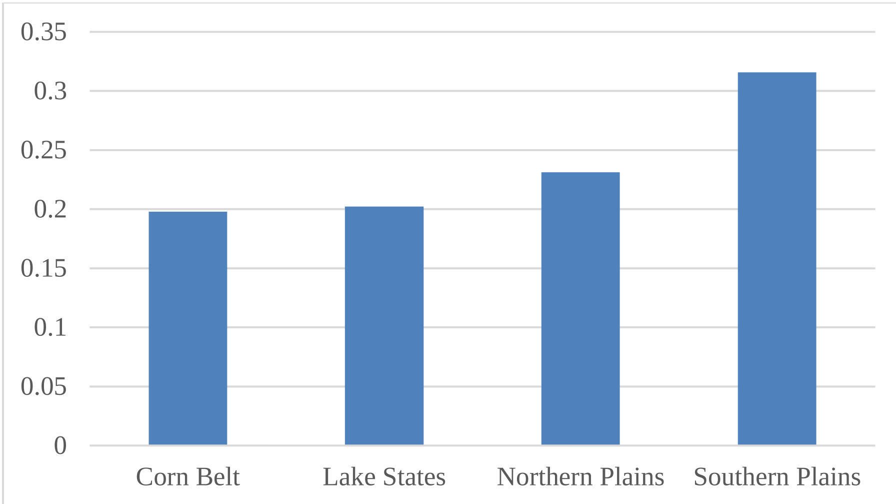

Figure 10. Average Coefficient of Variation of Yield (average over 1989-2013)

Source: USDA, NASS.

Table 6. Estimation Results for Corn APH in the Corn Belt

	Coverage Level							
Variable	50%	55%	60%	65%	70%	75%	80%	85%
lg_netprem_cpi_acre_price	-0.047**	-0.018	-0.170***	-0.114***	-0.137***	-0.149***	-0.230***	0.017
	-0.021	-0.05	-0.049	-0.027	-0.028	-0.055	-0.074	-0.101
lg_mean_lag_yd3	0.416***	0.493**	0.341**	0.276***	0.300***	0.534***	0.730***	0.237
	-0.067	-0.202	-0.146	-0.061	-0.087	-0.093	-0.225	-0.247
lg_cv_yield	-0.080*	-0.048	-0.077	-0.130***	-0.097*	-0.112**	0.035	-0.204*
	-0.041	-0.122	-0.078	-0.041	-0.05	-0.051	-0.103	-0.105
lg_acreplt	0.067***	0.117***	0.051**	0.063***	0.030**	0.021	0.029	0.100***
	-0.013	-0.040	-0.023	-0.011	-0.015	-0.018	-0.037	-0.029
lg_crp_acre	-0.012**	-0.028*	-0.022**	0.0004	0.004	0.010	-0.010	-0.022
	-0.006	-0.016	-0.011	-0.008	-0.007	-0.008	-0.013	-0.018
irr_per	-0.100	-0.171	0.026	0.065	0.060	0.112	-0.159	-0.174
	-0.085	-0.178	-0.126	-0.076	-0.064	-0.102	-0.144	-0.313
fe_per	-0.148	0.609	-0.162	0.064	-0.705	-0.843	0.075	-0.671
	-0.498	-0.895	-1.159	-0.444	-0.588	-0.753	-0.757	-1.485
Constant	1.251***	0.543	2.201***	2.147***	2.587***	1.568***	1.186	2.073*
	-0.302	-0.993	-0.682	-0.265	-0.414	-0.475	-1.157	-1.124
Observations	399	141	225	456	376	363	98	73
R-squared	0.536	0.482	0.44	0.621	0.467	0.557	0.522	0.442
F-stats	66.91	12.7	27.2	83.83	32.52	49.55	18.62	10.09
[p-value]	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Breusch-Pagan/ Cook-Weisberg Test	X	X	X	X	X	X	X	X
Model Specification Test		X	X					

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. (Robust) standard errors presented below the parameters estimated.

Table 7. Estimation Results for Corn APH in Lake States

	Coverage Level							
Variable	50%	55%	60%	65%	70%	75%	80%	85%
lg_netprem_cpi_acre_price	-0.180***	-0.138***	-0.138***	-0.153***	-0.114**	-0.157***	-0.203**	-0.192
	-0.031	-0.049	-0.043	-0.025	-0.045	-0.053	-0.08	-1.463
lg_mean_lag_yd3	0.418***	0.336***	0.644***	0.557***	0.551***	0.756***	0.583	-0.186
	-0.102	-0.129	-0.145	-0.071	-0.127	-0.145	-0.395	-5.717
lg_cv_yield	-0.098**	-0.188**	0.056	0.072	-0.064	0.019	-0.248	-0.103
	-0.041	-0.078	-0.109	-0.087	-0.068	-0.074	-0.161	-0.91
lg_acreplt	0.023*	0.055***	0.055**	0.060***	0.097***	0.033	0.233***	-0.047
	-0.013	-0.021	-0.023	-0.014	-0.027	-0.025	-0.073	-0.579
lg_crp_acre	-0.014**	-0.018*	-0.020**	-0.011**	-0.024**	-0.002	-0.095**	0.009
	-0.005	-0.01	-0.01	-0.005	-0.01	-0.011	-0.035	-0.348

Table 7. Continued.

	Coverage Level							
Variable	50%	55%	60%	65%	70%	75%	80%	85%
irr_per	-0.273**	-0.121	-0.166	0.007	-0.099	-0.031	0.196	-2.186
	-0.112	-0.129	-0.165	-0.089	-0.134	-0.182	-0.351	-13.961
fe_per	-0.172	0.418	0.606	0.655	0.986*	-1.171	4.523**	-5.217
	-0.45	-0.806	-0.739	-0.401	-0.584	-0.906	-1.825	-16.13
Constant	1.833***	1.777***	0.862	1.301***	0.817	0.736	-0.339	6.433
	-0.439	-0.631	-0.67	-0.306	-0.635	-0.624	-1.866	-33.493
Observations	283	170	186	286	180	153	39	9
R-squared	0.618	0.497	0.506	0.686	0.575	0.533	0.651	0.678
F-stats	52.23	20.45	24.98	64.37	18.66	25.7	8.28	0.3
[p-value]	0	0	0	0	0	0	0	0.8888
Breusch-Pagan/ Cook-Weisberg Test	X	X	X	X	X	X		
Model Specification Test				X	X		X	

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. (Robust) standard errors presented below the parameters estimated.

Table 8. Estimation Results for Corn APH in Northern Plains

	Coverage Level							
Variable	50%	55%	60%	65%	70%	75%	80%	85%
lg_netprem_cpi_acre_price	-0.121**	-0.004	-0.305***	0.001	-0.097	-0.188*	-0.259**	-0.284**
	-0.053	-0.09	-0.071	-0.032	-0.09	-0.104	-0.111	-0.125
lg_mean_lag_yd3	0.698***	0.724***	0.599***	0.848***	0.720***	0.530***	0.890**	-0.257*
	-0.116	-0.17	-0.151	-0.051	-0.147	-0.173	-0.336	-0.15
lg_cv_yield	-0.319***	-0.257	-0.164	-0.174***	-0.057	-0.174	0.082	-0.618***
	-0.068	-0.159	-0.117	-0.038	-0.075	-0.107	-0.247	-0.148
lg_acreplt	0.068***	0.047	0.051**	0.029***	0.067***	0.071***	0.002	-0.005
	-0.017	-0.034	-0.026	-0.007	-0.025	-0.026	-0.056	-0.035
lg_crp_acre	-0.032***	-0.092***	0.0005	-0.017**	-0.007	-0.026	0.005	-0.041*
	-0.012	-0.025	-0.021	-0.007	-0.013	-0.018	-0.024	-0.02
irr_per	-0.196**	-0.238	-0.039	-0.041	-0.007	-0.054	0.142	-0.237
	-0.082	-0.198	-0.155	-0.051	-0.092	-0.119	-0.244	-0.155
fe_per	0.769	0.543	0.65	-0.018	1.247	1.209	2.436	1.366
	-0.852	-1.454	-1.009	-0.39	-1.187	-1.123	-2.617	-1.314
Constant	-0.303	0.393	0.671	-0.336	0.114	1.206	0.533	5.798***
	-0.535	-0.735	-0.659	-0.238	-0.643	-0.76	-1.496	-0.951
Observations	288	103	131	335	239	241	64	38
R-squared	0.672	0.612	0.596	0.806	0.596	0.465	0.399	0.693
F-stats	80.75	21.41	25.92	244.3	49.63	41.01	17.24	16.62
[p-value]	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Breusch-Pagan/ Cook-Weisberg Test	X				X	X	X	X
Model specification test	X			X				

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. (Robust) standard errors presented below the parameters estimated.

Table 9. Estimation Results for Corn APH in Southern Plains

Variable	Coverage Level					
	50%	55%	60%	65%	70%	75%
lg_netprem_cpi_acre_price	-0.221**	-0.131	-0.248*	-0.216*	-0.155	-0.654***
	-0.102	-0.161	-0.127	-0.119	-0.134	-0.126
lg_mean_lag_yd3	0.469***	0.569**	0.455**	0.702***	0.781***	0.850***
	-0.109	-0.209	-0.167	-0.079	-0.132	-0.17
lg_cv_yield	-0.474***	-0.026	-0.167	-0.129*	0.09	0.002
	-0.119	-0.231	-0.151	-0.0754	-0.13	-0.197
lg_acreplt	-0.007	0.0333	-0.021	0.016	0.001	-0.03
	-0.023	-0.060	-0.042	-0.017	-0.0251	-0.0354
lg_crp_acre	0.029**	-0.005	0.040*	0.007	0.046***	0.029*
	-0.012	-0.028	-0.021	-0.01	-0.017	-0.017
irr_per	0.312**	0.634**	0.615**	0.439***	0.525**	0.232
	-0.143	-0.279	-0.251	-0.132	-0.196	-0.228
fe_per	0.426	-0.121	-1.175	0.586	1.553	-2.079*
	-0.872	-1.63	-1.437	-0.683	-1.132	-1.03
Constant	0.821	0.892	1.742*	0.55	0.225	1.757**
	-0.505	-1.159	-0.888	-0.452	-0.695	-0.838
Observations	111	31	39	143	54	35
R-squared	0.832	0.759	0.864	0.748	0.829	0.894
F-stats	104.62	10.36	28.25	90.9	31.91	32.66
[p-value]	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Breusch-Pagan/ Cook-Weisberg Test	X			X		
Model Specification Test				X		

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. (Robust) standard errors presented below the parameters estimate.

The Demand for Corn APH Insurance

The estimation results for APH demand are summarized in tables 6 through 9 for the Corn Belt, Lake States, Northern Plains, and Southern Plains, respectively. The prefix "lg_" denotes that the variable is measured in logarithm. Breusch-Pagan (1979) and Cook-Weisberg (1983) test is applied to test for heteroskedasticity. The variances of error are all equal is assumed in the null hypothesis of the Breusch-Pagan and Cook-Weisberg test. "X"s in the rows of Breusch-Pagan/Cook Weisberg test in tables 6 through 9 indicate the regressions are rejected by the null hypothesis at the 95% confidence interval, and robust standard errors are used in these regressions.

In this study, link tests are applied to test for model specification. The basic idea of the link test is that any additional independent variable should be statistically insignificant if the model is correctly specified (Bruin 2006). According to Bruin (2006), the link test creates two variables: predicted dependent variable (y_hat) and the square of the predicted dependent variable (y_hatsq). Then the model is refit only using these two variables as predictors. In this study, the results of link tests suggest that models are well specified excepted at the 55% and 60% coverage levels in the Corn Belt, at the 65%, 70%, and 80% coverage levels in the Lake States, at the 50% coverage level in the Northern Plains, and at the 65% coverage level in the Southern Plains.

To address the misspecification problem, linear-linear models are used at the 55% and 60% coverage levels in the Corn Belt (table 10), the linear-log models are used at the 65%, 70%, and 80% coverage levels in the Lake States (table 11), the linear-log model is used at the 50% coverage level in the Northern Plains (table 12), and the log-linear model is used at the 65% coverage level in the Southern Plains (table 13). Furthermore, variance inflation factors are used to diagnose collinearity problem. Among all the estimations, the highest VIF is less than 10. Therefore, multicollinearity does not appear to be a considerable problem. Elasticities at the 55% and 60% coverage levels in the Corn Belt, the 50% coverage level in the Northern Plains, and the 65% coverage level in the Southern Plains are calculated at variable means at each coverage level and region and are reported in tables 14 through 17.

Table 10. Estimation Results for Corn APH in the Corn Belt (55% and 60%)

	Coverage Level	
Variable	55%	60%
netprem_cpi_acre_price	-0.579	-2.070***
	-0.516	-0.462
mean_lag_yd3	0.174***	0.175***
	-0.066	-0.055
lg_cv_yield	-5.798	-8.505*
	-6.051	-4.614
lg_acreplt	5.333***	3.294***
	-1.33	-1.21
lg_crp_acre	-1.422**	-1.458**
	-0.683	-0.633
irr_per	-10.394	-1.042
	-9.526	-7.889
fe_per	6.366	6.304
	-43.302	-58.792
Constant	-16.85	11.249
	-15.151	-13.945
Observations	141	225
R-squared	0.53	0.459
F-stats	21.44	41.14
[p-value]	0.0000	0.0000
Breusch-Pagan/ Cook-Weisberg Test		X

Note: Dependent variables are liab_cpi_acre_price in both regressions.
Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. (Robust) standard errors presented below the parameters estimated.

Table 11. Estimation Results for Corn APH in the Lake States (65%, 70%, and 80%)

	Coverage Level		
Variable	65%	70%	80%
lg_netprem_cpi_acre_price	-9.083***	-6.773**	-14.086**
	-1.355	-2.717	-6.381
lg_mean_lag_yd3	33.320***	40.167***	49.572
	-3.607	-7.351	-31.399
lg_cv_yield	2.283	-2.219	-17.871
	-3.211	-4.201	-12.752
lg_acreplt	2.594***	4.923***	18.149***
	-0.696	-1.358	-5.829
lg_crp_acre	-0.474*	-1.183**	-6.948**
	-0.246	-0.531	-2.745
irr_per	-1.353	-6.674	13.896
	-4.663	-9.084	-27.894
fe_per	18.565	54.16	329.995**
	-20.198	-36.319	-144.933
Constant	-99.285***	-158.151***	-310.968**
	-15.842	-36.275	-148.208
Observations	286	180	39
R-squared	0.701	0.554	0.638
F-stats	81.67	27.3	7.79
[p-value]	0.0000	0.0000	0.0000
Breusch-Pagan/ Cook-Weisberg Test	X	X	

Note: Dependent variables are liab_cpi_acre_price in the regressions.
Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. (Robust) standard errors presented below the parameters estimated.

Table 12. Estimation Results for Corn APH in the Northern Plains (50%)

Variable	50%	Variable	65%
lg_netprem_cpi_acre_price	-8.017***	netprem_cpi_acre_price	-0.544
	-1.965		-0.352
lg_mean_lag_yd3	25.329***	mean_lag_yd3	0.433***
	-3.685		-0.025
lg_cv_yield	-13.578***	lg_cv_yield	-8.293***
	-2.558		-1.941
lg_acreplt	1.948***	lg_acreplt	0.909**
	-0.573		-0.369
lg_crp_acre	-0.826*	lg_crp_acre	-0.339
	-0.465		-0.36
irr_per	-1.404	irr_per	3.433
	-3.5		-2.591
fe_per	27.311	fe_per	4.258
	-28.124		-19.801
Constant	-100.762***	Constant	-6.48
	-16.684		-5.718
Observations	288	Observations	335
R-squared	0.699	R-squared	0.838
F-stats	92.76	F-stats	241.26
[p-value]	0.0000	[p-value]	0.0000
Breusch-Pagan/ Cook-Weisberg Test		Breusch-Pagan/ Cook-Weisberg Test	

Note: Dependent variables are liab_cpi_acre_price in the regressions.
Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
Standard errors presented below the parameters estimated.

Table 13. Estimation Results for Corn APH in the Southern Plains (65%)

Variable	65%
netprem_cpi_acre_price	-0.037**
	-0.019
mean_lag_yd3	0.007***
	-0.001
cv_yield	0.307
	-0.455
lg_acreplt	0.007
	-0.017
lg_crp_acre	0.016
	-0.013
irr_per	0.569***
	-0.159
fe_per	0.01
	-0.813
Constant	3.007***
	-0.255
Observations	144
R-squared	0.722
F-stats	104.46
[p-value]	0.0000
Breusch-Pagan/ Cook-Weisberg Test	X

Note: Dependent variable is lg_liab_cpi_acre_price.
Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors presented below the parameters estimated.

In the Lake States, there are only nine observations at the 85% coverage level, which results in limited power for the F-test (table 7). Among all the other coverage levels and regions, the p-values of the F-tests are zero to four decimal places (table 6-13), which mean that the models are statistically significant. In table 6-13, the coefficients of determination, or R^2, range from 0.399 (at the 80% coverage level in the Northern Plains) to 0.894 (at the 75% coverage level in the Southern Plains), which suggests that the model could explain from 39.9% to 89.4% of the total variation in the demand for liabilities by the variation in the independent variables. The results indicate that explanatory variables explain the demand for corn APH insurance fairly well.

The elasticities of demand with respect to each variable are reported in tables 14 through 17 for the Corn Belt, Lake States, Northern Plains, and Southern Plains, respectively. The negative correlation between the per dollar net premium and the amount of per dollar liability purchases (table 14-17) is consistent with theoretical expectations. In the Corn Belt (table 14), the elasticity of demand with respect to per dollar net premium at the 50% coverage level is small (-0.047), and the elasticity at the 55% is statistically insignificant (-0.028). The results in table 14 imply that corn producers in the Corn Belt are not likely to significantly change their demand for corn APH insurance at the 50% and 55% coverage levels due to the changes in subsidies. These producers may purchase the low coverage levels to meet the requirements for loan applications. As shown in table 14, the price elasticities are statistically significant but inelastic at the 60%, 65%, 70%, 75%, and 80% coverage levels (-0.106, -0.114, -0.137, -0.149, -0.230, respectively). Although they are all price-inelastic, the elasticity at 80% coverage level (-0.230) is about five times of the elasticity at the 50% coverage level (-0.047). The results imply that producers are more sensitive to changes in premium at high coverage levels (e.g. 80% coverage level) than low coverage levels (e.g. 50% and 55%) in the Corn Belt. The results also prove the importance of differentiating coverage levels in the analysis of demand for corn insurance (table 14).

Table 14. Estimated Demand for Corn APH Insurance in the Corn Belt

Variable	50%	55%	60%	65%	70%	75%	80%	85%
netprem_cpi_acre_price	-0.047**	-0.028	-0.106***	-0.114***	-0.137***	-0.149***	-0.230***	0.017
mean_lag_yd3	0.416***	0.377***	0.347***	0.276***	0.300***	0.534***	0.730***	0.237
cv_yield	-0.080*	-0.096	-0.128*	-0.130***	-0.097*	-0.112**	0.035	-0.204*
acreplt	0.067***	0.088***	0.050***	0.063***	0.030**	0.021	0.029	0.100***
crp_acre	-0.012**	-0.024***	-0.022**	0.0004	0.004	0.01	-0.01	-0.022
irr_per	-0.100	-0.172	-0.016	0.065	0.06	0.112	-0.159	-0.174
fe_per	-0.148	0.105	0.095	0.064	-0.705	-0.843	0.075	-0.671

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors presented below the parameters estimated.

In table 14, the elasticities of demand with respect to the preceding three-year's average yield is statistically significant in the Corn Belt at each coverage level, except for the 85% coverage level (0.416, 0.377, 0.347, 0.276, 0.300, 0.534, and 0.730, respectively). So except for the 85% coverage level, corn producers in the Corn Belt with higher expected yield tend to purchase more APH insurance.

In the Corn Belt, the relative yield risk has statistically significant effects at each coverage level, except for the 55% and 80% coverage levels (table 14). Corn producers with higher relative yield risk tend to insure less acres at these coverage levels (50%, 60%, 65%, 70%, 75%, and 85%), but the magnitude is modest (table 14). As shown in table 14, the magnitude of relative yield risk elasticity is the largest at the 85% coverage level (-0.204), and it is more than 2.5 times the elasticity at the 50% coverage level (-0.080), which implies that producers' purchase decisions on per dollar liabilities at the 85% coverage level are more responsive of the relative yield risk.

The signs for corn planted acres in the Corn Belt are in line with expectations (table 14 row 5). The elasticities of demand with respect to corn planted acres range from 0.021 to 0.100 (at the 75% and 85% coverage level, respectively). With a 10% increase in the corn planted acres, the purchases of per dollar liabilities would be increased by 1.00% at the 85% coverage level.

In the Corn Belt, the enrolled acres of CRP have only modest effects on the demand for corn insurance (table 14 row 6), and there are only statistically significant effects at the relatively low coverage levels (50%, 55%, and 60%). The per dollar liability purchases would decrease by 0.12%, 0.24%, and 0.22% with a 10% increase in the CRP enrolled acres at the 50%, 55%, and 60% coverage level, respectively. And the correlation between the enrolled acres in CRP and the APH purchases is not statistically significant at high coverage levels, such as the 65%, 70%, 75%, 80%, and 85% coverage levels.

Although the percentage of irrigated cropland could reflect the production environment and the percentage of cropland operated by females could affect the risk averse coefficients, the two variables have statistically insignificant effects on the demand for corn APH insurance across all coverage levels in the Corn Belt (table 14 rows 7 and 8).

Table 15. Estimated Demand for Corn APH in the Lake States

Variable	50%	55%	60%	65%	70%	75%	80%
netprem_cpi_acre_price	-0.180***	-0.138***	-0.138***	-0.147***	-0.094**	-0.157***	-0.158**
mean_lag_yd3	0.418***	0.336***	0.644***	0.540***	0.558***	0.756***	0.557
cv_yield	-0.098**	-0.188**	0.056	0.037	-0.031	0.019	-0.201
acreplt	0.023*	0.055***	0.055**	0.042***	0.068***	0.033	0.204***
crp_acre	-0.014**	-0.018*	-0.020**	-0.008*	-0.016**	-0.002	-0.078**
irr_per	-0.273**	-0.121	-0.166	-0.022	-0.093	-0.031	0.156
fe_per	-0.172	0.418	0.606	0.301	0.752	-1.171	3.709**

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors presented below the parameters estimated.

There is no effective sample size for regression at the 85% coverage level in the Lake States with nine observations, so the estimated elasticities at the 85% coverage level are not reported in table 15. In the Lake States (table 15), the premium effects are statistically significant and negative across all coverage levels. The elasticities of demand for corn APH insurance with respect to per dollar premium vary across coverage levels (table 15). For example, the elasticity of demand for corn APH insurance with respect to per dollar premium is -0.180 at the 50% coverage level in the Lake States, while the corresponding elasticity is -0.094 at the 70% coverage level in this region (table 15). The magnitude of elasticities of demand for corn APH insurance with respect to per dollar premium are relatively large at the lowest coverage level and the highest coverage levels.

The average yield in the preceding three years appears to have statistically significant and positive effects on the demand for crop insurance with the exception of the 80% coverage level. Among the other six coverage levels (50% to 75%), the elasticities for the average yield in the preceding three years range from 0.336 (55% coverage level) to 0.756 (75% coverage level), which are inelastic (table 15). The relative yield risk only has statistically significant effects at the 50% and 55% coverage levels, and the elasticity of demand for corn APH insurance with respect to relative yield risk is -0.098 and -0.188 at the 50% and 55% coverage level, respectively (table 15). As expected, the elasticities of demand for corn APH insurance with respect to planted acres are statistically significant and positive (table 15 row 4) except for the 75% coverage level. The elasticities of demand for corn APH insurance with respect to the enrolled acres of CRP are in line with expectations. The elasticities of demand for corn APH insurance with respect to the irrigated acres are only statistically significant at the 10% confidence interval at the 50% coverage level in the Lake States. So with a ten percentage point increase in irrigated acres, the per dollar liability purchase for corn APH insurance is expected to decrease by 2.73% at the 50% coverage land (table 15). As shown in table 15, the elasticity of demand for corn APH insurance with respect to percentage of female operated cropland only has a statistically significant effect at the 80% coverage level and it is elastic (3.709). With a one percentage point increase in the percentage of female operated cropland, the purchase for corn APH insurance would increase by 3.71% at the 80% coverage level in the Lake States.

Table 16. Estimated Demand for Corn APH in the Northern Plains

Variable	50%	55%	60%	65%	70%	75%	80%	85%
netprem_cpi_acre_price	-0.170***	-0.004	-0.305***	-0.038	-0.097	-0.188*	-0.259**	-0.284**
mean_lag_yd3	0.538***	0.724***	0.599***	0.809***	0.720***	0.530***	0.890**	-0.257*
cv_yield	-0.289***	-0.257	-0.164	-0.137***	-0.057	-0.174	0.082	-0.618***
acreplt	0.041***	0.047	0.051**	0.015***	0.067***	0.071***	0.002	-0.005
crp_acre	-0.018*	-0.092***	0.0005	-0.006	-0.007	-0.026	0.005	-0.041*
irr_per	-0.030	-0.238	-0.039	0.057	-0.007	-0.054	0.142	-0.237
fe_per	0.581	0.543	0.650	0.070	1.247	1.209	2.436	1.366

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors presented below the parameters estimated.

The elasticities of demand for APH insurance in the Northern Plains are summarized in table 16. The elasticity of demand with respect to per dollar premium at the 85% coverage level (-0.284) is approximately 1.7 times of the elasticity at the 50% coverage level (-0.170). The average corn yield in the preceding three years has statistically significant effects at each coverage level, but the effects change across coverage levels (table 16). The per dollar purchase of corn APH insurance is expected to increase by 0.809% with 1% increase in the yield expectation at the 65% coverage level, while it is expected to increase by 0.257% with 1% increase in the yield expectation at the 85% coverage level. As shown in table 16, the relative yield risk has statistically significant effects on the demand at the 50%, 65%, and 85% coverage levels (-0.289, -0.137, and -0.618, respectively). The elasticity of demand with respect to relative risk at the 85% coverage level (-0.618) is approximately 4.5 times of the elasticity at the 65% coverage level which is -0.137 (table 16). The elasticity of demand with respect to the enrolled acres in CRP is only statistically significant at the 50%, 55%, and 85% coverage levels and the magnitude of elasticity varies across these three coverage levels (table 16). Similar as the Corn Belt, the percentage of the irrigated cropland and the percentage of female operated cropland do not have statistically significant effect on producers' purchase decisions on corn APH insurance.

Table 17. Estimated Demand for Corn APH in the Southern Plains

Variable	50%	55%	60%	65%	70%	75%
netprem_cpi_acre_price	-0.221**	-0.131	-0.248*	-0.227**	-0.155	-0.654***
mean_lag_yd3	0.469***	0.569**	0.455**	0.711	0.781***	0.850***
cv_yield	-0.474***	-0.026	-0.167	0.09	0.0898	0.00228
acreplt	-0.00714	0.0333	-0.0209	0.007	0.0012	-0.0298
crp_acre	0.0286**	-0.0047	0.0402*	0.016	0.0456***	0.0287*
irr_per	0.312**	0.634**	0.615**	0.569***	0.525**	0.232
fe_per	0.426	-0.121	-1.175	0.010	1.553	-2.079*

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors presented below the parameters estimated.

In the Southern Plains, coverage levels are only available for 50% to 75% with a 5% increment (table 17). The elasticity of demand with respect to per dollar liabilities at the 75% coverage level (-0.654) is approximately three times of the elasticity at the 50% coverage level (-0.221). The historical average yield has statistically significant effects at each coverage level (0.469, 0.569, 0.455, 0.711 0.781, and 0.850 at the 50%, 55%, 60%, 65%, 70%, and 75%, respectively). The relative yield risk only has statistically significant effects at the 50% coverage level (-0.474) (table 17). There is no statistically significant effects of corn planted acres on the demand for APH insurance in the Southern Plains (table 17). The elasticities of demand for corn APH insurance with respect to the enrolled acres of CRP are statistically significant and positive at the 50%, 60%, 70% and 75% coverage levels (table 17). Producers normally enroll cropland with low productivity in the CRP program. As more land enrolled in the CRP program, the expected yield for the remaining cropland would increase. At the 50%, 60%, 70% and 75% coverage levels, the relationship between the expected yield and the demand for corn APH insurance is statistically significant and positive. So that more acres enrolled in the CRP program would results in higher expected yield and more corn APH insurance purchases in the Southern Plains.

Unlike other regions, the elasticities of demand for corn APH insurance with respect to the percentage of irrigated cropland is statistically significant at most coverage levels (55%, 60%, 65%, and 70%). The elasticities of demand for corn APH insurance with respect to the percentage of irrigated cropland are inelastic (0.312, 0.634, 0.615, 0.569, 0.525, and 0.232 at the 55%, 60%, 65%, and 70%, respectively). The female effects are statistically significant and negative at the 75% coverage level (table 17).

Table 18 reproduces the results in table 14 through 17 for the elasticities of demand for APH insurance with respect to per dollar net premium, the planted acres, and the average yield in the preceding three years, and the relative yield risk across regions.

Table 18. Estimation Elasticities of Demand for APH Insurance

		APH_50	APH_55	APH_60	APH_65	APH_70	APH_75	APH_80	APH_85
netprem_cpi_acre_price	Corn Belt	-0.047**	-0.028	-0.106***	-0.114***	-0.137***	-0.149***	-0.230***	0.017
	Lake States	-0.180***	-0.138***	-0.138***	-0.147***	-0.094**	-0.157***	-0.158**	
	Northern Plains	-0.170***	-0.004	-0.305***	-0.038	-0.097	-0.188*	-0.259**	-0.284**
	Southern Plains	-0.221**	-0.131	-0.248*	-0.227**	-0.155	-0.654***		
acreplt	Corn Belt	0.067***	0.088***	0.050***	0.063***	0.030**	0.021	0.029	0.100***
	Lake States	0.023*	0.055***	0.055**	0.042***	0.068***	0.033	0.204***	
	Northern Plains	0.041***	0.047	0.051**	0.015***	0.067***	0.071***	0.002	-0.005
	Southern Plains	-0.007	0.033	-0.021	0.007	0.001	-0.030		
mean_lag_yd3	Corn Belt	0.416***	0.377***	0.347***	0.276***	0.300***	0.534***	0.730***	0.237
	Lake States	0.418***	0.336***	0.644***	0.54***	0.558***	0.756***	0.557	
	Northern Plains	0.538***	0.724***	0.599***	0.809***	0.720***	0.530***	0.890**	-0.257*
	Southern Plains	0.469***	0.569**	0.455**	0.711	0.781***	0.850***		
cv_yield	Corn Belt	-0.080*	-0.096	-0.128*	-0.130***	-0.097*	-0.112**	0.035	-0.204*
	Lake States	-0.098**	-0.188**	0.056	0.037	-0.031	0.019	-0.201	
	Northern Plains	-0.289***	-0.257	-0.164	-0.137***	-0.057	-0.174	0.082	-0.618***
	Southern Plains	-0.474***	-0.026	-0.167	0.090	0.090	0.002		

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors presented below the parameters estimated.

Generally, the elasticities of corn APH insurance demand with respect to per dollar of net premium change across coverage levels and regions (table 18). Although the premium effects vary among coverage levels and regions, there is a pattern. The elasticities of demand for corn APH insurance with respect to per dollar net premium tend to be larger at relatively high coverage levels (table 18). Take the Corn Belt as an example to illustrate the changes among coverage levels. As shown in table 18, the elasticity of demand for corn APH insurance with respect to per dollar net premium is -0.230 at the 80% coverage level, which is about five times of the elasticity at the 50% coverage level (-0.047). Also, in the Southern Plains the elasticity of demand with respect to per dollar premium is -0.654 at the 75% coverage level, which is approximately three times of the elasticity at the 50% coverage level (-0.221) (table 18). The elasticities of demand for corn

APH insurance with respect to per dollar net premium also tend to be larger in riskier regions. In table 18, at the 75% coverage level, the magnitude of elasticities of corn APH insurance with respect to per dollar net premium are -0.149, -0.157, -0.188, and -0.654 in the Corn Belt, Lake States, Northern Plains, and Southern Plains, respectively. The increasing magnitude is consistent with increasing relative yield risk and the decreasing expected yield through the Corn Belt, Lake States, Northern Plains, and Southern Plains (figures 9 and 10). As shown in figures 9 and 10, the corn production in the Corn Belt has the highest expected yield and lowest relative yield risk among the four regions, while corn production exhibits the lowest expected yield and the highest relative yield risk in the Southern Plains. Corn producers are exposed to higher risk in the Southern Plains and are more responsive to the changes in premium than producers in the other three regions.

Generally, more corn planted acres would induce more insured acres among most coverage levels in the Corn Belt, Lake States, and Northern Plains, but the relationship between the planted acres and the demand for corn APH insurance is statistically insignificant in the Southern Plains (table 18). As the total corn planted acres decrease through the Corn Belt, Lake States, Northern Plains, and Southern Plains, the effects of the planted acres on the demand for corn insurance diminish. For example, at the 65% coverage level the elasticities of demand for corn APH insurance with respect to corn planted acres are 0.063, 0.042, 0.015 and 0.007 (statistically insignificant), respectively, in the Corn Belt, Lake States, Northern Plains and Southern Plains, respectively (table 18).

The largest elasticities of corn APH insurance with respect to the expected yield are 0.730, 0.756, 0.890, and 0.850 in the Corn Belt, Lake States, Northern Plains, and

Southern Plains, respectively (table 18). Although producers' expected yield also has different effects on the demand for corn APH insurance at different coverage levels and regions, the magnitude of the largest elasticities in each region is similar. The elasticities of corn APH demand are positive among most coverage levels and regions with an exception of the 85% coverage level in the Northern Plains. Corn producers in the Northern Plains with higher yield expectations tend to purchase less APH insurance at the 85% coverage level.

As shown in table 18, at the 50% coverage level, as the relative yield risk increases through the Corn Belt, Lake States, Northern Plains, and Southern Plains, the magnitude of elasticities of demand with respect to relative yield risk increases (-0.078, -0.100, -0.257, and -0.503 in the Corn Belt, Lake States, Northern Plains, and Southern Plains, respectively) (table 18). The largest elasticity of corn APH insurance with respect to the relative yield risk is in the Northern Plains at the 85% coverage level (-0.618). With higher production risk, corn producers tend to purchase less APH insurance at the 85% coverage level in the Northern Plains.

Table 19. Estimation for Corn CRC Insurance Demand in the Corn Belt

	Coverage Level							
Variable	50%	55%	60%	65%	70%	75%	80%	85%
lg_netprem_cpi_acre_price	-0.015	0.033	-0.040	-0.083**	-0.167***	-0.255***	-0.226***	-0.083
	-0.036	-0.040	-0.032	-0.036	-0.034	-0.078	-0.059	-0.069
lg_mean_lag_rev_cpi3	-0.088	-0.082	-0.194***	-0.113***	-0.152***	-0.194***	0.436***	0.440***
	-0.065	-0.070	-0.062	-0.034	-0.031	-0.044	-0.102	-0.138
lg_cv_rev	-0.009	0.226**	0.168*	-0.023	0.033	-0.062	0.038	-0.054
	-0.081	-0.091	-0.092	-0.044	-0.034	-0.041	-0.044	-0.048
lg_acreplt	0.148***	0.127***	0.110***	0.108***	0.088***	0.090***	0.017	0.061**
	-0.023	-0.023	-0.022	-0.014	-0.014	-0.015	-0.023	-0.025
lg_crp_acre	-0.037***	-0.059***	-0.045***	-0.022***	-0.017***	-0.019**	-0.001	0.004
	-0.010	-0.012	-0.014	-0.006	-0.006	-0.008	-0.006	-0.011
irr_per	-0.204	-0.177	-0.109	0.099	0.004	0.157	-0.037	0.099
	-0.126	-0.177	-0.125	-0.092	-0.068	-0.115	-0.082	-0.106
fe_per	1.239*	-0.066	-0.305	-0.902*	-1.469***	-0.226	-1.701***	-1.635*
	-0.748	-0.688	-0.931	-0.536	-0.381	-0.623	-0.527	-0.838
Constant	3.301***	3.866***	4.772***	4.219***	4.948***	5.405***	2.545***	1.670*
	-0.45	-0.42	-0.392	-0.279	-0.252	-0.351	-0.708	-0.904
Observations	182	91	187	422	363	330	163	143
R-squared	0.345	0.439	0.335	0.487	0.567	0.42	0.627	0.539
F-stats	12.54	9.28	12.65	43.01	48.33	20.04	26.11	17.09
[p-value]	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Breusch-Pagan/ Cook-Weisberg Test	X		X	X	X	X	X	X
Model Specification Test						X	X	

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. (Robust) standard errors presented below the parameters estimated

Table 20. Estimation for Corn CRC Insurance Demand in the Lake States

	LS_CRC_50	LS_CRC_55	LS_CRC_60	LS_CRC_65	LS_CRC_70	LS_CRC_75	LS_CRC_80	LS_CRC_85
	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price
lg_netprem_cpi_acre_price	-0.213***	-0.323***	-0.190***	-0.239***	-0.285***	-0.229***	-0.208***	-0.177
	-0.054	-0.084	-0.058	-0.042	-0.062	-0.062	-0.071	-0.148
lg_mean_lag_rev_cpi3	-0.129	0.014	-0.005	0.031	-0.113	0.052	1.104***	0.363
	-0.083	-0.19	-0.097	-0.046	-0.087	-0.081	-0.244	-0.562
lg_cv_rev	0.018	-0.023	0.295**	0.221***	0.406***	0.334***	0.123	-0.066
	-0.134	-0.217	-0.129	-0.083	-0.114	-0.118	-0.134	-0.373
lg_acreplt	0.120***	0.078**	0.077**	0.105***	0.075*	0.031	-0.075	0.043
	-0.030	-0.038	-0.030	-0.018	-0.040	-0.026	-0.047	-0.080
lg_crp_acre	-0.021*	-0.015	-0.037***	-0.019*	-0.011	0.029**	0.040	0.014
	-0.013	-0.017	-0.013	-0.011	-0.017	-0.013	-0.025	-0.074
irr_per	-0.227	-2.096***	-0.307	-0.176	-0.258**	-0.193	-0.238	0.029
	-0.229	-0.631	-0.188	-0.118	-0.129	-0.161	-0.249	-0.677
fe_per	1.283	3.198**	0.675	0.583	0.212	0.829	-0.308	-0.562
	-0.922	-1.377	-0.997	-0.633	-1.051	-0.776	-1.186	-2.917
Constant	3.960***	3.807***	4.150***	3.688***	5.126***	4.262***	-0.665	2.453
	-0.445	-1.076	-0.605	-0.306	-0.598	-0.495	-1.308	-3.247
Observations	141	57	128	240	148	126	55	28
R-squared	0.428	0.489	0.29	0.451	0.338	0.382	0.569	0.237
F-stats	12.18	6.70	7.00	19.92	12.75	8.16	8.86	0.89
[p-value]	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.5352
Breusch-Pagan/ Cook-Weisberg	X			X	X	X		
Model specification test								

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors presented below the parameters estimated.

Table 21. Estimation for Corn CRC Insurance Demand in the Northern Plains

	NP_CRC_50	NP_CRC_55	NP_CRC_60	NP_CRC_65	NP_CRC_70	NP_CRC_75	NP_CRC_80	NP_CRC_85
	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price
lg_netprem_cpi_acre_price	-0.042	-0.205	-0.290***	-0.005	-0.051	0.176	0.075	0.009
	-0.095	-0.140	-0.094	-0.061	-0.07	-0.119	-0.076	-0.139
lg_mean_lag_rev_cpi3	0.074	0.140	0.186**	0.230***	0.141**	0.054	0.839***	0.686***
	-0.081	-0.128	-0.083	-0.038	-0.054	-0.065	-0.100	-0.210
lg_cv_rev	-0.014	-0.011	0.046	-0.142***	0.002	-0.035	0.061	-0.108
	-0.115	-0.114	-0.082	-0.050	-0.047	-0.052	-0.053	-0.096
lg_acreplt	0.024	0.039	0.035	0.036**	0.022	0.084***	0.069***	-0.004
	-0.029	-0.042	-0.025	-0.014	-0.017	-0.022	-0.016	-0.042
lg_crp_acre	0.002	0.011	0.014	-0.008	0.017*	-0.011	0.002	0.02
	-0.021	-0.037	-0.019	-0.010	-0.010	-0.014	-0.011	-0.024
irr_per	0.491***	0.241	0.348***	0.398***	0.455***	0.487***	-0.031	0.176
	-0.113	-0.203	-0.108	-0.047	-0.052	-0.063	-0.076	-0.151
fe_per	0.314	0.043	2.140*	0.859	0.987	2.817***	1.045	-3.308**
	-1.397	-1.572	-1.269	-0.764	-0.692	-0.796	-0.822	-1.626
Constant	3.177***	2.893***	2.889***	2.414***	3.096***	2.646***	-1.215**	0.520
	-0.588	-0.845	-0.617	-0.314	-0.374	-0.532	-0.601	-1.249
Observations	177	78	157	319	250	226	97	76
R-squared	0.244	0.227	0.387	0.439	0.437	0.421	0.663	0.379
F-stats	7.8	2.41	13.43	46.22	33.41	29.82	25.04	5.93
[p-value]	0.0000	0.0288	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Breusch-Pagan/ Cook-Weisberg test		X		X	X	X		
Model specification test				X	X	X		

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. (Robust) standard errors presented below the parameters estimated.

Table 22. Estimation for Corn CRC Insurance Demand in the Southern Plains

	SP_CRC_50	SP_CR_55	SP_CRC_60	SP_CRC_65	SP_CRC_70	SP_CRC_75
	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price	lg_liab_cpi_acre_price
lg_netprem_cpi_acre_price	-0.331**	-0.094	-0.373***	-0.242*	-0.501***	-0.670***
	-0.136	-0.364	-0.122	-0.122	-0.155	-0.216
lg_mean_lag_rev_cpi3	0.333***	0.564***	0.797***	0.519***	0.819***	0.613**
	-0.078	-0.131	-0.110	-0.083	-0.095	-0.225
lg_cv_rev	0.229*	-0.067	-0.005	0.160**	-0.171*	0.023
	-0.115	-0.194	-0.105	-0.064	-0.086	-0.150
lg_acreplt	0.074**	0.050	0.021	0.080***	-0.008	-0.021
	-0.028	-0.093	-0.024	-0.022	-0.022	-0.044
lg_crp_acre	0.072***	0.068	0.036**	0.041***	0.021	0.053**
	-0.020	-0.059	-0.014	-0.014	-0.014	-0.024
irr_per	0.741***	0.738*	0.361*	0.471***	0.669***	0.364
	-0.242	-0.381	-0.204	-0.175	-0.183	-0.297
fe_per	-0.031	-3.435	3.341**	3.776***	1.629	2.844*
	-1.406	-2.521	-1.326	-1.073	-1.017	-1.430
Constant	0.924	-0.432	-0.705	0.092	0.273	1.968
	-0.594	-1.089	-0.652	-0.609	-0.801	-1.622
Observations	61	16	44	95	54	27
R-squared	0.786	0.946	0.885	0.777	0.877	0.852
F-stats	44.7	19.92	56.09	43.23	46.98	15.58
[p-value]	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Breusch-Pagan/ Cook-Weisber[illegible]	X		X			
Model specification test						

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors presented below the parameters estimated.

The Demand for Corn CRC Insurance

Estimation results for CRC insurance demand are summarized in tables 19-22 for the Corn Belt, Lake States, Northern Plains, and Southern Plains, respectively. In tables 19-22, “X”s in the rows of Breusch-Pagan/Cook Weisberg test indicate heteroscedasticity occurs, and robust standard errors are used. The estimations for corn CRC insurance at the 75% and 80% coverage levels in the Corn Belt and at 65%, 70% and 75% coverage levels in the Northern Plains are rejected by the null hypothesis of link tests at the 95% confidence interval. To deal with the misspecification problem, linear-linear models are used at the two coverage levels (75% and 80%) in the Corn Belt (table 23), and log-log, linear-log, and linear-linear models are used at the 65%, 70%, and 75% coverage levels in the Northern Plains (table 24), respectively. The variance inflation factors (VIF <10) show no evidence of serious multicollinearity between any of the model variables.

Table 23. Estimation Results for Corn in the Corn Belt (75% and 80%)

	CB_CRC_75	CB_CRC_80
	liab_cpi_acre_price	liab_cpi_acre_price
netprem_cpi_acre_price	-1.500***	-1.817***
	-0.349	-0.431
mean_lag_rev_cpi3	-0.044***	0.129***
	-0.008	-0.026
lg_cv_rev	-1.963	5.546
	-3.202	-3.593
lg_acreplt	8.220***	0.993
	-1.294	-1.676
lg_crp_acre	-2.228***	-0.077
	-0.496	-0.563
irr_per	7.669	-5.822
	-8.478	-8.503
fe_per	-54.858	-168.593***
	-46.207	-46.817
Constant	55.668***	79.975***
	-14.811	-21.041
Observations	330	163
R-squared	0.44	0.643
F-stats	31.26	36.66
[p-value]	0	0
Breusch-Pagan/ Cook-Wei	X	X

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors presented below the parameters estimated.

Table 24. Results for CRC in the Northern Plains (65%, 70%, and 75%)

NP_CRC_65		NP_CRC_70		NP_CRC_75	
	lg_liab_cpi_		liab_cpi_acr		liab_cpi_acr
lg_netprem_cpi_acre_price	0.017	lg_netprem_cpi_acre_price	-3.535	netprem_cpi_acre_price	0.869
	-0.058		-4.5070		-0.6050
lg_mean_lag_rev_cpi3	0.236***	lg_mean_lag_rev_cpi3	10.533***	lg_mean_lag_rev_cpi3	5.016
	-0.040		-3.4640		-4.4940
lg_cv_rev	-0.129**	lg_cv_rev	0.488	lg_cv_rev	-2.145
	-0.051		-3.5160		-4.5660
lg_acreplt	0.049***	lg_acreplt	0.825	lg_acreplt	5.316***
	-0.014		-0.9260		-1.2940
lg_crp_acre	-0.020**	lg_crp_acre	1.566**	lg_crp_acre	0.107
	-0.010		-0.7600		-0.9540
lg_irr_per	0.066***	irr_per	38.376***	irr_per	43.813***
	-0.010		-4.3340		-5.3100
lg_fe_per	0.029*	fe_per	47.014	fe_per	209.705***
	-0.017		-46.1510		-63.8570
Constant	2.687***	Constant	-9.353	Constant	-30.771
	-0.337		-25.1720		-29.9180
Observations	319	Observations	250	Observations	226
R-squared	0.435	R-squared	0.4620	R-squared	0.4520
F-stats	39.040	F-stats	29.6700	F-stats	25.6800
[p-value]	0.000	[p-value]	0.0000	[p-value]	0.0000
Breusch-Pagan/ Cook-Weisberg test	X	Breusch-Pagan/ Cook-Weisberg test		Breusch-Pagan/ Cook-Weisberg test	

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. (Robust) standard errors presented below the parameters estimated.

The coefficients of determination, or R^2, range from 0.227 to 0.946 in tables 19 through 24, which suggest that the model could explain from 22.7% (at 55% coverage level in the Northern Plains) to 94.6% (at 55% coverage level in the Southern Plains) of the total variation in the demand of per dollar liabilities by the variation in the independent variables. In tables 19 through 24, the F-tests are statistically significant (p-values are zero to four decimal places) except for the 85% coverage level in the Lake States and the 55% coverage level in the Northern Plains (the p-value of the F-test is 0.5352 and 0.0288, respectively). Overall, the model explains the demand for corn CRC insurance fairly well.

Table 25. Estimated Elasticities of Demand for Corn CRC in the Corn Belt

	CB_CRC_50	CB_CRC_55	CB_CRC_60	CB_CRC_65	CB_CRC_70	CB_CRC_75	CB_CRC_80	CB_CRC_85
netprem_cpi_acre_price	-0.015	0.033	-0.040	-0.083**	-0.167***	-0.146***	-0.200***	-0.083
mean_lag_rev_cpi3	-0.088	-0.082	-0.194***	-0.113***	-0.152***	-0.195***	0.432***	0.440***
cv_rev	-0.009	0.226**	0.168*	-0.023	0.033	-0.020	0.051	-0.054
acreplt	0.148***	0.127***	0.110***	0.108***	0.088***	0.086***	0.009	0.061**
crp_acre	-0.037***	-0.059***	-0.045***	-0.022***	-0.017***	-0.023***	-0.001	0.004
irr_per	-0.204	-0.177	-0.109	0.099	0.004	0.080	-0.054	0.099
fe_per	1.239*	-0.066	-0.305	-0.902*	-1.469***	-0.572	-1.551***	-1.635*

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The elasticities of demand for corn CRC insurance in the Corn Belt with respect to each variable are reported in table 25. In the Corn Belt, the net premium effects are statistically significant for the relatively high coverage levels, such as 65%, 70%, 75%, and 80% with the elasticity of -0.083, -0.167, -0.146, and -0.200, respectively. The effects of expected revenue has statistically significant effects at most coverage levels, except for the two lowest coverage levels (50% and 55%) (table 25). The elasticity of demand for corn CRC insurance with respect to expected revenue is -0.194, -0.113, -0.152, -0.195, 0.432, and 0.440 at the 60%, 65%, 70%, 75%, 80%, and 85% coverage levels, respectively. Generally, with higher expected revenue, corn producers in the Corn Belt purchase more insurance at high coverage levels and less at low coverage levels to better protect their revenue. More specifically, the purchases of corn CRC insurance at the 80% and 85% coverage levels are expected to increase, while the purchases of corn CRC liabilities at lower coverage levels (e.g., 60%, 65%, 70%, and 75%) would decrease, and there would be no statistically significant changes at the 50% and 55% coverage levels (table 25). Thus, with higher expected revenue, corn producers' purchases move from low coverage levels to high coverage levels. The variability of expected revenue on the demand for corn CRC insurance also proves the importance of differentiating coverage levels in corn insurance analysis. The elasticities of demand for corn CRC insurance with respect to the relative revenue risk are positive and significant at the 55% and 60% coverage levels. The total corn planted acres tend to affect producers' purchases of CRC insurance statistically significantly with the exception of the 80% coverage level, and producers are more responsive to the changes in corn planted acres in relatively low coverage levels than high coverage levels (0.148, 0.127, 0.110, 0.108, 0.088, 0.086, and 0.061 at the 50%, 55%, 60%, 65%, 70%, 75%, and 85% coverage levels, respectively) (table 25). The enrolled acres in CRP have statistically significant effects on the demand for CRC insurance at the 50%, 55%, 60%, 65%, 70%, and 75% coverage levels, and the elasticities are -0.037, -0.059, -0.045, -0.022, -0.017, and -0.023, respectively) (table 25). There is no statistically significant relationship between the percentage of irrigated cropland and the demand for corn CRC insurance due to the limited use of irrigation in the region. The female effects change significantly across the 50%, 65%, 70%, 75%, 80% and 85% coverage levels in the Corn Belt (table 25). A one percentage point increase in the percentage of cropland operated by female, the demand for corn CRC insurance would be expected to increase by 1.24% at the 50% coverage level, while the demand for corn CRC insurance would decrease at 65%, 70%, 80%, and 85% coverage levels by 0.90%, 1.47%, 1.55%, and 1.64%, respectively (table 25).

Table 26. Elasticities of Demand for Corn CRC in the Lake States

	LS_CRC_50	LS_CRC_55	LS_CRC_60	LS_CRC_65	LS_CRC_70	LS_CRC_75	LS_CRC_80	LS_CRC_85
netprem_cpi_acre_price	-0.213***	-0.323***	-0.190***	-0.239***	-0.285***	-0.229***	-0.208***	-0.177
mean_lag_rev_cpi3	-0.129	0.014	-0.005	0.031	-0.113	0.052	1.104***	0.363
cv_rev	0.018	-0.023	0.295**	0.221***	0.406***	0.334***	0.123	-0.066
acreplt	0.120***	0.078**	0.077**	0.105***	0.075*	0.031	-0.075	0.043
crp_acre	-0.021*	-0.015	-0.037***	-0.019*	-0.011	0.029**	0.04	0.014
irr_per	-0.227	-2.096***	-0.307	-0.176	-0.258**	-0.193	-0.238	0.029
fe_per	1.283	3.198**	0.675	0.583	0.212	0.829	-0.308	-0.562

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Estimation results for the Lake States are summarized in table 26. Since there are only 28 observations at the 85% coverage level in the Lake States, the estimated elasticities are not reported in table 26 at this coverage level. The elasticities of demand for CRC insurance with respect to per dollar net premium are -0.213, -0.323, -0.190, -0.239, -0.285, -0.229, and -0.208 at the 50%, 55%, 60%, 65%, 70%, 75%, and 80% coverage levels, respectively (table 26). The magnitude of the elasticity of demand for CRC insurance in the Lake States is larger than the elasticity of demand for APH insurance at each coverage level (table 15 and 26). For instance, at the 55% coverage level, the elasticity of demand for APH insurance with respect to per dollar net premium is -0.180 and for CRC insurance, the elasticity is -0.323, which is 1.8 times the elasticity of demand for APH insurance. The relationship between the demand for corn CRC insurance and the expected revenue is only statistically significant at the 80% coverage level in the Lake States as shown in table 26. As the relative revenue risk increases, the demand for corn CRC insurance increases, and the elasticities of demand for corn CRC insurance with respect to the relative revenue risk are 0.295, 0.221, 0.406, and 0.334 at the 60%, 65%, 70%, and 75% coverage level, respectively (table 26). The effects of corn planted acres are in line with expectations and the elasticities of demand for corn CRC insurance with respect to the total corn planted acres are 0.120, 0.078, 0.077, 0.105, and 0.075 at the 50%, 55%, 60%, 65%, and 70%, respectively (table 26). The effects of the enrolled acres in CRP are negative at the 50%, 60%, and 65% (-0.021, -0.037,-0.019, respectively) while the effects are positive at the 75% coverage level, which prove the importance of differentiating coverage levels in the analysis of corn insurance (table 26). With higher percentage of irrigated cropland, the demand for corn CRC insurance is expected to decrease at the 55% and 70% coverage levels (-2.096 and -0.258, respectively). The demand for corn CRC insurance with respect to the percentage of cropland operated by females is elastic at the 55% coverage level, and the elasticity is 3.198.

Table 27. Estimated Elasticities of Demand for Corn CRC in the Northern Plains

	NP_CRC_50	NP_CRC_55	NP_CRC_60	NP_CRC_65	NP_CRC_70	NP_CRC_75	NP_CRC_80	NP_CRC_85
netprem_cpi_acre_price	-0.042	-0.205	-0.290***	0.017	-0.044	0.097	0.075	0.009
mean_lag_rev_cpi3	0.074	0.14	0.186**	0.236***	0.132***	0.058	0.839***	0.686***
cv_rev	-0.014	-0.011	0.046	-0.129**	0.006	-0.025	0.061	-0.108
acreplt	0.024	0.039	0.035	0.049***	0.01	0.061***	0.069***	-0.004
crp_acre	0.002	0.011	0.014	-0.020**	0.020**	0.001	0.002	0.020
irr_per	0.491***	0.241	0.348***	0.263***	0.480***	0.503***	-0.031	0.176
fe_per	0.314	0.043	2.140*	0.923*	0.588	2.406***	1.045	-3.308**

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

In the Northern Plains (table 27), the net premium effects are only significant at the 60% coverage level and the elasticity of demand for corn CRC insurance with respect to per dollar net premium is -0.290. With higher expected revenue, corn producers would purchase higher liabilities in the Northern Plains (table 27). The relative revenue risk only statistically significantly affects corn producers’ purchase decisions on CRC insurance at the 65% coverage level with an elasticity of -0.129 (table 27). The effects of corn planted acres are modest on the demand for corn CRC insurance in the Northern Plains, and the elasticities of demand for CRC insurance with respect to corn planted acres are 0.049, 0.061, and 0.069 at the 65%, 75%, and 80% coverage levels. The elasticities of demand for corn CRC insurance with respect to the enrolled acres in CRP are positive and statistically significant at the 65% and 70% coverage levels (table 27*).* The percentage of irrigated cropland has positive and statistically significant effects at the 50%, 60%, 65%, 70%, and 75% coverage levels (table 27). Similar to the Corn Belt, with higher percentage of cropland operated by females, the demand for CRC insurance would increase at lower coverage levels (60%, 65%, and 75%), and decrease at the 85% coverage levels. The elasticities of demand for corn CRC insurance with respect to the percentage of cropland operated by females are quite elastic at the 75% and 85% coverage levels (2.406 and -3.308, respectively) (table 27).

Table 28. Estimated Elasticities for Corn CRC in the Southern Plains

	SP_CRC_50	SP_CR_55	SP_CRC_60	SP_CRC_65	SP_CRC_70	SP_CRC_75
netprem_cpi_acre_price	-0.331**	-0.094	-0.373***	-0.242*	-0.501***	-0.670***
mean_lag_rev_cpi3	0.333***	0.564***	0.797***	0.519***	0.819***	0.613**
cv_rev	0.229*	-0.067	-0.005	0.160**	-0.171*	0.023
acreplt	0.074**	0.050	0.021	0.080***	-0.008	-0.021
crp_acre	0.072***	0.068	0.036**	0.041***	0.021	0.053**
irr_per	0.741***	0.738*	0.361*	0.471***	0.669***	0.364
fe_per	-0.031	-3.435	3.341**	3.776***	1.629	2.844*

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Elasticities of demand for the Southern Plains are summarized in table 28. The R^2 values in the Southern Plains are relatively high, compared to other three regions (the Corn Belt, Lake States, and Northern Plains), ranging from 0.777 to 0.946 (table 22). The per dollar net premium effects are statistically significant at each coverage level with an exception of the 55% coverage level, and the elasticity is -0.331, -0.373, -0.242, -0.501, and -0.670 at the 50%, 60%, 65%, 70%, and 75% coverage level, respectively (table 28). In the Southern Plains, the magnitude of elasticities of demand for CRC insurance is larger than the magnitude for the elasticity of demand for APH insurance at each coverage level (tables 22 and 28). The enrolled acres in CRP have a positive and statistically significant effect at the 50%, 60%, 65%, and 75% coverage levels. The percentage of irrigated cropland has statistically significant positive effects at the 50%-70% coverage levels. The elasticities of demand for CRC insurance with respect to irrigation percentage are 0.741, 0.738, 0.361, 0.471, and 0.669 at the 50%, 55%, 60%, 65%, and 70%, respectively. With higher percentages of cropland operated by females, the demand for corn CRC insurance would increase at the 60%, 65%, and 75% coverage levels with elasticities of demand of 3.341, 3.776, and 2.844, respectively.

Table 29. Estimated Elasticities of Demand for CRC Insurance

		CRC_50	CRC_55	CRC_60	CRC_65	CRC_70	CRC_75	CRC_80	CRC_85
netprem_cpi_acre_price	Corn Belt	-0.015	0.033	-0.04	-0.083**	-0.167***	-0.146***	-0.200***	-0.083
	Lake States	-0.213***	-0.323***	-0.190***	-0.239***	-0.285***	-0.229***	-0.208***	-0.177
	Northern Plains	-0.042	-0.205	-0.290***	0.017	-0.044	0.097	0.075	0.009
	Southern Plains	-0.331**	-0.094	-0.373***	-0.242*	-0.501***	-0.670***		
acreplt	Corn Belt	0.148***	0.127***	0.110***	0.108***	0.088***	0.086***	0.009	0.061**
	Lake States	0.120***	0.078**	0.077**	0.105***	0.075*	0.031	-0.075	0.043
	Northern Plains	0.024	0.039	0.035	0.049***	0.01	0.061***	0.069***	-0.004
	Southern Plains	0.074**	0.05	0.021	0.080***	-0.008	-0.021		
mean_lag_rev_cpi3	Corn Belt	-0.088	-0.082	-0.194***	-0.113***	-0.152***	-0.195***	0.432***	0.440***
	Lake States	-0.129	0.014	-0.005	0.031	-0.113	0.052	1.104***	0.363
	Northern Plains	0.074	0.14	0.186**	0.236***	0.132***	0.058	0.839***	0.686***
	Southern Plains	0.333***	0.564***	0.797***	0.519***	0.819***	0.613**		
cv_rev	Corn Belt	-0.009	0.226**	0.168*	-0.023	0.033	-0.02	0.051	-0.054
	Lake States	0.018	-0.023	0.295**	0.221***	0.406***	0.334***	0.123	-0.066
	Northern Plains	-0.014	-0.011	0.046	-0.129**	0.006	-0.025	0.061	-0.108
	Southern Plains	0.229*	-0.067	-0.005	0.160**	-0.171*	0.023		

Note: Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 29 summarizes the elasticities of demand with respect to per dollar net premium, total corn planted acres, expected revenue, and relative revenue risk reported in tables 25-28. First of all, the results fail to reject the hypothesis that the elasticities of corn insurance demand change over coverage levels and regions. In the Corn Belt, the effects of the per dollar net premium are statistically significant over the relatively high coverage levels (65%, 70%, 75%, and 80% coverage levels). In the Lake States, the effects of the per dollar net premium are statistically significant over all coverage levels with the exception of the 85% coverage level. In the Northern Plains, the effects are only statistically significant at the 60% coverage level. In the Southern Plains, the effects are statistically significant at each coverage level with the exception of the lowest coverage level (55%).

Among all the statistically significant effects, the magnitude of elasticities of the demand for CRC insurance with respect to per dollar net premium changes across regions.

Take the 60% and 75% coverage levels as an example (table 29). In the Corn Belt, the effects of per dollar net premium are statistically insignificant at the 60% coverage level, while the elasticities increase through the Lake States, Northern Plains, and Southern Plains (-0.190, -0.290, and -0.373, respectively). At the 75% coverage level, the elasticity of demand with respect to per dollar net premium in the Southern Plains is -0.670, which is about 4.6 times the elasticity in the Corn Belt (-0.146) (table 29). Therefore, differentiating coverage levels and regions in the analysis of corn CRC insurance demand would be essential.

The elasticities of corn CRC insurance demand with respect to total corn planted acres are inelastic and tend to decrease with increasing coverage levels in the Corn Belt and Lake States (table 29). Take the Corn Belt as an example. The elasticity of CRC insurance demand with respect to the total corn planted acres at the 50% coverage level is 0.148, which is about 2.4 times the elasticity at the 85% coverage level (0.061). The total corn planted acres only have statistically significant effects at some coverage levels in the Northern Plains and Southern Plains (65%, 75%, and 80% coverage levels in the Northern Plains, and 50% and 65% coverage levels in the Southern Plains). The Corn Belt has the largest corn planted acres and the largest elasticities of demand for corn CRC insurance with respect to corn planted acres compared to the other three regions at each coverage level.

The elasticities of corn CRC insurance demand with respect to expected revenue reported in table 29 are inelastic for all coverage levels in the four regions, except for the elasticity at the 80% coverage level in the Lake States, which is elastic (1.104). The negative and statistically significant expected revenue effects only appear in the Corn Belt at 60%, 65%, 70%, and 75% coverage levels (-0.194, -0.113, -0.152, and -0.195, respectively). With higher expected revenue, corn producers in the Corn Belt would purchase less per dollar liabilities at the 60%, 65%, 70%, and 75% coverage levels, while they would purchase more insurance at the 80% and 85% coverage (0.432 and 0.440, respectively) (table 29). There is a positive relationship between the expected revenue and the purchases of insurance in the other three regions (the Lake States, Northern Plains, and Southern Plains).

The effects of relative revenue risk on the demand for CRC insurance change significantly across coverage levels and regions. The elasticities of demand for CRC insurance with respect to relative revenue risk are statistically significant at the 55% and 60% coverage level (0.226 and 0.168, respectively) in the Corn Belt (table 29). The elasticities are statistically significant and positive at the 60%, 65%, 70%, and 75% (0.295, 0.221, 0.406, and 0.334, respectively). The elasticities of demand for corn CRC insurance with respect to relative revenue risk is statistically significant and negative at the 65% coverage level in the Northern Plains (-0.129). In the Southern Plains, the elasticities are statistically significant and positive at the 50% and 65% coverage levels (0.229 and 0.160, respectively), while the demand for corn CRC insurance is negative at the 70% coverage level in the Southern Plains (-0.171) (table 29). Generally, relative revenue risk does not have statistically significant effects on the two tails of coverage levels, which means producers who tend to purchase relatively low or high coverage levels are not affected by the change of relative revenue risk significantly. But producers' purchase decisions are affected by relative revenue risk if they intended to purchase medium coverage levels of corn CRC insurance.

Comparison of APH and CRC Elasticities of Demand

The elasticities of demand for insurance with respect to per dollar net premium not only change across coverage levels and regions, but the elasticities also change between insurance plans (table 30). In the Corn Belt and Northern Plains, the demand for corn APH insurance is more price responsive than the demand for corn CRC insurance, while the elasticities of demand for corn CRC insurance with respect to per dollar net premium are larger than the corresponding elasticities for corn APH insurance in the Lake States and Southern Plains. For example, in the Southern Plains, the elasticity of corn APH insurance with respect to per dollar net premium is -0.248, while the corresponding elasticity for corn CRC insurance is -0.373 at the 60% coverage level (table 30).

Table 30. Estimated Elasticities of Demand for APH and CRC Insurance

		50%	55%	60%	65%	70%	75%	80%	85%
Corn Belt	APH	-0.047**	-0.028	-0.106***	-0.114***	-0.137***	-0.149***	-0.230***	0.017
	CRC	-0.015	0.033	-0.04	-0.083**	-0.167***	-0.146***	-0.200***	-0.083
Lake States	APH	-0.180***	-0.138***	-0.138***	-0.147***	-0.094**	-0.157***	-0.158**	
	CRC	-0.213***	-0.323***	-0.190***	-0.239***	-0.285***	-0.229***	-0.208***	-0.177
Northern Plains	APH	-0.170***	-0.004	-0.305***	-0.038	-0.097	-0.188*	-0.259**	-0.284**
	CRC	-0.042	-0.205	-0.290***	0.017	-0.044	0.097	0.075	0.009
Southern Plains	APH	-0.221**	-0.131	-0.248*	-0.227**	-0.155	-0.654***		
	CRC	-0.331**	-0.094	-0.373***	-0.242*	-0.501***	-0.670***		

Results presented in table 30 also indicate the necessity for separating insurance plans, regions, and coverage levels in the analysis of corn insurance demand, which was overlooked in previous studies. The elasticity of demand for corn CRC insurance with respect to per dollar net premium is -0.670 at the 75% coverage level in the Southern Plains and it is -0.047 at the 50% coverage level in the Corn Belt (table 30). Although the elasticities are price-inelastic, a 1% change in the net premium would induce 14 times larger effect at the 75% coverage level in the Southern Plains than the effect at the 50% coverage level in the Corn Belt (table 30).

Summary

This study evaluated the demand for corn insurance in the major corn production regions. The estimated elasticities of demand for corn APH insurance with respect to per dollar net premium range from -0.654 (75% coverage level in the Southern Plains) to -0.047 (50% coverage level in the Corn Belt). The elasticities of demand for corn CRC insurance with respect to per dollar net premium range from -0.670 (75% coverage level in the Southern Plains) to -0.083 (65% coverage level in the Corn Belt) (table 30). The estimated average demand elasticities for liability per planted acre are -0.73 in Iowa in Goodwin (1993), -0.24 in Heartland in Goodwin (2001), -0.13 in Illinois, Idaho, Iowa, and Ohio in O'Donoghue (2014). Since this study is the only one that separated coverage levels in the analysis of corn insurance demand, it is difficult to compare the estimated elasticities of corn insurance demand at each coverage level with existing studies at each coverage level. But overall, the elasticities derived in this analysis are basically consistent with results reported in other studies.

Results also suggest that producers in riskier regions are more responsive to the change of per dollar net premium. For instance, with a 1% decrease in the per dollar net premium, producers in the Corn Belt would increase their purchase for corn APH insurance at the 50% coverage level by 0.047%, while producers in the Southern Plains would increase the purchase by 0.221%. So the change in the Southern Plains is quadrupled compared to the change in the Corn Belt. In O'Donoghue (2014), the elasticities of demand for corn insurance measured as liabilities per acre are -0.13, -0.24, and -0.25 in the Midwest, Lake, and Northern Plains, respectively, which also exhibit the patterns that producers in riskier regions tend to be more responsive to corn insurance, although the pattern was not mentioned in his study.

Results in this study also show the importance of separating coverage levels, regions, and insurance plans in the study for corn insurance demand. Although the elasticities of demand for APH and CRC insurance with respect to per dollar premium are price-inelastic, the elasticities vary significant across coverage levels and regions. For example, the elasticity of demand for CRC insurance at the 75% coverage level in the Southern Plains is -0.670, which is more than 14 times of the elasticity of demand for APH insurance at the 50% in the Corn Belt (-0.047). However, the differences were overlooked in current related studies.

In the literature, females are considered to be more risk averse than males (e.g., Holt and Laury 2002; Charness and Gneeze 2012). Results from O'Donoghue (2014) suggest that there is positive correlation between the acres operated by females and the demand for crop insurance. However, the female effects have a different story if the coverage levels are differentiated. In the Corn Belt, the expected corn yield is high and the relative yield risk is relatively low comparing to other regions. Higher percentage of female operated cropland would induce more corn CRC insurance purchased at the low coverage level, such as the 50% coverage level, and result in less insurance purchased at the high coverage levels, such as the 80% and 85% coverage levels. Females may tend to be more protective by purchasing crop insurance, but they would like to purchase more corn CRC insurance at low coverage levels in the Corn Belt.

Furthermore, this study proposes a different way to measure the quantity of insurance purchase and the price of crop insurance. In the study both the quantity of insurance purchase and premium are normalized by divided by the projected prices, considering the projected price could affect these two variables simultaneously.

Policy Implications

Federal crop insurance has undergone scrutiny regarding the significantly increased government costs. Critics of federal crop insurance continually propose bills to cut government subsidies on crop insurance premiums, such as Senate Bill 666 and Senate Bill 2244 in the 114th Congress. Reforms are proposed in the recently released Obama Administration's 2017 Budget, and the reforms call for an $18 billion cut to the FCIP over 10 years, according to the Administration. Under this situation, it is important to have a general view of the changes in demand if premium subsidies are reduced.

In CRS Report R43951 (Shields 2015), a 10 percentage point reduction in crop insurance premium subsidies is proposed. Table 31 shows how the purchases of corn crop insurance would likely change with a 10 percentage points decrease in federal premium subsidies.

Table 31. Estimated Changes of Corn Insurance Demand

		50%	55%	60%	65%	70%	75%	80%	85%
APH	Corn Belt	-0.701%	-	-1.656%	-1.932%	-2.322%	-2.709%	-4.792%	-
	Lake States	-2.687%	-2.156%	-2.156%	2.492%	-1.593%	-2.855%	-3.292%	-
	Northern Plains	-2.537%	-	-4.766%	-	-	-3.418%	-5.396%	-7.474%
	Southern Plains	-3.299%	-	-3.875%	-3.847%	-	-11.891%	-	-
CRC	Corn Belt	-	-	-	-1.407%	-2.831%	-2.655%	-4.167%	-
	Lake States	-3.179%	-5.047%	-2.969%	-4.051%	-4.831%	-4.164%	-4.333%	-
	Northern Plains	-	-	-4.531%	-	-	-	-	-
	Southern Plains	-4.940%	-	-5.828%	-4.102%	-8.492%	-12.182%	-	-

Note: "-" denotes statistically insignificant change.

A uniform percentage point reduction in the federal premium subsidy rate across coverage levels would result in significantly different responses in producers' participation in the FCIP by region and insurance type. For example, in the Corn Belt, the changes at relatively high coverage levels (75% and 80%) are greater than they are at the 50% coverage level, both for corn yield and revenue insurance policies. Thus, a small reduction in premium subsidy rates across coverage levels would result in a greater reduction in participation in high coverage policies in the Corn Belt, which contradicts a major purpose of the 2000 ARPA. (One of the major objectives of the 2000 ARPA was to encourage more participation at coverage levels higher than the 65% coverage level.)

A uniform percentage point reductions in the premium subsidy rates across coverage levels would also lead to significantly different purchase decisions across regions. For example, for yield insurance, the expected change at the 75% coverage level in the Southern Plains (-11.891%) would be 17 times greater than it is at the 50% coverage level in the Corn Belt (-0.701%). The significantly different effects could also be expected for the demand for revenue insurance. Therefore, the government may consider applying different changes to the subsidy rates across regions, coverage levels, and insurance types to insure significant use of crop insurance.

Conclusions

The highly subsidized crop insurance program has been one of the most expensive agricultural programs, thus it is important to determine the need for high premium subsidies. Although several studies examined the elasticities of corn insurance demand, none of them differentiated coverage levels, and few of them separated insurance plans. Consequently, this undermines the effectiveness of the implications provided in the existing studies. In this study the demand for corn insurance is estimated at each coverage level, region, and insurance plan. This analysis finds empirical support for varying elasticities of corn insurance demand among coverage levels, insurance plans, and regions, Therefore, the change of subsidies could have significantly different effects across coverage levels, insurance plans, and regions. The demand for corn yield insurance at low coverage levels in less risky regions, such as the 50% coverage level in the Corn Belt, is expected to have modest response to the change of subsidies, while the demand for corn yield insurance at high coverage levels in riskier regions, such as the 75% coverage level in the Southern Plains, would be more price-sensitive. Therefore, changing subsidies at different coverage levels in different regions would trigger significantly different purchase responses.

Government Accountability Office (GAO 2015) claims that the federal government costs in the crop insurance program are “substantially” higher in regions with higher crop production risks than in other regions by providing cheaper crop insurance. The “cheaper” insurance is realized by setting the county base premium rates much lower than the target premium rates. Although RMA disagrees with GAO's claim, it does not have more information to refute GAO's argument since RMA does not monitor and report government costs in riskier regions. This study shows that in order to keep high participation and high coverage levels, the government premium subsidies should be higher in riskier regions since the demand for corn insurance is more price sensitive in riskier regions and higher coverage levels. But how large the differences should be to balance participation and actuarial fairness between different risk regions deserves more attention and future research.

To estimate the elasticities of demand for corn insurance, this study assumes there is no adverse selection in the corn insurance market. However, the existence of adverse selection is one of the longstanding problems in the analysis of crop insurance. The study would be improved if adverse selection is incorporated in the estimation of demand for corn insurance.

CHAPTER III

THE DEMAND FOR WHEAT CROP INSURANCE

Introduction

The federal crop insurance program (FCIP) has been expanded significantly in recent decades. In 1990, 101.36 million acres of land were enrolled in the crop insurance program with a liability of $12.82 billion. In 2015, the corresponding figures are 296.04 million acres of land with a liability of $96.54 billion. Figure 11 shows the total enrolled acres in the federal crop insurance program in 1981 through 2015 and figure 12 shows the liabilities purchased during the same time period. Overall, the federal crop insurance program has been a popular risk management tool for farmers.

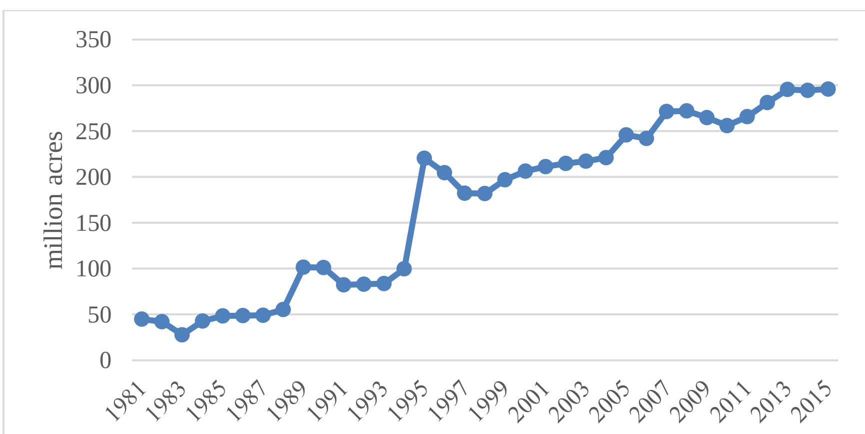

Figure 11. Total Enrolled Acreage in the FCIP

Source: USDA's RMA, Summary of Business Reports and Data; Glauber (2004).

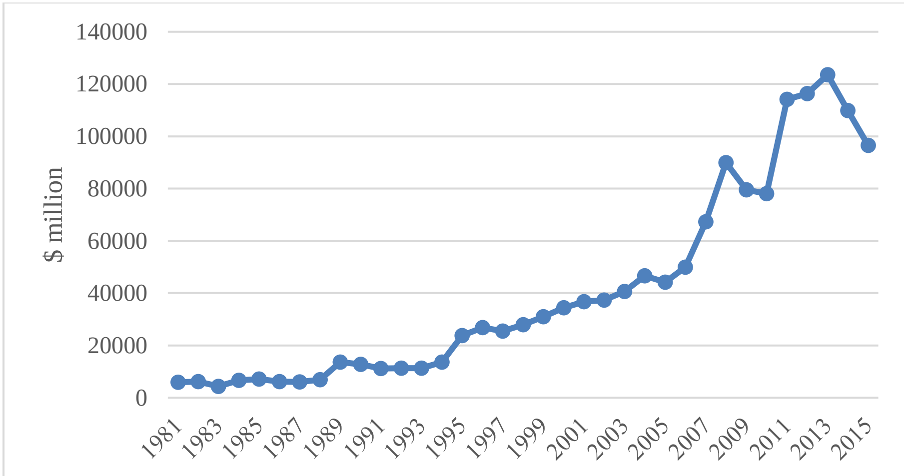

Figure 12. Total Crop Insurance Liabilities in the Federal Crop Insurance

Source: USDA's RMA, Summary of Business Reports and Data; Glauber (2004).

With the implementation of the 2014 Farm Bill, the importance of the FCIP was strengthen by offering more options and replacing previous farm programs (Goodwin 2014; Orden and Zulauf 2015), such as the direct payment and countercyclical payment programs. However, the crop insurance program has been criticized because of its high costs and high loss ratio.

Figure 13 shows the premium subsidies of the federal crop insurance program. Figure 14 shows the loss ratio and adjusted loss ratio history of the crop insurance program.[1] The federal crop insurance program is highly subsidized from the US Treasury. The annual subsidy cost increased from $215.10 million to $6.01 billion from 1990 to

[1] The loss ratio is computed as indemnities divided by premium and the adjusted loss ratio is computed as indemnities divided by net premium.

2015 (figure 13) and the adjusted loss ratio increased from 1.57 to 2.35 from 1990 to 2014 (figure 14). The average subsidy rate in the most recent ten years (2006-2015) is 61%.[2] The average subsidy rate increased from 26% in 1990 to 62% in 2015.

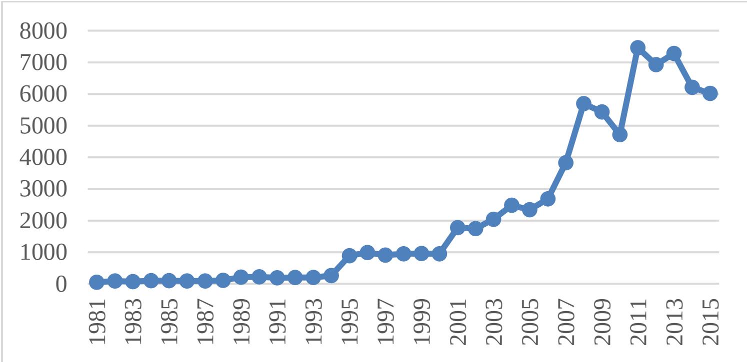

Figure 13. Federal Crop Insurance Premium Subsidies

Source: USDA's RMA, Summary of Business Reports and Data.

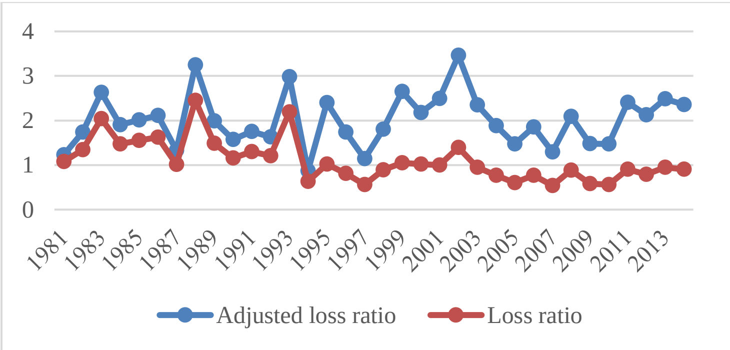

Figure 14. Federal Crop Insurane Loss Ratios and Adjusted Loss Ratios

Source: USDA's RMA, Summary of Business Reports and Data; Glauber (2004).

[2] The subsidy rate is computed as premium subsidies divided by gross premium

Under the current farm bill, federal crop insurance is the most expensive agriculture program according to Congressional Budget Office (CBO)'s cost estimate. With the large spending on the crop insurance program, proposals to reduce or limit crop insurance subsidy were submitted (Shields 2015; Davis, Anderson, and Young 2014). For example, Senators Shaheen and Coburn proposed to set a $70,000 per farm premium subsidies. Although no premium subsidy reduction or limits were applied by the 2014 Farm Bill, there could be future amendments on premium subsidies, and Congress needs to find "what reductions (if any) to premium subsidies can be tolerated" (Shields 2015). Therefore, knowledge of how producers may respond to subsidy changes could provide important insights for future policy making. In this study, wheat is chosen as an example, and the method of analysis could be applied to other field crops.

Background

Wheat Production in the U.S.

Wheat is one of the most important crops in the United States. It ranks third in both planted acreage and gross value, behind corn and soybeans. In 2015, the total planted acreage for wheat is approximately 56 million, and the planted acreage for corn and soybeans are 89 million and 84 million, respectively. Figure 15. Total Planted Acreage of Wheat in 1970-2015

shows the planted acreage of wheat in 1970-2015. The total planted acres of wheat decreased from its historical high in 1981 with 88 million acres because of the decreased returns relative to other crops and government policies. Wheat farmers had to idle a certain portion of their wheat land to participate in the voluntary wheat program under the 1981 Agriculture and Food Act (Johnson, Rizzi, Short, and Fulton 1982). In 1985, 90% of wheat planted acreage was enrolled in the set-aside program with 20%-35% set aside levels (Babcock, Carter, and Schmitz 1990; Outlaw et al. 2008).

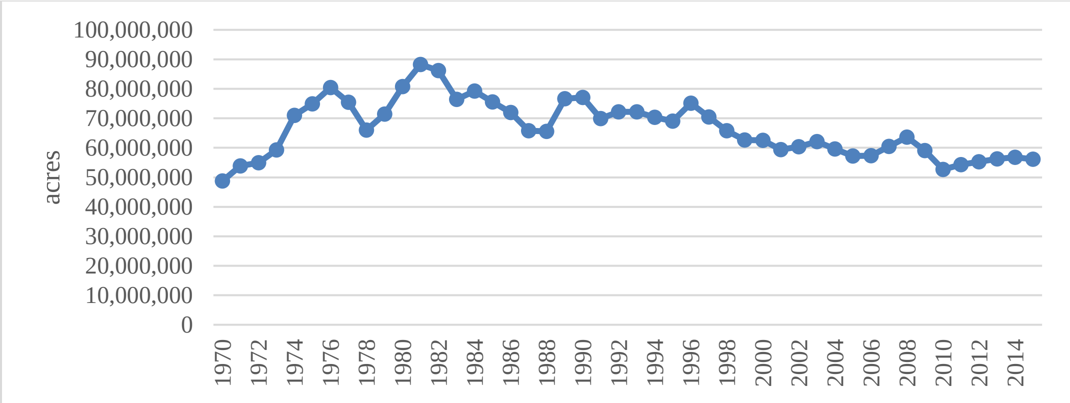

Figure 15. Total Planted Acreage of Wheat in 1970-2015

Source: USDA's NASS.

Wheat is produced in almost every state, but the production practices, costs, and yield varies across regions (Vocke and Ali 2013). Figure 16 shows the planted acreage in each state in 2015. The Northern Plains and Southern Plains are major wheat producing regions. In the present study, three major wheat producing regions are analyzed, including the Pacific Northwest, the Northern Plains, and the Southern Plains**.** Table 32 shows the definition of each region.

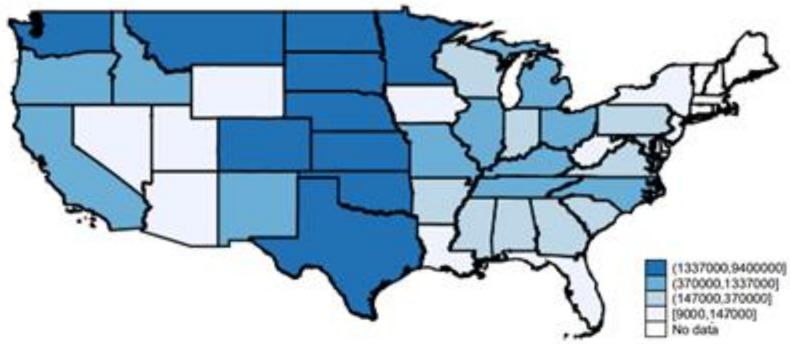

Figure 16. Wheat Planted Acreage in 2015

Source: USDA's NASS.

Table 32. The Definition of Regions

Regions	States
Pacific Northwest	California, Oregon, Washington
Northern Plains	Kansas, Montana, North Dakota, Nebraska, South Dakota
Southern Plains	Oklahoma, Texas

There are ten states included in the three regions. These ten states are among the 11 leading states in terms of the average gross value of wheat in the most recent five years (2010-2014). The gross value is calculated as the product of the average state yield, the wheat planted acres, and the price received by producers. Figure 17 shows the average gross values for the 11 leading states.

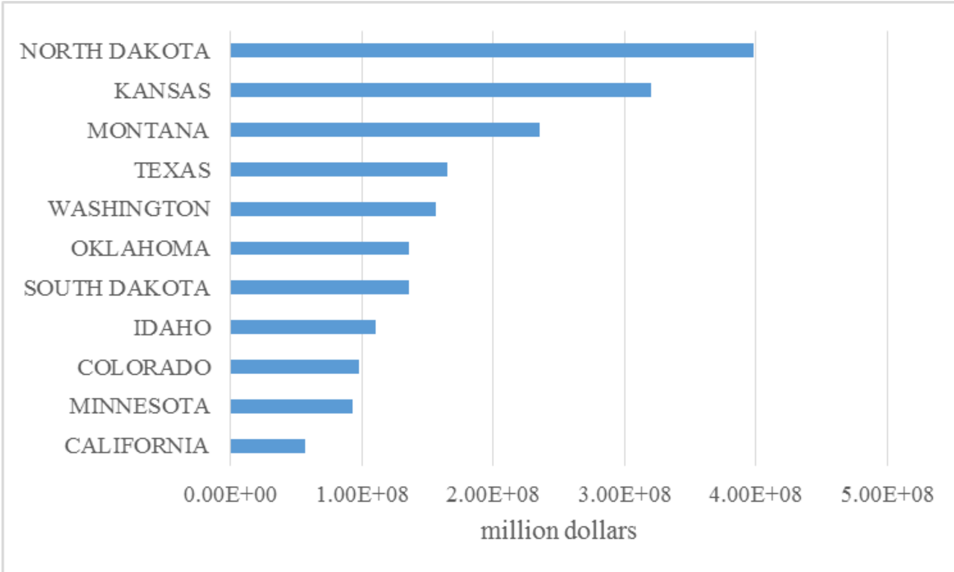

Figure 17. Leading Gross Values of Wheat in the U.S. (averaged over 2010-2014)

Source: USDA's NASS.

The Northern Plains is a major wheat producing region. In the present study, Kansas, Montana, North Dakota, Nebraska, and South Dakota are grouped in this region. The average planted acres in the most recent five years (2010-2014) in the Northern Plains account for 48% of the average annual planted acres in the United States. The Southern Plains and the Pacific Northwest account for 20% and 7% of the average annual planted acres of wheat, respectively.

Wheat yield varies widely across the United States with a national average yield of 43.5 bushels per acre in the most recent five years (2010-2014). During 2010 to 2014, the Pacific Northwest region had the highest average yield (71.75 bushels per acre), followed by the Northern Plains (40.95 bushels per acre) and the Southern Plains (28.80

bushels per acre). According to Vocke and Ali (2013), the Northern Plains had the highest production cost per bushel compared to other regions due to the high costs for fertilizer, herbicides, and fungicides.

Figure 18 shows the marketing year average wheat price from 1980 to 2014. The wheat price reached a historical high in 2012 with $7.77 per bushel and the average wheat price received by farmers was $6.71/bushel in 2010-2014. In 2014, the total supply in the United States was 2,760 million bushels and 1,153 million bushels were used domestically. Approximately 35% of total wheat supply was used as food, 3% of total wheat supply was used as seed, and 4% was used as feed and residual.

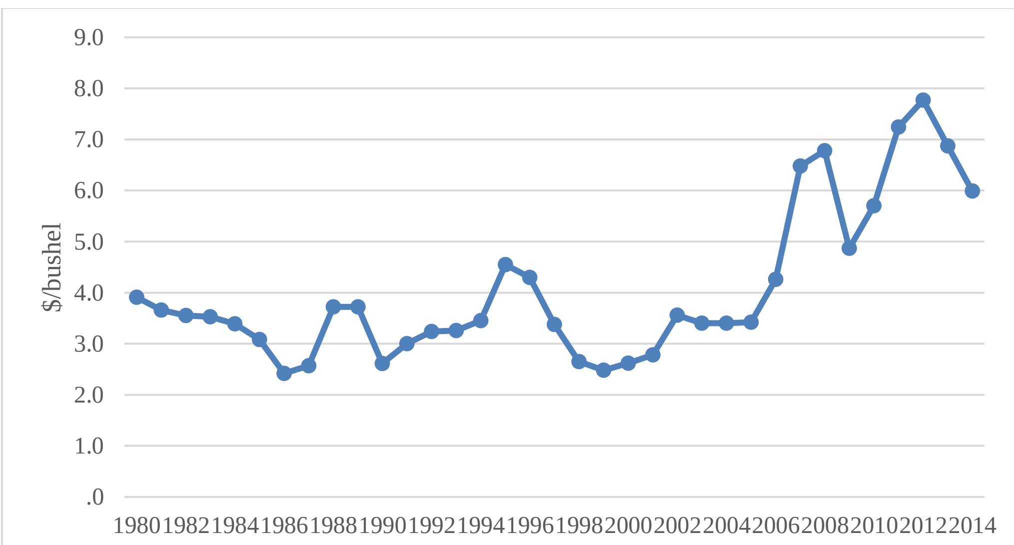

Figure 18. Marketing Year Weighted Average Prices of Wheat in the U.S.

Source: USDA's ERS.

Wheat Insurance

In general, the participation rate increased over time with a jump in 1995. Figure 19 shows total wheat planted acreage of wheat and the total enrolled acreage in the federal crop insurance program of wheat in the U.S. during 1989 to 2015. Figure 20 shows the participation rate of wheat which is measured as the ratio of wheat enrolled acreage in the federal crop insurance to the total planted acreage of wheat. In 1990, the total wheat planted acreage was 77,041,000, and the enrolled acreage of wheat in the federal crop insurance program was 36,379,062. Thus, approximately 47% of wheat planted acreage was covered by the federal insurance program. In 2015, the ratio of wheat insured acreage to the wheat planed area is about 82% as the planted acreage is 56,079,000 and the insured acreage is 46,090,746.

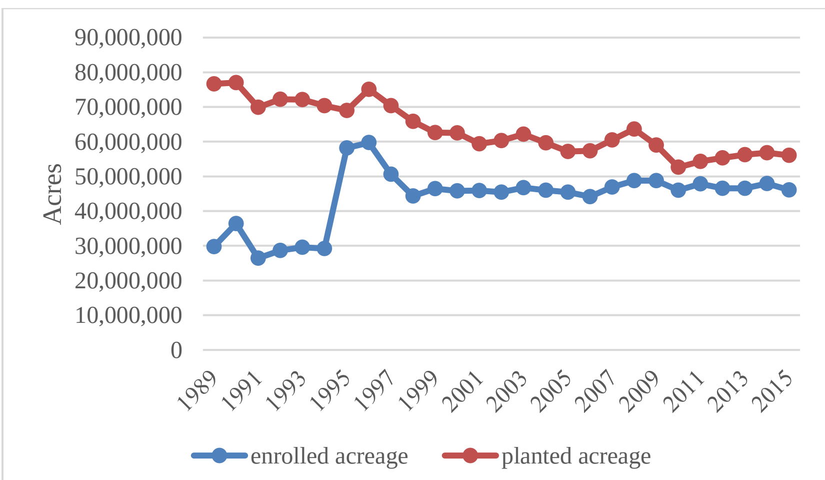

Figure 19. Wheat Planted Acreage and Enrolled Acreage in the U.S. in 1989-2015

Source: USDA's NASS; USDA's RMA, Summary of Business Reports and Data.

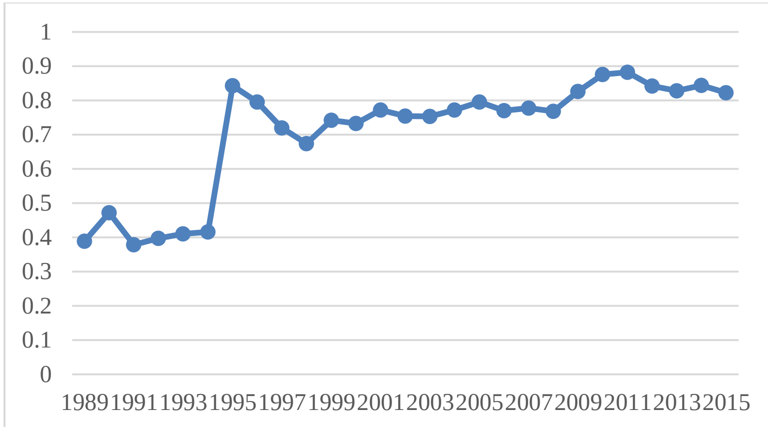

Figure 20. The Federal Wheat Insurance Participation Rate

Source: USDA's NASS; USDA's RMA, Summary of Business Reports and Data.

With the implementation of the 1994 Federal Crop Insurance Reform Act (FCIRA), the participation rate of wheat doubled from 42% in 1994 to 84% in 1995. First of all, the FCIRA increased federal premium subsidies. Premium rates are set based on the average historical rate of loss (Hazell, Pomareda, and Valdes 1986). Producers who enroll in the federal crop insurance program only pay a portion of the gross premium since the enactment of the Federal Crop Insurance Act (FCIA) in 1980. So the federal crop insurance is cheaper to wheat producers when the FCIRA increased subsidy rates. Secondly, the FCIRA introduced the Catastrophic Level of Coverage (CAT) which is fully subsidized by the government. In 1995, more than 27 million acres of wheat planted area were enrolled under the CAT coverage, which accounts for 47% of total wheat insured acreage. Thirdly, the FCIRA made the participation in the crop insurance program mandatory to be eligible for deficiency payments, certain loans, and other benefits. With the three major changes, the participation rate of wheat increased dramatically in 1995.

The mandatory participation requirement was repealed by Congress in the 1996 Farm Bill (Sherrick et. al. 2004), and the participation rate of wheat decreased from 84% in 1995 to 67% in 1998. The wheat insurance participation rate increased at the end of the 1990s when the revenue insurance policy (CRC), group risk plan (GRP), and income protection (IP) were introduced in 1997 (Serra, Goodwin, and Featherstone 2003). The wheat crop insurance participation rate increased from 67% in 1998 to 74% in 1999.

The Agricultural Risk Protection Act (ARPA) of 2000 substantially increased premium subsidies to expand crop insurance coverage. For example, the subsidy rate at the 75% coverage level under the APH plan was increased by 31 percentage point. The changes of subsidy rates under the ARPA are reported in table 33. On average, about 56% of the gross premium is subsidized by the government.

Table 33. Basic Unit Subsidy Levels Pre- and Post-ARPA

Coverage Level	Pre-ARPA		Post-ARPA
	APH	CRC	
50/100	55%	42%	67%
65/100	42%	32%	59%
70/100	32%	25%	59%
75/100	24%	18%	55%
85/100	13%	10%	38%

Source: Kelly 2001; Jose 2001.

Literature Review

Patrick (1988) used a Tobit model to estimate the demand for crop and rainfall insurance for wheat producers in Malee in 1958-1959 and 1977-1978. Patrick’s study estimated the premium producers would like to pay for crop insurance. The results show that producers were willing to pay less premium with higher expected yield. The results also show that wheat farm characteristics and growers’ risk attitude have effects on the amount of premium that wheat producers were willing to pay.

Smith and Baquet (1996) analyzed the demand for wheat insurance on 370 Montana wheat farms by using the Heckman two-stage approach. This is the first study that analyzed the participation and coverage levels simultaneously. However, there is no elasticity reported at each coverage level. A mailed survey was used to collect wheat farmers’ purchase decisions in 1990. The probability of purchasing wheat insurance is estimated in the first stage and the liability purchases were estimated in the second stage. In the estimation, they also separated producers with positive expected returns and negative expected returns from crop insurance programs. The results indicate that the demand for coverage levels were expected to decrease when premiums increased. Results also show that the elasticity of demand for wheat insurance with respect to price increases when the yield is more variable for producers with negative expected returns, while the elasticity of demand for wheat insurance decreases when the yield is more variable for producers with positive expected returns. The results also show that operator age, years of farming experience, farm size, and off-farm income have statistically insignificant effects on the demand for wheat insurance in Montana.

Serra, Goodwin, and Featherstone (2003) used simultaneous equation probit models and farm level data to estimate the changes in the participation for crop insurance of Kansas farmers in 1993 through 2000. During this period, many policy changes happened as discussed earlier, such as the launch of the CAT coverage and the revenue protection program. The probability of purchasing crop insurance was estimated in the first stage and the choice of the coverage level was estimated in the second stage. The major crops in Kansas including wheat, corn, sorghum, and soybeans were estimated together in their study, and a normalized yield was used. The mean coefficient of variation of yields in the preceding 10 years was utilized to measure the production risk level. The results show that the relationship between premium rates and the demand for crop insurance is statistically insignificant in 1995 and 1996 when the mandatory requirement was applied. The results also show that the magnitude of elasticities of demand for crop insurance with respect to premium rate decreased by the end of the 1990s when new insurance policies were introduced and subsidy rates increased. They also found that the use of inputs has statistically insignificant effects on the demand for crop insurance.

The acreage response, insurance participation, the Conservation Reserve Program (CRP) enrollment, and input use were analyzed simultaneously in multiequation models by Goodwin, Vandeveer, and Deal (2004). Corn and soybean produced in the Corn Belt and wheat as well as barley produced in the Northern Great Plains are estimated in the study. The elasticity of demand for wheat insurance measured in terms of liabilities per planted acre with respect to premium rate was -0.12.

County-level insurance participation data in 1997 and 2002 were used to estimate the demand for federal corn, soybean, and wheat insurance by O'Donoghue (2014). Results show that the demand for federal crop insurance varied among production regions and crops. The elasticities of demand for wheat insurance were -0.15 and -0.27 in the Southern Plains and the Northern Plains, respectively, if the liabilities per acre were used to measure the insurance purchases. The elasticities of demand for wheat insurance were -0.19 and -0.14 in the Southern Plains and the Northern Plains, respectively, if the acres of buy-up coverage were used.

Model Framework

Wheat producers are assumed to maximize their utility by making decisions, subject to farm and market constraints. A linear equation is commonly used in the study of the demand for crop insurance (e.g., O'Donoghue 2014). Assume the demand for wheat insurance can be represent by:

(1) $$y_i = \alpha + X_i \beta + \varepsilon_i$$

where y_i is the choice of wheat insurance under the maximization problem. X_i is a vector matrix including factors affecting producers' decisions on crop insurance and ε_{1k} is the residual term. Following previous studies, we assume the demand for wheat insurance is affected by the characteristics of the wheat insurance program, market environment, and factors for the farms, which are grouped into the X_i matrix.

One of the problems in the study of crop insurance is how to define the price and quantity relevant variables for the crop insurance demand. Insured acreage (e.g., Goodwin 1993), participation rate (e.g., Smith and Baquet 1996), and liability purchases (e.g., Goodwin, Vandeveer, and Deal 2004) are commonly used to measure the quantity of insurance demanded. Goodwin (1993) pointed out that liability is the “true measure” of the quantity purchases of crop insurance. However, the unit quantity is computed as the liability divided by the total planted acres in Goodwin (1993). In the present study, the insured acreage is used to adjust the unit price instead of total planted acreage because producers purchase crop insurance to protect the yield loss on insured cropland, not the total planted area.

In Serra, Goodwin, and Featherstone (2003), the price relevant variable is measured by the ratio of the net premium to the liability. In a recent study by the Government Accountability Office (GAO), the cost related variable is constructed as the costs per dollar of crop value. In the present study, the unit price is computed as the normalized net premium per acre per dollar of crop value (normalized premium divided by the product of insured acres and projected prices of wheat). Both liabilities and premium are normalized by the Consumer Price Index (CPI). The net premium is calculated as the gross premium minus government premium subsidies.

Variable Selection

Table 34 presents the construction of each variable in the present study. The selection of the relevant variables considered the related existing studies on the demand for crop insurance. The total planted acreage is a common variable in the analysis of the demand for crop insurance since the insured acres and the planted acres should have direct relationship. The mean yield in the preceding three years was used to measure producers' expectation of wheat yield. Since there are technology development, the mean in recent years should be preferred to the yield averaged over a long period, such as the ten years' average yield used in Goodwin, Vandeveer, and Deal (2004). Considering the possible low yield in one year due to unfavorable weather, the mean yield in the previous three years would be more reasonable to be incorporated in the model than the lagged yield used in previous studies (e.g., Goodwin 1993; Wang et. al. 1998).

Table 34. Variable Definition

Variables	Definition	Notation in this study
Dependent variable	normalized liabilities per acre/projected price	liab_cpi_acre_price
Price relevant variable	normalized net premium per acre/projected price	netprem_cpi_acre_price
Expected yield	average yield in the preceding three years	mean_lag_yd3
CV of yield	coefficient of variation of historical corn yield	cv_yield
Planted acres	planted acres of wheat	acreplt
Enrolled acres in CRP	enrolled acres in CRP	crp
Percentage of irrigated cropland	the ratio of acres of irrigated cropland to acres of total cropland in each county	irr_per
Percentage of cropland operated by females	the ratio of acres operated by females to acres of total cropland in each county	fe_per

Variability of yield is an important variable in the study of crop insurance. The coefficient of variations (CV) of historical yield is utilized to represent the relative yield risk (table 34). The CV of yield is computed as the ratio of the standard deviation of yield to the average yield at the county level (1989-2013). Since the study is constructed over regions, the relative yield risk should be preferable to the variance of yield used in some studies, such as O'Donoghue (2014).

CRP idles land from agricultural production. Thus increasing CRP enrollment decreases the number of acres that can buy crop insurance. CRP idles marginal land with low agricultural production value (Baker and Galik 2009). If land enrolled in the CRP was used to grow wheat it would probably decrease the county average wheat yield. So reducing marginal land will increase the county average yield and reduce the risk of wheat production for the county. Thus the greater the CRP acreage in a county, the higher county average yield and lower yield risk.

The percentage of irrigated cropland in the county is incorporated in the model because irrigated wheat yields are higher and have lower relative risk. Similar variables were also included in other studies, such as O'Donoghue (2014) and Goodwin (1993). The female effect is considered in recent crop insurance studies as females are assumed to be more risk averse than males (Eckel and Grossman 2008, Charness and Gneeze 2012, O'Donoghue 2014) . If females are more willing to participate in crop insurance programs than males, the percentage of cropland operated by females in a county would affect the insurance purchases at the county level.

To guarantee the variability of the price relevant variable, the pooled cross-sectional data in 1998 and 2002 are used as the ARPA was launched in 2000. The net premium paid by producers changed as the premium subsidies changed for the ARPA. The changes for the subsidy rates are shown in table 33. Specially, this study focuses on buy-up coverage since the premium for CAT coverage is fully subsidized by the government and producers only need to pay the administration fee. Both APH and CRC were available for wheat producers in 1998 and 2002. APH protects producers from low yield and CRC is a revenue protection. Considering these two insurance plans are different in terms of premium rates and insurance guarantees, the results could be biased if the two policies are combined in the study of the demand for wheat insurance. However, there is not enough data to estimate the demand for CRC insurance policy independently as the APH insurance policy is more popular than the CRC insurance policy. For example, in 1998, the total insured acres for federal wheat insurance and the APH policy were 44,355,379 and 39,397,331, respectively. Thus, about 89% of total enrolled acres in the federal crop insurance program was under the APH policy in 1998. Therefore, the demand for APH is the focus of this study.

Due to the data limitation, each county is treated as an individual. Although using farm level data could increase the variation, there is no available secondary data at the farm-level to conduct this study. Since the purpose of this study is to get an approximation of the demand for wheat yield insurance over the major wheat producing regions, the use of county level data is appropriate.

Logarithmical transformation is popular in demand analysis. The natural logarithm transformation of each variable is used in the basic form of the model. Thus, the beta coefficients are elasticities directly. Linear-linear and log-linear forms are also used in this study at some coverage levels. In the linear-linear transformation, the model takes the form as shown in equation (1) and the elasticity is calculated by

(2) $$E = \beta \frac{\bar{x}}{\bar{y}}$$

where $\bar{x}$ and $\bar{y}$ denotes the mean of the independent and dependent variables.

If the model is regressed in the log-linear form, the model takes the form as

(3) $$\log(y_i) = \alpha + X_i \beta + \varepsilon_i$$

then the elasticity is calculated by

(4) $$E = \beta \bar{x}$$

where $\bar{x}$ represents the mean of the independent variable.

As the data are compiled at the county-level, non-participation is not a significant problem. Thus, there is no need to adjust for non-participation in the model. Cross-sectional data are used in this analysis and Ordinary Least Square regression is used for the estimation of the demand for wheat yield insurance.

Data

The study uses a pooled cross-sectional data at the county-level. The data are drawn from several sources. Crop insurance participation information at the county level is drawn from the files compiled by USDA's Risk Management Agency (RMA). In the data files, information about crop insurance liabilities, premium, premium subsidies, and insured acres at each individual coverage level is aggregated to the county level by RMA.

Wheat yield, crop prices, and total planted acreage at the county level are collected from the QuickStats tool available through the USDA's National Agricultural Statistics Survey (NASS) website and are used to compute producers' expectation of yield and the relative yield risk for each county.

Annual Consumer Price Index (CPI) is obtained from the Bureau of Labor Statistics (BLS) to adjust the deflation of monetary variables. Information about irrigated cropland and cropland operated by females and males are derived from the 1997 and 2002 Census of Agriculture conducted by the USDA's NASS. CRP participation information is obtained from the files compiled by the USDA's Farm Service Agency (FSA). The projected prices are computed followed the Commodity Exchange Price Provisions (CEPP).

Results and Discussions

The Pacific Northwest

The estimation results for the Pacific Northwest are reported in table 35. The prefix "lg_" denotes the natural logarithm of the variable. There are only 13, 11, and 14 observations at the 55%, 80%, and 85% coverage levels for the Pacific Northwest in the dataset, so these three coverage levels are not included in the estimation. To test for homoscedasticity, the Breusch-Pagan (1979) and Cook-Weisberg (1983) test is applied for each coverage level. The null hypothesis of the Breusch-Pagan (1979) and Cook-Weisberg (1983) test assumes the variance of the error term is constant. The null hypothesis is not rejected at the 95% confidence interval for each coverage level in the Pacific Northwest region.

To test for the specification of the models, two variables are created after regression: predicted dependent variable (liabilities per acre per dollar of wheat value) and the squared term of the predicted dependent variable. The liabilities per acre per dollar of wheat value is regressed on the predicted variable and the squared term. The procedures are also called "Specification Link Test." If the beta coefficient of the squared term is statistically significant at the 95% confidence interval, the model is considered to be misspecified; otherwise, the null hypothesis that the model is well specified cannot be rejected. In the Pacific Northwest, the squared terms do not have statistically significant effects on the liability purchases at each coverage level. Therefore, the models are assumed to be well specified for the Pacific Northwest.

The R^2 ranges from 0.36 (at the 50% coverage level) to 0.59 (at the 70% coverage level). As the p-value is less than 0.05 at each coverage level, the model failed to reject the null hypothesis that all the slopes are zero at the 95% confidence interval. Moreover, the variance inflation factors (VIF) are used to test for multicollinearity. According to Wooldridge (2010), VIF's less than 10 indicate that multicollinearity is not a significant problem. Table 36 reports the results of the VIF test at each coverage level. The results of VIF test show that multicollinearity is not a significant problem for the Pacific Northwest.

Table 35. Estimation Results for Wheat APH Pacific Northwest

	Coverage Levels				
Variables	50%	60%	65%	70%	75%
lg_netprem_cpi_acre_price	-0.105	-0.302	-0.365***	0.031	-0.175
	-0.206	-0.231	-0.122	-0.173	-0.113
lg_mean_lag_yd3	0.848**	1.238***	0.793***	0.705**	0.640***
	-0.315	-0.410	-0.231	-0.258	-0.231
lg_cv_yield	-0.069	-0.221	-0.083	0.206	-0.133
	-0.289	-0.505	-0.136	-0.229	-0.185
lg_acreplt	-0.004	-0.002	0.038	0.128*	0.058
	-0.063	-0.108	-0.049	-0.063	-0.052
lg_crp_acre	0.083	0.046	-0.089*	-0.235***	-0.094*
	-0.060	-0.099	-0.048	-0.064	-0.048
irr_per	0.664	0.235	0.316	-0.353	0.251
	-0.477	-0.584	-0.269	-0.348	-0.237
fe_per	2.934	6.315	1.408	0.444	1.651
	-2.146	-4.312	-1.712	-1.792	-1.562
Constant	0.068	-1.341	2.098**	3.739***	2.660***
	-1.363	-1.650	-0.914	-1.015	-0.914
Observations	41	25	51	33	52
R-squared	0.363	0.531	0.5510	0.5880	0.513
F-stats	2.69	2.75	7.54	5.10	6.63
[p-value]	0.0255	0.0421	0.0000	0.0011	0.0000

Note: Standard errors presented below the parameters estimated. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 36. VIF of the Independent Variables for the Pacific Northwest

Variables	**50%**	**60%**	**65%**	**70%**	**75%**
lg_netprem_cpi_acre	5.55	4.18	4.28	3.67	3.76
lg_mean_lag_yd3	2.21	1.97	2.42	2.17	2.56
lg_cv_yield	2.51	1.76	2.12	2.55	2.33
lg_acreplt	3.28	5.03	3.73	2.93	4.19
lg_crp_acre	5.20	6.10	5.93	3.33	6.67
irr_per	5.93	3.69	3.95	4.01	2.89
fe_per	2.40	1.53	1.47	1.49	1.43

The demand equations are estimated in log-log form in the Pacific Northwest, so the beta coefficients are elasticities (table 35). The signs of the elasticities of demand with respect to the net premium are in line with expectations with one exception (table 35). The exception is the elasticity of wheat APH insurance demand with respect to the net premium per dollar of wheat value at the 70% coverage level (0.031) (table 35). Although the beta coefficient of the net premium is positive at the 70% coverage level, it is statistically insignificant. The elasticity of demand for wheat APH insurance with respect to net premium per acre per value is statistically significant at the 65% coverage level for the Pacific Northwest and it is price-inelastic (-0.37). With a ten-percent increase in the net premium per acre per dollar of wheat value, the purchase of liabilities are expected to decrease by 3.70%. In 2002, the total liabilities at the 65% coverage level was about $18.7 million in the Pacific Northwest. Therefore, with a ten percent increase in the premium subsidy at the 65% coverage level, the liabilities would increase $691,900. The results indicate the importance of separating coverage levels in the study of the demand for wheat insurance as the elasticities of demand vary by coverage level from -0.10 to -0.37 (table 35).

The demand for wheat yield insurance with respect to expected yield is elastic at the 60% coverage level (1.238) while the demand is inelastic for the other coverage levels (0.848, 0.793, 0.705, and 0.640 at 50%, 65%, 70%, and 75%, respectively). The results indicate that wheat producers with higher expected yield would purchase more wheat yield insurance at each level of coverage in the Pacific Northwest (table 35).

There is no statistically significant relationship between the demand for wheat yield insurance and the relative yield risk, the percentage of irrigated cropland, and the percentage of cropland operated by females in the Pacific Northwest (table 35). Also, the total wheat planted area does not have statistically significant effects on the demand for wheat yield insurance, except at the 70% coverage level (table 35). At the 70% coverage level, with a 10% increase in the planted acres, the purchase of liabilities would be expected to increase by 1.28%.

The enrolled acres in the CRP have statistically significant and negative effects at the 65%, 70%, and 75% coverage levels, and the effects are modest (table 35). The negative signs are in lines with expectations as the CRP reduces the number of acres that can buy crop insurance. The elasticities of demand for wheat yield insurance with respect to the enrolled acres in the CRP are -0.089, -0.235, and -0.094 at the 65%, 70%, and 75% coverage levels, respectively.

The Northern Plains

The Northern Plains is a major wheat growing region. In the present study, the Northern Plains include Kansas, Montana, North Dakota, Nebraska, and South Dakota. The estimation results for the Northern Plains are reported in table 37 and the results of VIF test are in table 38. The estimation at the 50% coverage level is rejected by the null hypothesis of the “Specification Link Test” and a linear-linear model is used to address the problem. Estimation results of the linear-linear model and the results of the corresponding VIF tests are reported in table 39 and table 40. The “X”s in the row of Breusch-Pagan/Cook Weisberg test at the 55% and 65% coverage levels (table 37) and at the 50% coverage level (table 39) indicate that the models failed the null hypothesis of the homoscedasticity test at these three coverage levels. Robust regressions are applied and robust standard errors are reported below the parameters estimated for the three coverage levels. All VIF’s are less than 3 (table 38 and 40) indicate that the multicollinearity problem is not noteworthy.

Table 37. Estimation Results for Wheat APH in the Northern Plains

Variables	50%	55%	60%	65%	70%	75%	80%	85%
	lg_liab_cpi_acre	lg_liab_cpi_acre	lg_liab_cpi_acre	lg_liab_cpi_acre	lg_liab_cpi_acre	lg_liab_cpi_acre	lg_liab_cpi_acre	lg_liab_cpi_acre
lg_netprem_cpi_acre_price	-0.165***	-0.026	-0.174**	-0.271***	-0.154***	-0.264***	-0.279**	-0.274*
	-0.046	-0.093	-0.07	-0.038	-0.047	-0.041	-0.131	-0.147
lg_mean_lag_yd3	0.445***	0.540***	0.619***	0.490***	0.380***	0.412***	0.390**	0.468**
	-0.064	-0.140	-0.116	-0.041	-0.062	-0.053	-0.173	-0.174
lg_cv_yield	-0.093*	-0.163	-0.217**	-0.140***	-0.087	-0.147***	-0.037	-0.402*
	-0.053	-0.107	-0.090	-0.041	-0.054	-0.046	-0.131	-0.219
lg_acreplt	0.014	0.098**	0.035	0.011	0.031***	0.020**	0.036	0.020
	-0.012	-0.038	-0.022	-0.006	-0.009	-0.008	-0.029	-0.032
lg_crp_acre	-0.013	-0.069*	-0.018	-0.019**	-0.025**	-0.033***	-0.030	-0.029
	-0.013	-0.035	-0.021	-0.008	-0.012	-0.010	-0.033	-0.039
irr_per	0.203***	-0.010	0.095	0.048	0.149**	0.114**	0.197	-0.008
	-0.062	-0.1280	-0.130	-0.044	-0.059	-0.048	-0.170	-0.223
fe_per	-1.765***	-2.232**	-1.430*	-0.046	-0.868*	-1.356***	2.366*	4.998
	-0.567	-1.062	-0.853	-0.430	-0.487	-0.428	-1.319	-2.962
Constant	2.614***	1.899**	1.811***	2.888***	3.201***	3.476***	3.475***	2.926***
	-0.315	-0.768	-0.608	-0.190	-0.305	-0.253	-0.922	-0.841
Observations	300	99	147	398	256	333	66	31
R-squared	0.310	0.363	0.332	0.416	0.309	0.398	0.278	0.477
F-stats	18.73	9.06	9.87	36.57	15.87	30.75	3.20	3.00
[p-value]	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0063	0.0216
Breusch-Pagan/ Cook-Weisberg test		X		X				

Note: (Robust) standard errors presented below the parameters estimated. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 38. VIF of the Independent Variables for the Northern Plains

Variables	50%	55%	60%	65%	70%	75%	80%	85%
lg_netprem_cpi_acre_price	1.20	1.23	1.16	1.37	1.35	1.29	1.46	1.38
lg_mean_lag_yd3	1.35	1.51	1.8	1.26	1.38	1.34	1.54	1.74
lg_cv_yield	1.14	1.1	1.24	1.17	1.17	1.18	1.28	1.18
lg_acreplt	1.55	1.46	1.45	1.97	1.58	1.76	1.81	1.64
lg_crp_acre	1.85	1.67	2.11	2.05	1.77	2.02	2.47	2.06
irr_per	1.23	1.24	1.27	1.38	1.47	1.45	2.22	1.35
fe_per	1.12	1.3	1.17	1.1	1.21	1.13	1.36	1.99

Table 39. Estimation Results for Wheat APH in the Northern Plains (50%)

Variable	50%
	liab_cpi_acre
netprem_cpi_acre_price	-8.478**
	-3.600
mean_lag_yd3	0.908***
	-0.164
lg_cv_yield	-7.654
	-5.048
lg_acreplt	0.932
	-1.135
lg_crp_acre	-1.125
	-0.921
irr_per	15.585***
	-5.474
fe_per	-131.744**
	-54.637
Constant	45.797***
	-14.710
Observations	300
R-squared	0.269
F-stats	
[p-value]	
Breusch-Pagan/ Cook-Weisberg test	X

Note: Robust standard errors presented below the parameters estimated. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 40. VIF of the Independent Variables at the 50% Coverage Level

Variables	50%
	liab_cpi_acre
netprem_cpi_acre_price	-8.478**
	-3.600
mean_lag_yd3	0.908***
	-0.164
lg_cv_yield	-7.654
	-5.048
lg_acreplt	0.932
	-1.135
lg_crp_acre	-1.125
	-0.921
irr_per	15.585***
	-5.474
fe_per	-131.744**
	-54.637
Constant	45.797***
	-14.710
Observations	300
R-squared	0.269
F-stats	
[p-value]	
Breusch-Pagan/ Cook-Weisberg test	X

Note: Robust standard errors presented below the parameters estimated. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Elasticities of demand for wheat yield insurance at the 50% coverage level in the Northern Plains are computed following equation (2) at the means based on estimation results shown in table 40. Elasticities at each coverage level in the Northern Plains are reported in table 41.

Table 41. Estimated Elasticities of Wheat APH in the Northern Plains

Variables	50%	55%	60%	65%	70%	75%	80%	85%
netprem_cpi_acre_price	-0.127**	-0.026	-0.174**	-0.271***	-0.154***	-0.264***	-0.279**	-0.274*
mean_lag_yd3	0.421***	0.540***	0.619***	0.490***	0.380***	0.412***	0.390**	0.468**
cv_yield	-0.101	-0.163	-0.217**	-0.140***	-0.087	-0.147***	-0.037	-0.402*
acreplt	0.012	0.098**	0.035	0.011	0.031***	0.020**	0.036	0.020
crp_acre	-0.015	-0.069*	-0.018	-0.019**	-0.025**	-0.033***	-0.030	-0.029
irr_per	0.207***	-0.010	0.095	0.048	0.149**	0.114**	0.197	-0.008
fe_per	-1.745**	-2.232**	-1.430*	-0.046	-0.868*	-1.356***	2.366*	4.998

Note: Robust standard errors presented below the parameters estimated. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The demand for wheat yield insurance with respect to premium per acre per dollar of wheat value is statistically significant at each coverage level except the 55% coverage level (table 41). The elasticities of demand with respect to net premium per acre per dollar of wheat value are -0.127, -0.174, -0.271, -0.154, -0.264, -0.279, and -0.274 at the 50%, 60%, 65%, 70%, 75%, 80%, and 85% coverage level, respectively (table 41). The magnitude of the elasticities is small at the relatively low coverage levels, such as the 50%, 55%, and 60% coverage levels and are larger at the relatively high coverage levels, such as the 75%, 80%, and 85% coverage levels. Therefore, the demand for wheat yield insurance in the Northern Plains is more price-responsive at high coverage levels than low coverage levels.

Similar as the Pacific Northwest, the demand for wheat yield insurance would be expected to increase if the expected yield increases (table 41). As shown in table 41, the relative yield risk has negative and statistically significant effects at the 60%, 65%, 75% and 85% coverage levels on the demand for wheat yield insurance in the Northern Plains (-0.217, -0.140, -0.147, and -0.402, respectively). With a ten-percent increase in the relative yield risk, the demand for wheat yield insurance is expected to decrease by 4.02%

at the 85% coverage level in the Northern Plains. The wheat planted acres only have modest effects on the demand for wheat yield insurance in the Northern Plains (table 41). At the 55%, 70%, and 75% coverage levels, the demand for wheat yield insurance would increase by 0.098%, 0.031%, and 0.020% with a one-percent increase in wheat planted acreage. As expected, the demand for wheat yield insurance would decrease if more acres are enrolled in the CRP (table 41). The effects of CRP are statistically significant at the 55%, 65%, 70%, and 75% coverage levels and the elasticities of demand for wheat yield insurance with respect to enrolled acres in the CRP are -0.069, -0.019, -0.025, and -0.033, respectively. The percentage of irrigated cropland has statistically significant effects on the demand for wheat yield insurance at the 50%, 70%, and 75% coverage levels and the corresponding elasticities are 0.207, 0.149, and 0.114, respectively (table 41). The percentage of cropland operated by females has statistically negative effects at the 50%, 55%, 60%, 70%, and 75% coverage levels, and the effects are statistically positive at the 80% coverage level in the Northern Plains (table 41). The elasticities of demand for wheat yield insurance with respect to the percentage of cropland operated by females are -1.745, -2.232, -1.430, -0.868, -1.356, and 2.366 at the 50%, 55%, 60%, 70%, 75%, and 80% coverage levels. Therefore, as the percentage of cropland operated by females grows, the demand for wheat yield insurance at the 80% coverage level is expected to increase by 2.366% while the demand at the lower coverage levels (50%, 55%, 60%, 70%, and 75% coverage levels) is expected to decrease. So women prefer to buy higher levels of insurance which is consistent with the risk aversion assumption.

Southern Plains

The estimation results in the Southern Plains are reported in table 42 and the results of VIF test are presented in table 43. The model at the 65% coverage level is rejected by the null hypothesis of the homoscedasticity test. Therefore, the robust test is applied and the robust standard errors are presented below the parameters estimated at the 65% coverage level. The regression at the 50% coverage level is rejected by the null hypothesis of the specification test. A log-linear model is used at the 50% coverage level to solve the misspecification problem and estimation results are presented in table 45. The VIF's are less than 3 (table 43 and 44) and imply that there is no severe multicollinearity problem at each coverage level in the Southern Plains.

Table 42. Estimation Results for Wheat APH in the Southern Plains

Variables	50%	55%	60%	65%	70%	75%
	lg_liab_cpi_acre	lg_liab_cpi_acre	lg_liab_cpi_acre	lg_liab_cpi_acre	lg_liab_cpi_acre	lg_liab_cpi_acre
lg_netprem_cpi_acre_price	-0.196***	-0.318***	-0.223***	0.027	-0.186***	-0.145*
	-0.046	-0.084	-0.069	-0.261	-0.059	-0.082
lg_mean_lag_yd3	0.577***	1.021***	0.677***	0.314**	0.519***	0.490***
	-0.068	-0.127	-0.12	-0.126	-0.095	-0.115
lg_cv_yield	-0.247***	-0.14	-0.114	-0.184**	0.002	-0.346***
	-0.079	-0.172	-0.122	-0.09	-0.109	-0.123
lg_acreplt	0.017	0.008	0.070*	0.07	0.039	0.03
	-0.018	-0.045	-0.037	-0.061	-0.029	-0.033
lg_crp_acre	-0.021**	0.024	-0.052***	-0.037*	-0.013	-0.009
	-0.01	-0.02	-0.019	-0.021	-0.014	-0.016
irr_per	0.262**	0.015	0.165	0.111	0.186	0.038
	-0.103	-0.196	-0.187	-0.133	-0.139	-0.168
fe_per	0.037	-0.318	1.191	0.185	-0.163	1.04
	-0.533	-0.884	-0.863	-0.532	-0.752	-0.934
Constant	1.827***	0.439	1.504***	2.528***	2.531***	2.204***
	-0.25	-0.602	-0.498	-0.49	-0.371	-0.48
Observations	228	74	90	266	121	89
R-squared	0.430	0.576	0.478	0.250	0.365	0.330
F-stats	23.72	12.79	10.71	12.63	9.29	5.71
[p-value]	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Breusch-Pagan/ Cook-Weisberg test				X		

Note: Robust standard errors presented below the parameters estimated. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 43. VIF of the Independent Variable for the Southern Plains

Variables	50%	55%	60%	65%	70%	75%
lg_netprem_cpi_acre_price	1.40	1.39	1.18	1.46	1.63	1.44
lg_mean_lag_yd3	1.32	1.24	1.18	1.37	1.25	1.18
lg_cv_yield	1.19	1.19	1.13	1.24	1.27	1.22
lg_acreplt	1.84	1.50	2.09	1.31	2.37	2.22
lg_crp_acre	1.83	1.81	2.35	1.85	2.00	2.16
irr_per	1.29	1.30	1.57	1.31	1.23	1.62
fe_per	1.09	1.16	1.15	1.13	1.11	1.27

Table 44. Estimation Results for Wheat APH in the Southern Plains (55%)

Variables	50%
	lg_liab_cpi_acre_price
netprem_cpi_acre_price	-0.020
	-0.018
mean_lag_yd3	0.030***
	-0.002
lg_cv_yield	-0.148**
	-0.062
lg_acreplt	0.027*
	-0.014
lg_crp_acre	-0.018**
	-0.008
lg_irr_per	0.016
	-0.011
lg_fe_per	0.004
	-0.030
Constant	1.407***
	-0.161
Observations	228
R-squared	0.633
F-stats	54.16
[p-value]	0.0000

Note: Standard errors presented below the parameters estimated. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 45. VIF of the Independent Variables (Southern Plains, 50%)

Variables	50%
netprem_cpi_acre_price	1.28
mean_lag_yd3	1.22
lg_cv_yield	1.18
lg_acreplt	1.83
lg_crp_acre	1.78
lg_irr_per	1.28
lg_fe_per	1.13

The model is in log-linear form at the 50% coverage level, thus the beta coefficients are not corresponding elasticities. The elasticities of demand for wheat yield insurance with respect to each independent variable are calculated following equation (4) at the means at the 50% coverage level in the Southern Plains. The elasticities of demand for wheat yield insurance at each coverage level are reported in table 46.

Table 46. Estimated Elasticities of Wheat APH in the Southern Plains

Variables	50%	55%	60%	65%	70%	75%
netprem_cpi_acre_price	-0.035	-0.318***	-0.223***	0.027	-0.186***	-0.145*
mean_lag_yd3	0.838***	1.021***	0.677***	0.314**	0.519***	0.490***
cv_yield	-0.148**	-0.140	-0.114	-0.184**	0.002	-0.346***
acreplt	0.028*	0.008	0.070*	0.070	0.039	0.030
crp_acre	-0.018**	0.024	-0.052***	-0.037*	-0.013	-0.009
irr_per	0.0899	0.015	0.165	0.111	0.186	0.038
fe_per	0.056	-0.318	1.191	0.185	-0.163	1.040

Note: Standard errors presented below the parameters estimated. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Although the elasticity of demand for wheat yield insurance with respect to net premium is positive at the 65% coverage level, it is statistically insignificant. The elasticities of demand for wheat yield insurance with respect to net premium per acre per dollar of wheat value are -0.318, -0.223, -0.186, and -0.145 at the 55%, 60%, 70%, and 75% coverage levels, respectively (table 46). In the Southern Plains, the demand for wheat yield insurance is price-inelastic among all coverage levels, and it is more price-sensitive at the 55% coverage level than other coverage levels. For example, the elasticity of demand for wheat yield insurance with respect to net premium at the 55% coverage level is about 9 times the elasticity at the 50% coverage level.

The demand for wheat yield insurance with respect to expected yield is elastic at the 55% coverage level in the Southern Plains and the elasticity is 1.021 (table 46). With a one-percent increase in the expected yield, the demand for wheat yield insurance is expected to increase by 1.021% at the 55% coverage level in the Southern Plains. Among all the other coverage levels, the demand for wheat yield insurance with respect to expected yield is inelastic and the elasticities are 0.838, 0.677, 0.314, 0.519, and 0.490 at the 50%, 60%, 65%, 70%, and 75% coverage levels (table 46).

The relative yield risk has statistically significant and negative effects at the 50%, 65%, and 75% coverage levels and the elasticities of demand for wheat yield insurance with respect to the relative yield risk are -0.148, -0.184, and -0.346, respectively (table 46). The amount of acres enrolled in the CRP has statistically significant effects on the demand for wheat yield insurance at the 50%, 60%, and 65% coverage levels (-0.018, -0.052, and -0.037, respectively) (table 46).

Although the irrigated cropland has higher expected yield and lower relative production risk, it does not significantly affect the demand for wheat yield insurance in the Southern Plains (table 46). The percentage of cropland operated by females does not significantly influence wheat producers' purchase decisions on yield insurance either (table 46).

Summary

The elasticities of demand for wheat yield insurance with respect to net premium per acre per dollar of wheat value are summarized in table 47. Overall, the elasticities change across coverage levels and regions. Take the 60% coverage level as an example. The elasticity of demand for wheat yield insurance is statistically insignificant at the 60% coverage level in the Pacific Northwest (-0.302), and the elasticities are -0.174 and -0.223 in the Northern Plains and Southern Plains, respectively (table 47). At the 65% coverage level, in the Southern Plains, the relationship between the net premium and the liability purchases is statistically insignificant, while the relationship is statistically significant in the Pacific Northwest and Northern Plains (table 47). Specially, the magnitude of the elasticities of demand for wheat yield insurance with respect to net premium also decreases from the Pacific Northwest to the Northern Plains at the 65% coverage level (elasticities are -0.365 and -0.271, respectively). The elasticity of demand for wheat yield insurance at the 65% coverage level in the Pacific Northwest is about 14 times of the corresponding elasticity in the Southern Plains (-0.365 and -0.027).

Table 47. Estimated Elasticities of Wheat APH with respect to Net Premium

Pacific Northwest	-0.105	-	-0.302	-0.365***	0.032	-0.175	-	-
Northern Plains	-0.127**	-0.026	-0.174**	-0.271***	-0.154***	-0.264***	-0.279**	-0.274*
Southern Plains	-0.035	-0.318***	-0.223***	0.027	-0.186***	-0.145*	-	-

Table 48 summarizes the elasticities of demand with respect to producers' expectations of yield in the three major wheat producing regions. With higher expected wheat yield, producers are expected to purchase more wheat yield insurance at each coverage level. The expected yield effects vary across coverage levels and regions. The magnitude of the elasticities is the largest in the Pacific Northwest at each coverage level (table 48). Consider the 65% coverage level as an example. The elasticity of demand for wheat yield insurance with respect to wheat expected yield is 0.793 at the 65% coverage level in the Pacific Northwest, while the corresponding elasticities are 0.490 and 0.314 in the Northern Plains and Southern Plains (table 48). Thus, the elasticity of demand for wheat insurance in the Pacific Northwest is about three time of the elasticity in the Southern Plains (0.793 and 0.314, respectively). The large magnitude of the elasticities of demand for wheat yield insurance with respect to expected yield maybe related to the higher expected wheat yield of wheat in the Pacific Northwest. The wheat average yield in 1995-1997 is used to estimate producers' expected yield for 1998 and the average yield in 1999-2001 is used to estimate producers' expected yield for 2002. Figure 21 shows the weighted average yield of wheat in 1995-2002. During the period, the Pacific Northwest had the highest expected yield compared to the other two regions (figure 21).

Table 48. Estimated Elasticities of Wheat APH with respect to Yield Expectation

Variables	**50%**	**55%**	**60%**	**65%**	**70%**	**75%**	**80%**	**85%**
Pacific Northwest	0.848**	-	1.238***	0.793***	0.705**	0.640***	-	-
Northern Plains	0.421***	0.540***	0.619***	0.490***	0.380***	0.412***	0.390**	0.468**
Southern Plains	0.838***	1.021***	0.677***	0.314**	0.519***	0.490***	-	-

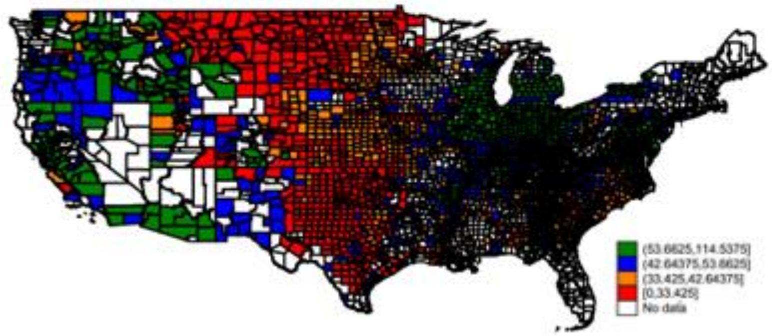

Figure 21. County Average Yield of Wheat in 1995-2002
Source: USDA's NASS.

Policy Implications

Crop Insurance has been targeted for cutting since the 2008 Farm Bill, especially when the federal budget is a concern. In this section, we estimate the possible changes of demand for wheat yield insurance if the government reduces wheat yield insurance subsidy rates by 10 percentage points, and the estimated changes in demand for each coverage level are listed in table 49.

Table 49. Expected Changes of Wheat Insurance Demand

	50%	55%	60%	65%	70%	75%	80%	85%
Pacific Northwest	-	-	-	-6.186%	-	-		
Northern Plains	-1.896%	-	-2.719%	-4.593%	-2.610%	-4.800%	-5.813%	-7.211%
Southern Plains	-	-4.969%	-3.484%	-	-3.153%	-2.636%		

Note: "-" denotes statistically insignificant change.

A 10 percentage points reduction in federal crop insurance premium subsidy rates will result in different changes in demand for wheat yield insurance across coverage levels (table 49). In the Pacific Northwest, the demand for wheat yield insurance is expected to decrease by 6.186% given a 10 percentage points reduction in premium subsidy rates (table 49). The expected changes in demand for wheat yield insurance are statistically insignificant among other coverage levels in the Pacific Northwest (table 49). In the Northern Plains, wheat producers are expected to reduce their demand for federal wheat yield insurance by 1.896%, 2.719%, 4.593%, 2.610%, 4.800%, 5.813%, and 7.211% at the 50%, 60%, 65%, 70%, 75%, 80%, and 85% coverage level, respectively, given a 10 percentage points cut in premium subsidies (table 49). The estimated change in demand at the 80% coverage level is 3.8 times greater than it is at the 50% coverage level in the Northern Plains (table 49). In the Southern Plains, wheat producers are expected to reduce their demand for federal wheat yield insurance by 4.969% at the 55% coverage level, while they will reduce the demand by 2.636% for the 75% coverage level (table 49). Thus, the same reduction in premium subsidy rates would result in different changes in demand for wheat yield insurance across coverage levels.

In the Northern Plains, wheat producers are more sensitive to the changes in premium subsidies for high coverage levels. For example, wheat producers are expected to reduce their demand for federal wheat yield insurance by -5.813% and -7.211% for the 80% and 85% coverage level, respectively, while they would reduce their demand for insurance slightly for the 50% and 60% coverage levels (-1.896% and -2.719%, respectively, see table 49). Therefore, a 10 percentage points reduction in premium subsidy rates would result in greater decreases in the demand for federal wheat yield insurance among high coverage levels in the Northern Plains. This result is counter to the major purpose of the 2000 ARPA, which intended to encourage producers to purchase crop insurance at relatively high coverage levels (Babcock and Hart 2005).

However, in the Southern Plains, wheat producers are more responsive to the premium changes at the 55% coverage level than other coverage levels. The demand for federal wheat insurance at 55% coverage level is expected to decrease by 4.969%, while the changes in demand for wheat insurance at the 80% and 85% coverage levels are statistically insignificant (table 49).

Moreover, the expected changes in demand for wheat yield insurance are different across regions. At the 75% coverage level, wheat producers would decrease their demand for federal yield insurance by 4.800% and 2.636% in the Northern Plains and Southern Plains, respectively (table 49). And the expected changes in wheat yield insurance demand for the 75% coverage level is statistically insignificant in the Pacific Northwest.

Overall, wheat producers would have different responses to the changes in subsidy rates across coverage levels and regions. The same reduction in federal premium subsidy rates would result in different decreases in the demand for wheat insurance. Therefore, the differences in elasticities across coverage levels and regions should be considered when the government applies a federal premium subsidy adjustment.

Conclusions

The present study is the first to explore the demand for wheat yield insurance across coverage levels and major producing regions. The results show that the demand for wheat yield insurance with respect to net premium per acre per dollar of wheat value is inelastic and the net premium effects vary across coverage levels and regions. The elasticity of demand for wheat yield insurance with respect to net premium is statistically insignificant at the 55% coverage level in the Northern Plains (-0.026) and it is -0.365 and statistically significant at the 65% coverage level in the Pacific Northwest. The estimated elasticities are basically consistent with the findings in previous studies. The elasticities of demand for wheat insurance are reported as -0.12 and -0.27 by Goodwin, Vandeveer, and Deal (2004) and O'Donoghue (2014), respectively.

The results find a strong relationship between the demand for wheat yield insurance and the expected yield of wheat. As expected yield increases, the demand for wheat yield insurance increases at each coverage level in the three regions, but the yield effects change over coverage levels and regions. The demand for wheat yield insurance with respect to expected yield is elastic at the 60% coverage level in the Pacific Northwest at 1.238 (table 48). The demand for wheat yield insurance with respect to expected yield is inelastic among other coverage levels and the elasticity of demand for wheat yield insurance with respect to expected yield ranges from 0.390 (80% coverage level in the Northern Plains) to 0.848 (50% coverage level in the Southern Pains).

The present study points out the importance of separating coverage levels and regions in the analysis of demand for wheat yield insurance. The net premium, the expected yield of wheat, the relative yield risk, the total planted acreage of wheat, the percentage of irrigated cropland, and the percentage of cropland operated by females have different effects on the demand for wheat yield insurance across coverage levels and regions. For example, the elasticity of demand for wheat yield insurance with respect to net premium at the 65% coverage level is about 14 times of the elasticity at the 55% coverage level. The percentage of cropland operated by females has statistically significant effects among relatively low coverage levels in the Northern Plains and the effects change to positive at the 80% coverage level in the Northern Plains.

The federal crop insurance is an integrate part of the farm safety net since passage of the 2014 Farm Bill. Although there is no reduction or restriction on the premium subsidies in the current farm bill, considering the expensive spending, there could be future adjustments on premium subsidy rates. The different elasticities across coverage levels and regions derived provide detailed insights into the effects of changing federal subsidy.

The objective of the study is to get an approximation of the demand for wheat insurance based on available data. One caveat of this study is that adverse selection is not included in the model. Considering the potential existence of adverse selection, further studies on the effect of adverse selection on the demand for wheat yield insurance would be useful.

CHAPTER IV

IMPACTS OF CLIMATE CHANGE ON FEDERAL CROP INSURANCE LOSS RATIOS

Introduction

Farming is risky due to the impacts of climate conditions, especially in rain-fed agricultural regions. Studies show that climate change is inevitable and climate variability increases with global warming (Thornton et al. 2014). As a result, farming is more risky and historical yield patterns are less reliable for the estimation of future production. The Risk Management Agency (RMA) designs and regulates the Federal Crop Insurance Program (FCIP) to help farmers manage risks. The FCIP has experienced rapid development since the 1980 Federal Crop Insurance Act. In 2015, approximately 300 million acres were insured in the FCIP and the corresponding liabilities were more than \$102 billion. Figure 22 shows the total ensured acreage under the FCIP.

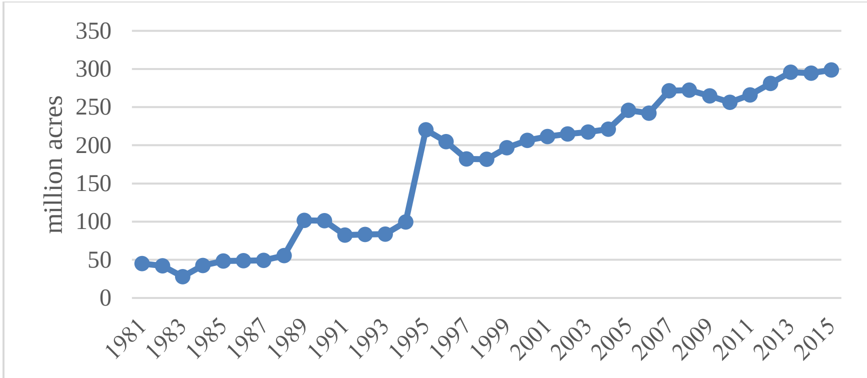

Figure 22. Total Ensured Acreage in the Federal Crop Insurance Program (FCIP)

Source: USDA, RMA, Summary of Business Reports.

The FCIP has undergone scrutiny regarding regional disparities (Glauber 2004; Babcock 2008; Woodard et al., 2011), overpricing (Babcock, Hart, and Hayes 2004) and government spending (Goodwin and Smith 2013). However, the impacts of climate change on the FCIP received very little attention. Figure 23 displays the national crop insurance gross loss ratios for all crops, all plans and all coverages. Relatively large gross lose ratios occurred in 1988 at 2.45 (indemnity/gross premium), 1993 at 2.19, 2002 at 1.39 and 2012 at 1.58 and these losses were mainly due to weather extremes. Figure 24 shows corn and soybean production in the U.S. during 1985-2015. The drought in 1988 was nationwide and cost $15.6 billion in losses of agriculture (Riebsame, Changnon, and Karl 1991; Wu and Wilhite 2004). In 1988, corn and soybean production were reduced by 45% and 26%, respectively, compared to the 1985-87 average (Wu and Wilhite 2004). In 1993, spring-seeded crops in the Midwest were destroyed by floods (Cassidy and Althaus 1994). According to Cassidy and Althaus (1994), more than 6 million acres of corn and soybean production were significantly affected by the 1993 floods. In 2002, western and eastern agricultural regions had severe droughts. The gross loss ratios of corn crop insurance were greater than three in Colorado (3.72), Kansas (3.46) and Ohio (3.85), and the loss ratios were greater than four in Pennsylvania (4.08) as well as Delaware (4.28). The high loss ratio in 2012 was also related to droughts and the damage mainly occurred in the Corn Belt. Figure 26 shows crop insurance loss ratios by county. The FCIP experienced high losses mainly in the Corn Belt, and the severe damage did not occur in the western and eastern counties in year 2012.

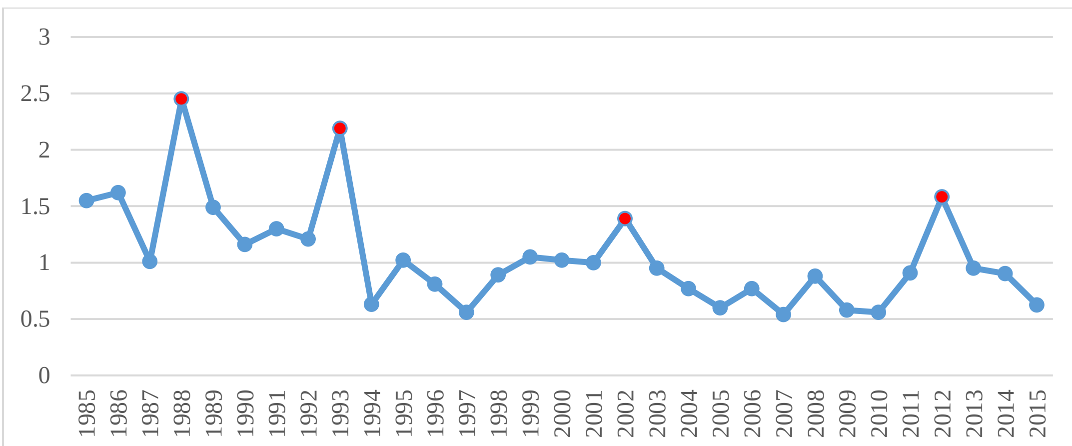

Figure 23. National Crop Insurance Gross Loss Ratios

Source: USDA, RMA, Summary of Business Reports.

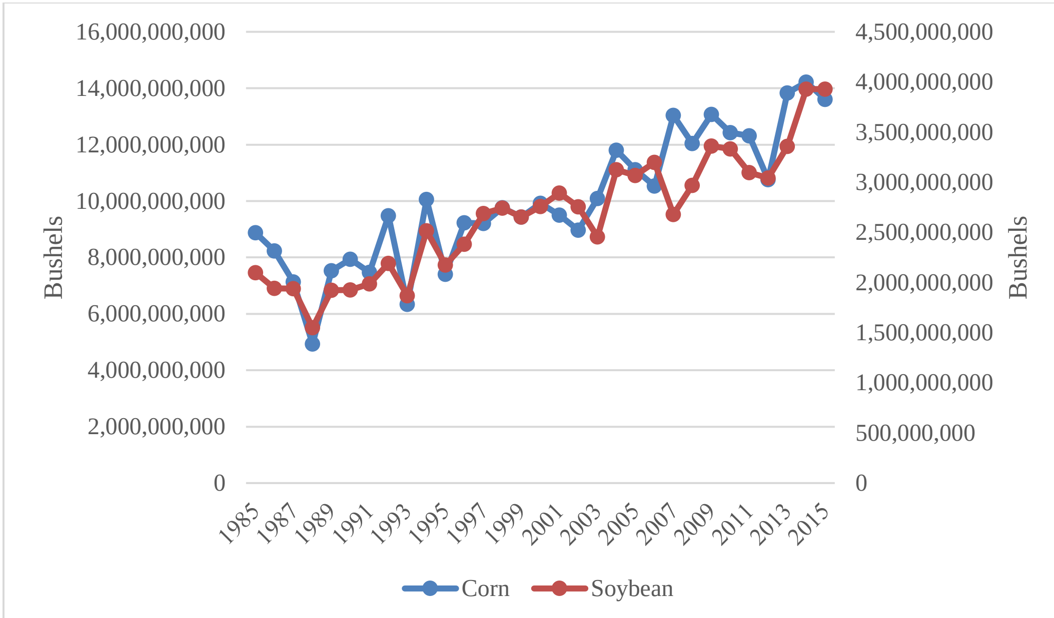

Figure 24. Corn Production in the U.S.

Source: USDA, NASS.

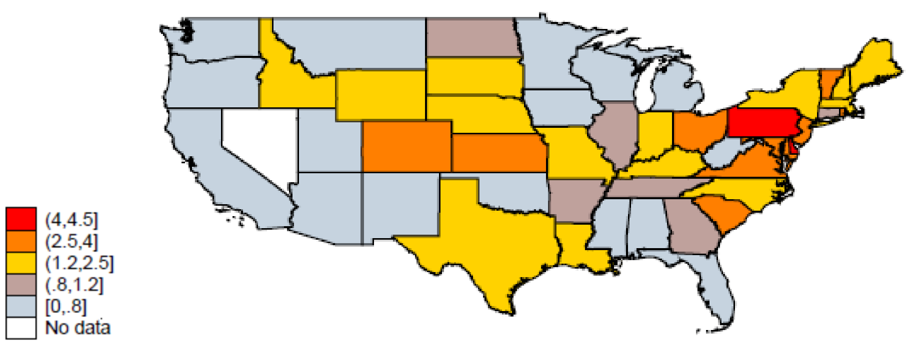

Figure 25. 2002 Corn Crop Insurance Gross Loss Ratios

Source: USDA, RMA, Summary of Business.

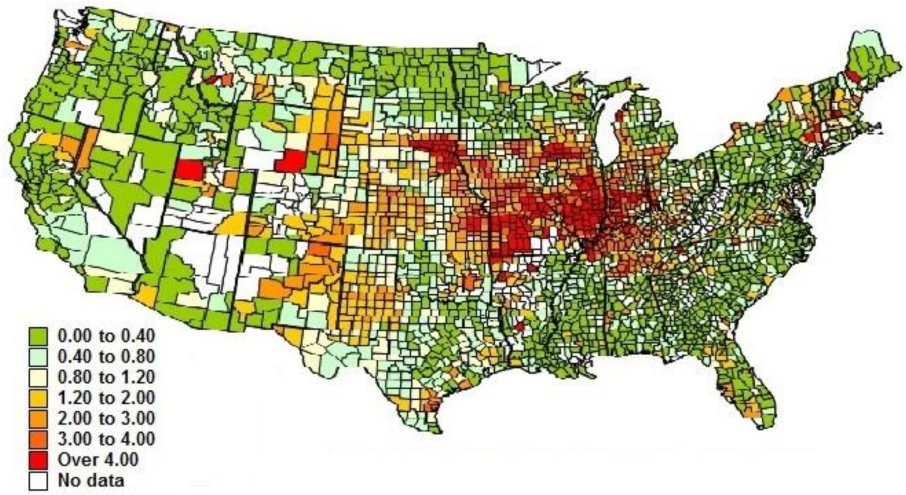

Figure 26. 2012 Crop Insurance Gross Loss Ratios by County

Source: Schnitkey and Sherrick 2013.

Moreover, these historical loss ratios were constructed based on gross premium, which are the ratios of crop insurance indemnities to gross premium. When examining the net loss ratios, which are the rates of crop insurance indemnities to net premium (gross premium - government subsidies), the losses of crop insurance were even higher when extreme weather happened. For example, the national net loss ratios were 3.25, 2.98, 3.46, and 4.22 in 1988, 1993, 2002, and 2012, respectively. In 2002, the net loss ratios were 6.77, 6.28, 6.73, 8.91 and 9.45 in Colorado, Kansas, Ohio, Pennsylvania and Delaware, respectively. Therefore, the losses of crop insurance were extremely high when natural disasters occurred.

When weather extremes happened, crop insurance indemnities also increased significantly because of the increased participation in the FCIP. Figure 27 presents crop insurance indemnity costs and liabilities for all crops, all regions and all contracts. In 1988, only 25% of eligible acreage participated in the FCIP (Glauber 2007). Although the natural disaster in 1988 had bigger range and more intensive than the weather extremes in the other three years (1993, 2002, and 2012), the indemnity payments of crop insurance in 1993 were the lowest. In 1988, the total crop insurance indemnity payment was approximately $1.07 billion, and the indemnity payment was more than $17.45 billion in 2012. The FCIP would have significantly large losses in the future if weather extremes occur considering the high participation in the crop insurance program.

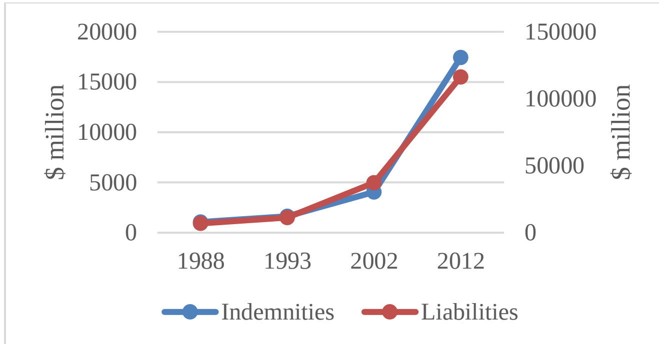

Figure 27. National Crop Insurance Indemnities and Liabilities

Source: Glauber 2002; USDA, RMA, Summary of Business.

The purpose of this chapter is to test the ability of APEX to be used for climate change analysis in a crop insurance setting. The analysis will be a proof of the concept for a methodology to analyze the impacts of climate change on the loss ratio of crop insurance for a representative farm. A more comprehensive analysis using the method can be undertaken for multiple crops and regions once the methodology has been tested and validated.

This chapter is constructed as the followings. In the first part, a crop and soil productivity simulation model (APEX) is parameterized and calibrated to estimate grain sorghum yields for an actual farm. A grain sorghum farm in Sherman, Texas is selected as a representative farm. The weather information projected by different weather models are used in the crop growth model to simulate the yield of grain sorghum for 25 years in the second part. In the third part, the simulated crop yields are applied in the crop insurance ratemaking procedures to estimate crop insurance premiums for alternative weather models.

Crop Yield Estimation

As the IPCC emphasized that the impacts of climate change on agriculture should be focused on regional models (Tan and Shibasaki 2003), a representative farm is selected to use local features to estimate the effects of climate change on the loss ratios of crop insurance in this study. A non-irrigated grain sorghum farm in Sherman County, Texas is randomly selected from the Agricultural Food and Policy Center (AFPC) database. The farm's ten years of annual yields, planted acreage, and RMA's T yield are available in the dataset. Table 50 lists the summary statistics of annual yields of non-irrigated grain sorghum for the selected farm. Figure 28 shows annual grain sorghum yields for the farm. The yield of non-irrigated grain sorghum in 2013 at the county level is missing in the NASS data base.

Table 50. Summary Statistics of Non-Irrigated Grain Sorghum Yields

	Farm	Sherman County	Texas
Mean	43.222	37.513	48.778
StDev	16.890	10.277	8.827
Min	13.000	19.000	34.000
Median	42.000	37.150	49.000
Max	77.000	56.800	60.700
CV	39.078	27.395	18.097

Source: USDA, NASS and private data.

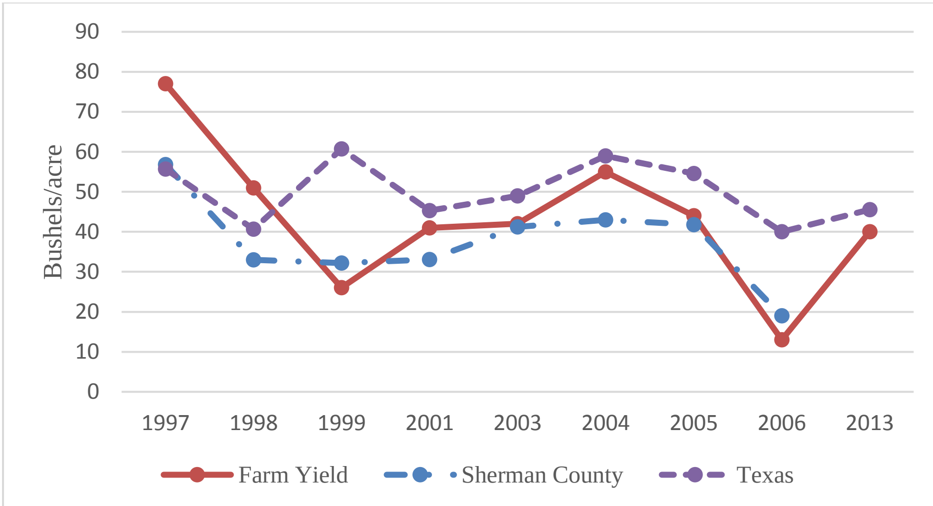

Figure 28. Annual Yields of Grain Sorghum at Different Levels

Source: USDA, NASS.

Among the three yield series, the coefficient of variation for non-irrigated grain sorghum is the largest at the farm level (39.078), which implies that the yield of grain sorghum is more variable at the farm level. During the ten years of available data, the farm's grain sorghum yield reached its maximum in 1997 and reached its minimum in 2006 at each level. The yield trend at the farm level is roughly consistent with the yield trend at the county level, but with larger variance.

The Agricultural Policy Environmental eXtender (APEX) model was used to estimate future crop yields in this study. Historical crop yields for the farm were used to calibrate and validate the APEX model. The APEX model is built on the Environmental Policy Integrated Climate (EPIC) model (Williams et al. 1995) and it is developed and maintained by the Blackland Research and Extension Center in Temple, Texas. The APEX model can be used to estimate the effects of temperature, precipitation, farm management, and fertilizer and pesticide use on crop yields for areas with homogeneous soils and management (Gassman et al. 2010). It has been widely tested and recognized as a reliable tool for crop yield simulation (Roloff, Dejong, and Nolin 1998; Bryant et al. 1992; Edwards et al., 1994; Wang et al. 2012). Fourteen main components are incorporated in the APEX model including: climate inputs, routing, crop growth and competition, hydrologic balance, livestock grazing, phosphorous and nitrogen cycling and losses, water and wind erosion, carbon cycling routine, manure management inputs, manure erosion, feedlot dust, reservoir and economic components. In this study, two interfaces (ArcAPEX and APEXeditor) of the APEX model are used.

ArcAPEX is a user interface which combines the Geographic Information System (GIS) and the APEX model (Tan and Shibasaki 2003). It is built as an extension to the ArcGIS software. In the APEX model, each research area should be relatively homogeneous regarding soils, land use, topography, weather and management. The homogeneous area is called a subarea or a Hydrologic Response Unit (HRU) in the APEX model. According to Wang, Tuppad, and Williams (2011), "Each sub-area is associated with a channel for routing." Generally, the delineation of subarea is difficult due to the complexity unless the boundaries of subareas are well known by researchers. In this study, the boundaries of the representative farm are unavailable due to limitations in the data source. Therefore, following Tuppad et al. (2009), the GIS platform (ArcMap) as well as the routing component in the APEX model are used to analyze and parametrize geometric and topographic characteristics, channel dimensions and slope distributions in order to delineate subareas. In addition to delineation, the integration of ArcGIS with the APEX model simulates crop yields and exports input data as well as parameters for future modeling.

APEXeditor (version APEX0806) is another interface of the APEX model. A series of Visual Basic for Applications (VBA) macros are built in a Microsoft Excel file. The APEXeditor interface can be used to read and revise input datasets as well as parameters and run the APEX model. It is a convenient tool to manipulate input datasets required by the APEX model. The datasets extracted from the ArcAPEX interface are revised in the APEXeditor interface to better fit local characteristics. A flowchart of the GIS- and Excel- based APEX interfaces is shown in figure 29.

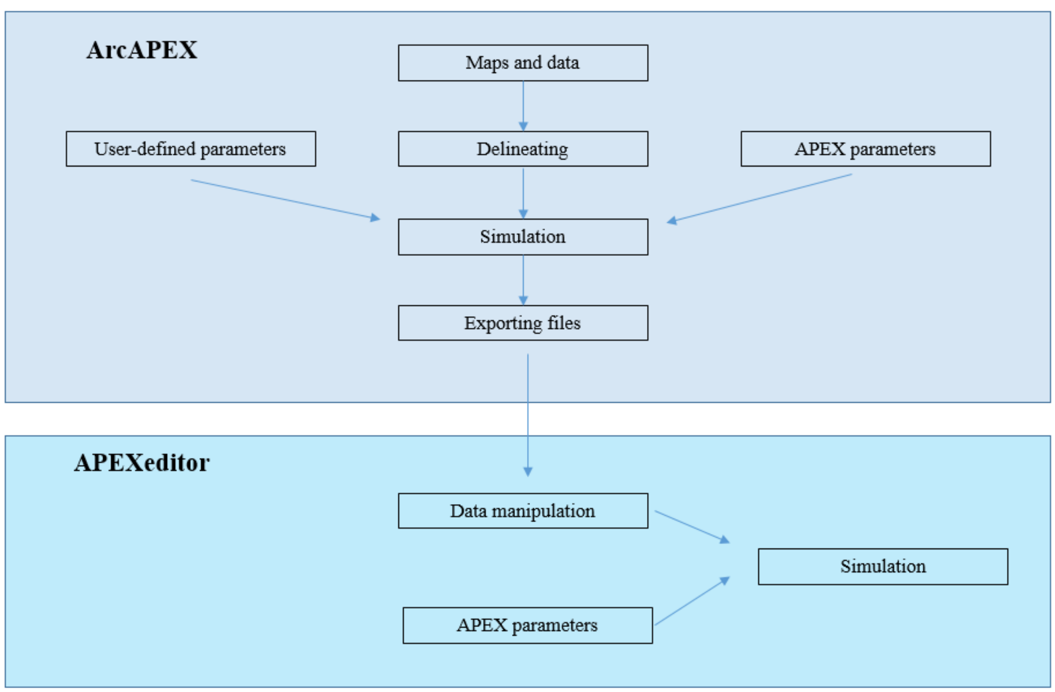

Figure 29. The Flowchart of ArcAPEX and APEXeditor

Subarea Delineation

Delineating of subareas is the first step in developing an APEX model. In this study, the boundaries of subareas are delineated based on a Digital Elevation Model (DEM). A 30-meter DEM for Sherman County, Texas is downloaded from the U.S. Geological Survey (USGS) Earthexplorer site (table 51). A projection of the DEM is generated by using tools in ArcMap (figure 30). A single-flow direction algorithm available in ArcMap is used to generate required flow information for subarea delineation (figure 31).

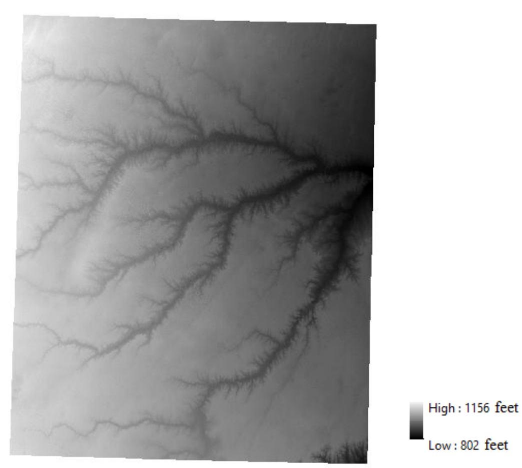

Figure 30. A DEM-based Projection of Sherman, Texas

Source: USGS. Available at: http://earthexplorer.usgs.gov/

Table 51. Data Source of the APEX Model

Input	Resolution	Source	Location/time period
Digital Elevation Model (DEM)	30m	U.S. Geological Survey EarthExplorer	Sherman County, Texas
Soils	1000m	Harmonized World Soil Database (HWSD)	Sherman County, Texas
Temperature	Daily	Climate Forecast System Reanalysis (CFSR)	1/1/1979 - 7/31/2014
Precipitation	Daily		
Solar radiation, relative humidity and wind	Daily		

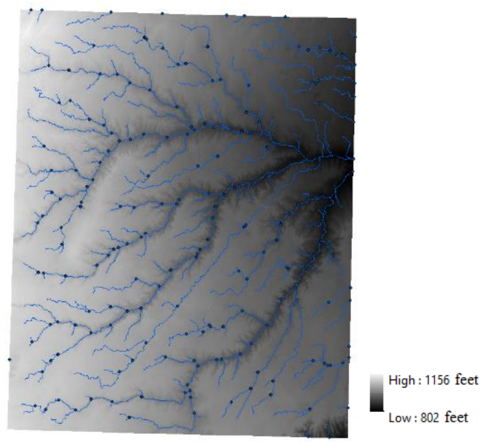

Figure 31. Flow Raster for Sherman County, Texas

An outlet is manually added on a randomly selected channel, and then a subarea associated with the outlet is automatically delineated by ArcAPEX (figure 32). The subarea delineated in ArcAPEX is 147.8 acres, which matches with the size of a field unit on the representative farm (148.9 acres). The latitude and longitude are 36.376 and -101.988 at the centroid of the subarea. Because the trend of non-irrigated grain sorghum yields in Sherman County, Texas is basically consistent with the corresponding trend in the representative farm, the delineated subarea is used to represent the farm in this study. Parameters in the APEX model are calibrated based on the farm's characteristics.

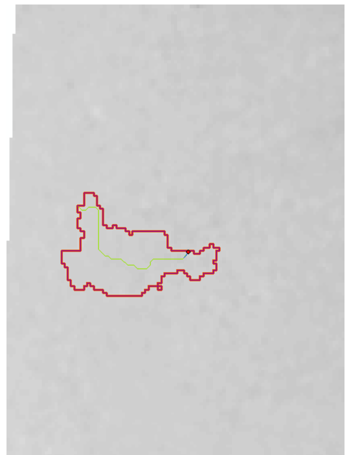

Figure 32. DEM-Based APEX Subarea Delineation

Subarea Analysis

After delineation, APEX parameters and datasets are defined based on the representative farm's characteristics. ArcAPEX has default folders for weather data. The closest weather station is selected by the algorithm in ArcAPEX and the weather data collected by this weather station are used in this part. The weather data are revised in the next part in the APEXeditor interface. Similarly, default soil data in ArcAPEX are applied in this part and revised in the APEXeditor interface. A single slope is assumed for the subarea, and the slope information is computed and analyzed by ArcAPEX. The APEX model is run in the ArcMap platform, and more than 40 datasets are generated by the interface. These datasets are exported into the APEXeditor interface in the next step for future adjustments to better fit the local features.

The input datasets and parameters required by the APEX model are extracted from ArcAPEX interface and imported into the APEXeditor for adjustments. The major changes in the datasets and parameters are related to soil data and weather data.

Soil information for Sherman County, Texas is extracted from the Harmonized World Soil Database (HWSD) (table 52). Instead of using the HSWD Viewer to manually query the dataset, the HWSD is accessed and queried in the open-source R project. Detailed code for R version 3.1.0 is attached in Appendix II.

The latitude of Sherman County, Texas ranges from 36.055 to 36.501, and the longitude ranges from -101.623 to -102.163. The boundary map for Sherman is shown in figure 33. A corresponding rectangular bounding box is created in R regarding the range of latitude and longitude of Sherman County, Texas. Based on the HWSD dataset, Kastanozems and Calcisols are the two soil types in this region (figure 34) and they account for 98.90% and 1.10% of the land, respectively. Because the latitude and longitude of the centroid of the subarea are 36.376 and -101.988, the corresponding soil type in the subarea is Kastanozems. The associated soil data file is extracted from the HWSD database by using the R project. There are three soil layers in the subarea, and all the three layers are loam. Detailed soil information is listed in Appendix III.

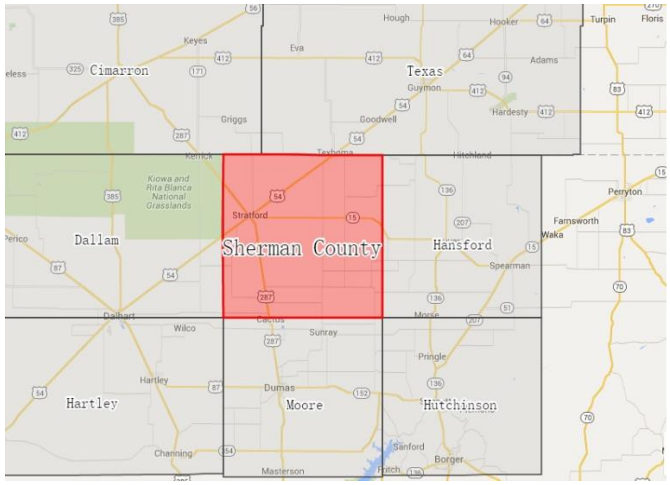

Figure 33. The Boundary Map for Sherman County in Texas, U.S.

Source: https://www.maptechnica.com/us-county-boundary map/county/Sherman/state/TX/countyid/48421

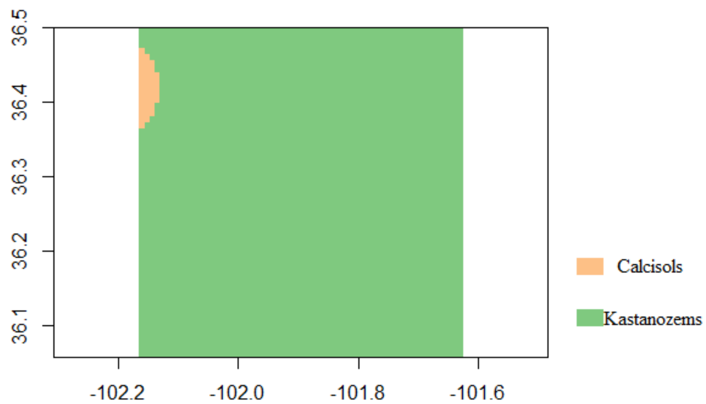

Figure 34. Soil Classes in Sherman County, Texas

The soil parameters collected from the HWSD dataset are not enough for running the APEX model. The soil albedo value is set at 0.17 at the beginning to test the model because the soil albedo ranges from 0.1 to 0.23 for clay loam (Orsini et al. 2000) and clay loam is the dominant soil in Sherman County, according to the Soil Survey of Sherman

County, Texas (1975). Soil hydrologic group could be set at 2 or 3 because loam soil belongs to group 2 and clay loam is in group 3. Another soil parameters, such as soil water tension, conductivity and water holding capability, are calculated in the Soil Water Characteristics Program (SWCP) based on the soil texture, organic matter, gravel content, salinity and compaction extracted from the HWSD (figure 35). The units in the SWCP are changed to metric unit to match with units in the APEX model. The computed results are shown in table 52. The soil parameters are used in the APEXeditor (version 0806) to revise the soil data generated by ArcAPEX.

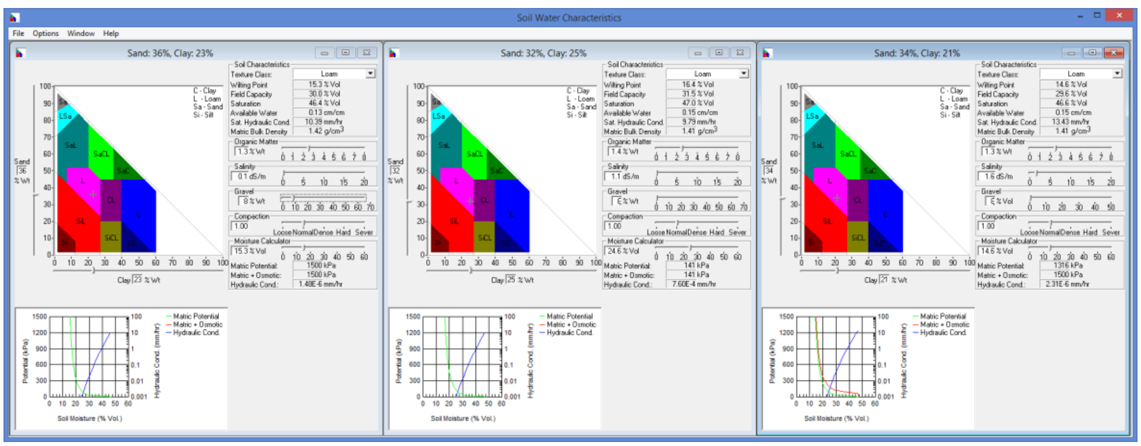

Figure 35. Soil Water Characteristics

Table 52. Soil Characteristics of Sherman County, Texas

Sequence	Sand %Wt	Clay %Wt	Silt %Wt	Gravel %Vol	Salinity dS/m	Organic Matter %Wt	Texture Class	Wilting Point %Vol	Field Capacity %Vol	Saturation %Vol
1	36	23	41	8	0.1	1.3	Loam	15.3	30.0	46.4
2	32	25	43	8	1.1	1.4	Loam	16.4	31.5	47.0
3	34	21	45	8	1.6	1.3	Loam	14.6	29.6	46.6

Table 52. Continued.

Sequence	Available Water	Saturated Hydraulic Conductivity	Bulk Density	Moisture	Matric Potential	Matric+Osmotic	Hydraulic Condition
	cm/cm	mm/hr	g/cm^3	%Vol	kPa	kPa	mm/hr
1	0.13	10.39	1.42	15.3	1500	1500	1.48E-6
2	0.15	9.79	1.41	24.6	141	141	7.60E-4
3	0.15	13.43	1.41	14.6	1316	1500	2.31E-6

Weather Information

The APEX model requires daily solar radiation (J/m^2), maximum temperature (°C), minimum temperature (°C), precipitation (mm), relative humidity and wind speed (m/s). In this study, weather data are requested from the National Centers for Environmental Information (NOAA) (requests can be submitted at http://www.ncdc.noaa.gov/cdo-web/) and the database of Global Weather Data for SWAT (GWDS) (request can be submitted at http://globalweather.tamu.edu). The NOAA weather data for Sherman County, Texas starts from July 1, 1911 and ends at May 2, 2016. Solar radiation, relative humidity and wind speed are missed in the NOAA dataset. An example of the NOAA dataset is shown in table 53. In the dataset, -9999 represents missing values.

Table 53. An Example of the NOAA Weather Data

STATION	STATION_NAME	ELEVATIO	LATITUDE	LONGITUD	DATE	PRCP	SNWD	SNOW	TSUN	TMAX	TMIN	AWND
GHCND:USW00003024	BORGER HUTCHINSON CO AIRPORT TX US	930.9	35.695	-101.395	19970601	-9999	-9999	-9999	-9999	88	59	-9999
GHCND:USW00003024	BORGER HUTCHINSON CO AIRPORT TX US	930.9	35.695	-101.395	19970602	-9999	-9999	-9999	-9999	84	63	-9999
GHCND:USW00003024	BORGER HUTCHINSON CO AIRPORT TX US	930.9	35.695	-101.395	19970603	-9999	-9999	-9999	-9999	78	62	-9999
GHCND:USW00003024	BORGER HUTCHINSON CO AIRPORT TX US	930.9	35.695	-101.395	19970604	-9999	-9999	-9999	-9999	76	59	-9999
GHCND:USW00003024	BORGER HUTCHINSON CO AIRPORT TX US	930.9	35.695	-101.395	19970605	-9999	-9999	-9999	-9999	79	59	-9999
GHCND:USW00003024	BORGER HUTCHINSON CO AIRPORT TX US	930.9	35.695	-101.395	19970606	-9999	-9999	-9999	-9999	80	61	-9999
GHCND:USW00003024	BORGER HUTCHINSON CO AIRPORT TX US	930.9	35.695	-101.395	19970607	-9999	-9999	-9999	-9999	79	64	-9999
GHCND:USW00003024	BORGER HUTCHINSON CO AIRPORT TX US	930.9	35.695	-101.395	19970608	-9999	-9999	-9999	-9999	73	58	-9999
GHCND:USW00003024	BORGER HUTCHINSON CO AIRPORT TX US	930.9	35.695	-101.395	19970609	-9999	-9999	-9999	-9999	73	58	-9999
GHCND:USW00003024	BORGER HUTCHINSON CO AIRPORT TX US	930.9	35.695	-101.395	19970610	-9999	-9999	-9999	-9999	75	59	-9999
GHCND:USW00003024	BORGER HUTCHINSON CO AIRPORT TX US	930.9	35.695	-101.395	19970611	-9999	-9999	-9999	-9999	93	64	-9999

Weather data collected from the GWDS covers the time period from January 1, 1979 to July 31, 2014. Although the time period in the GWDS datasets is shorter compared with the NOAA dataset, the GWDS data have all the weather variables required by the APEX model (solar radiation, maximum temperature, minimum temperature, precipitation, relative humidity and wind speed). Therefore, weather data requested from the Global Weather Database are used in this study.

In the GWDS, two weather datasets are available for Sherman County, Texas. The two datasets are collected from two weather stations. Both of the weather datasets cover the time period from January 1, 1979 to July 31, 2014. The latitude and longitude for the two weather stations are 36.062, -101.875 and 36.375, -101.875, respectively. The locations of the two weather stations are shown in figure 36.

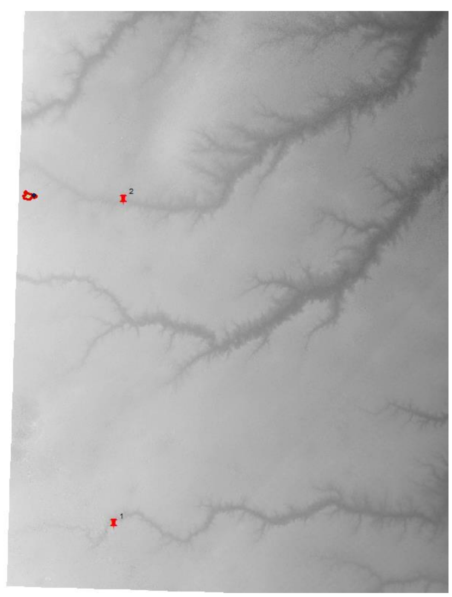

Figure 36. Two Weather Stations in the Subarea

According to figure 36, station 2 is much closer to the subarea in this study, compared with station 1. Therefore, weather data collected by weather station 2 is applied in the APEX model. Summary statistics of weather variables are shown in Appendix VI.

The setup of the APEX model is sensitive to format. The format of weather data is converted by using a component in the APEX Weather Generator (APEX WXGM). All input datasets associated with maximum temperature, minimum temperature, participation, wind, relative humidity and solar radiation are updated by the weather data collected from GWDS in APEXeditor interface.

Figure 37 shows the file structure in APEXeditor. Not only the input datasets and parameters, but all related files should be adjusted when changes have been made in the inputs. The APEX model is run for 17 years to represent the years in the farm dataset. Summary statistics of simulated yields and historical yields for non-irrigated grain sorghum are presented in table 55. The simulated yields are converted to busheles per acre to match with the units in the original yield dataset. Figure 38 shows the observed yields and simulated yields by the APEX model.

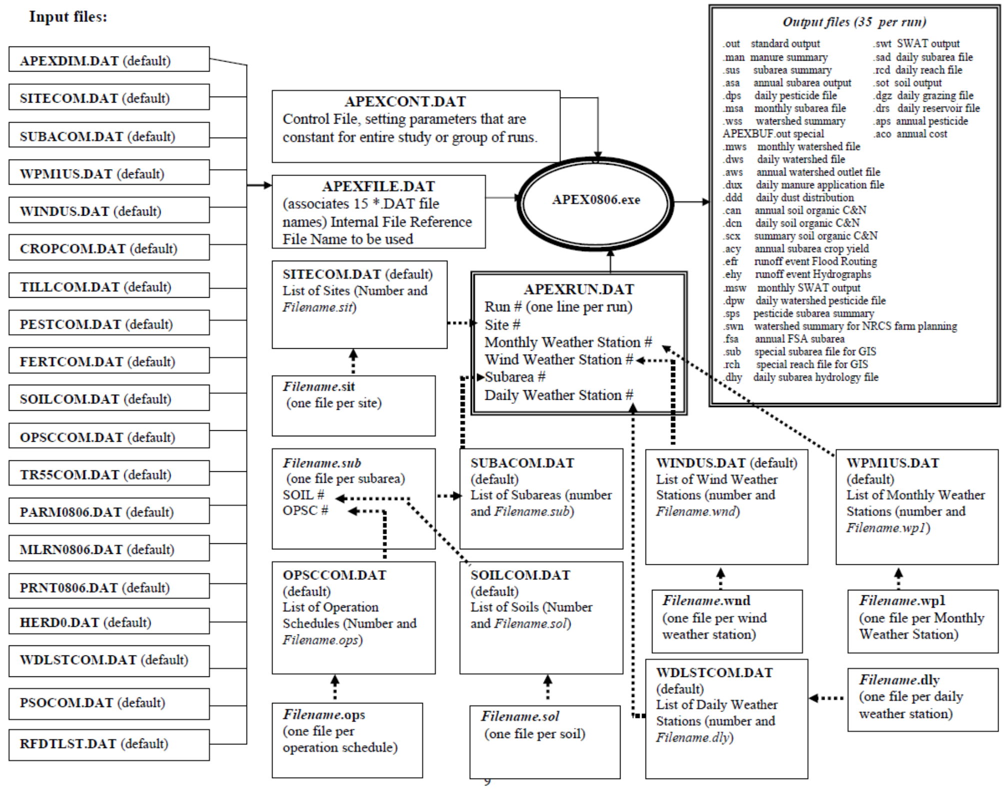

Figure 37. APEX Files Structure

Source: Steglich and Williams 2008.

Table 54. Summary Statistics of Farm Historical Yields and Estimated Yields

	Simulated Yields	Historical Yields
Mean	43.222	47.885
StDev	16.890	15.280
CV	39.078	31.910
Min	13.000	28.061
Median	42.000	45.600
Max	77.000	73.821

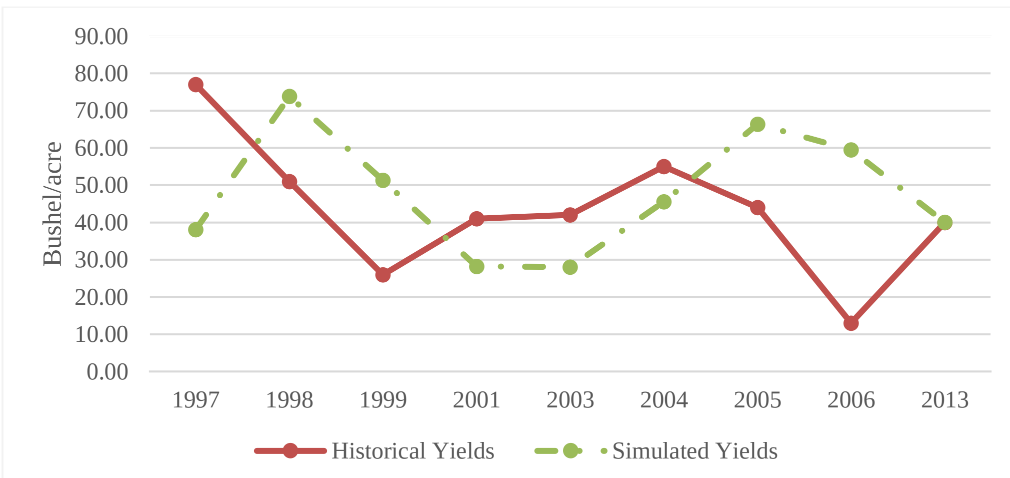

Figure 38. Historical Farm Yields and Simulated Yields

Calibration

The representative farm's historical yields data are used to calibrate the APEX model. The APEX model is calibrated by adjusting the parameters that are found sensitive in experts' opinions and literature (Gassman et al. 2009). Appendix VII shows the selected parameters for the calibration process. Figure 39 illustrates some simulations during the calibration process. Table 56 shows an example of the APEX output file.

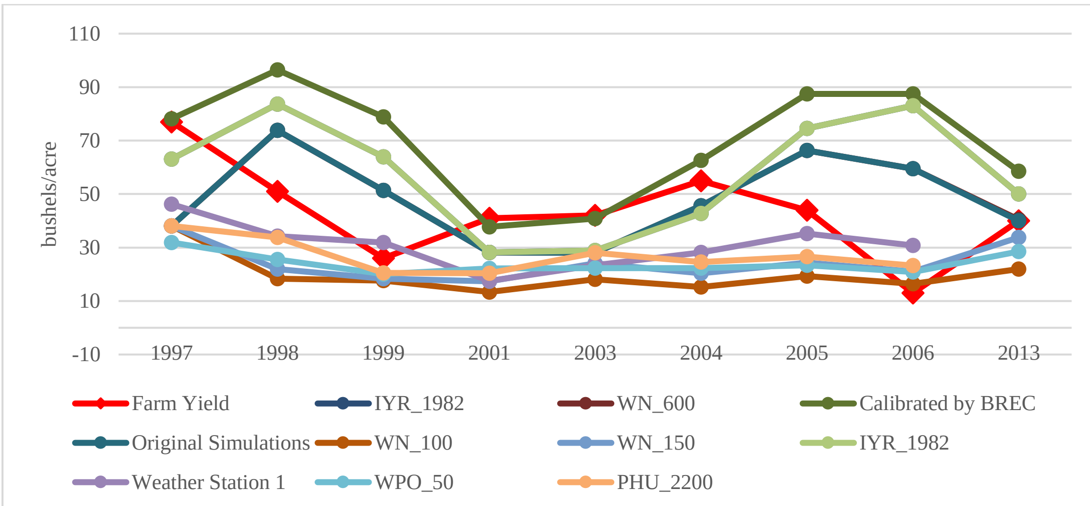

Figure 39. Examples of Simulation Results

The major difficulty for the calibration lays on the data limitations. Important information, such as operation schedules, the leaf area index, root depth and weight, and crop height, is missed in the database. Fortunately, experts at the Blackland Research and Extension Center (BREC) give great assistance in this section.

Irrationally high water stress is initially observed in the simulation outputs. For example, in year 2001, grain sorghum has water stress for 58 days during the 128 growing days. Although the low yields caused by water stress can be offset by adjusting other parameters, such as applying more fertilizer, the APEX model simulations did not initially reflect the observed yields well (figure 39). Therefore, weather information collected from weather station 1 is also tested in the APEX model in case the weather data provided by weather station 2 is biased (see "Weather Information" section for descriptions of the weather information). However, changing weather information and adjusting sensitive parameters did not improve the accuracy of the APEX model. The simulated yields could only reflect the representative farm's observed yields in year 2001 and 2003 (figure 39).

After careful experimentations and literature review, the poor fit problem is attributed to the weather data collected from the GWDS. The weather information in the GWDS is collected from the CFRS. The precipitation data in the CFRS is satellite-based estimates, not gauged rainfall data. Worqlul et al. (2014) discuss the error in daily precipitation data between the point-gauged data and the satellite-predicted precipitation data. Considering the irrationally high water stress in the APEX simulation outputs, the weather information is substituted by the gauged precipitation information provided by the BREC. The weather data provided by the BREC contains weather information in 1960 – 2010. Thus, the APEX model is adjusted to simulate grain sorghum yields through 2010.

The APEX model is built based on hundreds of parameters. However, only limited information is available in the representative farm's dataset. Fortunately, the APEX model is able to calculate and fill in the unknown parameters, and the process is referred to as “warm up.” Therefore, the crop yields in 1997 and 1998 are used to “warm up” the APEX model according to experts’ opinions.

Different sources of weather data are used in the APEX model, but none of them could predict the extremely low yield in year 2006 for the representative farm. Without detailed information to be incorporated in the APEX model (e.g., insect disasters, different operation schedules), the APEX model cannot capture the extremely low yields by only relying on the weather change in year 2006. Besides, the representative farm’s yield in year 2006 (13 bushels/acre) is 46% lower than the 2006 average yields in the Sherman County (19 bushels/acre), and 207% lower than the average 2006 grain sorghum yields in Texas (40 bushels/acre). Therefore, the observed yield in year 2006 is excluded and observed grain sorghum yields in 1999 – 2005 are selected to calibrate the APEX model.

The performance of the APEX model is evaluated by statistical comparisons and tests. The difference between the cumulative distribution functions (CDF) of the observed yields and simulated yields is measured by using the CDFDEV( ) function in Simetar©. The sum of the squared difference between two CDFs and a penalty for differences in the tails is calculated by the function (Richardson, Schumann, and Feldman 2006):

$$CDFDEV = \sum_{i=1}^{N}(F(x_i) - G(x_i))^2 + w_i$$

Where $F(x_i)$ is the CDF of the observed yields and the $G(x_i)$ is the CDF of the simulated yields by the APEX model, and w_i represents the penalty function. The best calibrated model is selected based on the smallest results of the CDFEDV( ) function. Because the unit of simulated yields from the APEX model is ton/hectare, the observed yields (bushel/acre) are converted to tons/hectare, and all the calculations are based on yields as ton/hectare for convenience. Figure 40 shows the observed grain sorghum yields and the simulated yields by the calibrated APEX model. The CDF difference between the observed yields and simulated yields is 0.41, and it is 0.35 between the representative farm's yields and the average yields of Sherman County, Texas in 1999 – 2005. The CDF difference is 0.24 between the observed yields and the simulated yields by the selected calibrated model, while the difference is 0.82 between the farm's observed yields and the average yields of Sherman County, Texas in 1997 – 2005. Therefore, considering the limited data availability, the calibrated model is considered to a good fit of the observed yields.

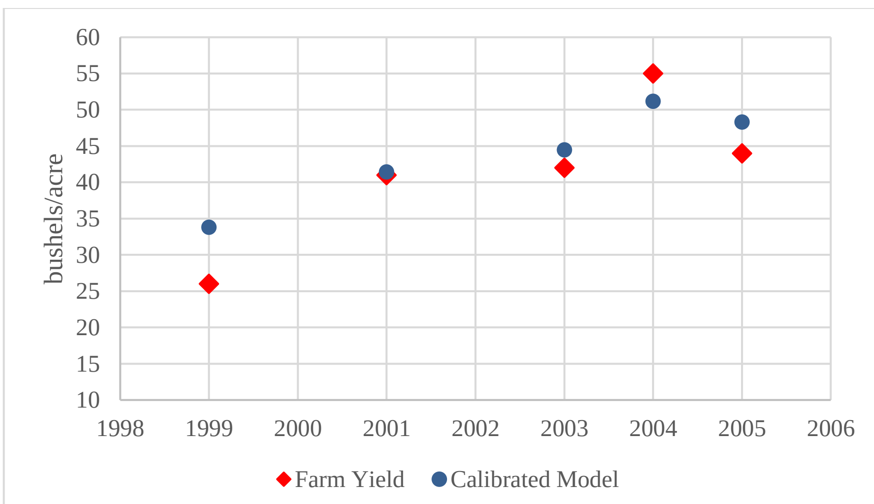

Figure 40. Comparisons of Grain Sorghum Yields

The Student's t-test and F-test are used to test the simulated grain sorghum yields generated by the calibrated APEX model. Statistical test results are presented in table 55. The Student's t-test fails to reject the null hypothesis that the means of the observed yields and the simulated yields are equal at the 95% confidence level. The F-test fails to reject the null hypothesis that the variances in the observed yields and the simulated yields are equal at the 95% confidence level. Therefore, there is no statistical difference between the means and variances in the observed yields and simulated yields. Overall, the calibrated model is considered as a good fit.

Table 55. Statistical Test Results

Distribution Comparison of Two Data Series				
Confidence Level		95.00%		
	Test Value	Critical Value	P-Value	
2 Sample t Test	-0.40	2.97	0.700	*Fail to Reject the Ho that the Means are Equal*
F Test	2.38	6.39	0.211	*Fail to Reject the Ho that the Variances are Equal*

Impactions of Climate Change on Federal Crop Insurance

The focus of this part is on describing how to project climate change impacts on federal crop insurance through the effects on crop yields. To do so, a) weather projections are generated through the use of multi-model ensembles under three scenarios; b) daily precipitation and temperature (both minimum and maximum) simulated by the weather projections are incorporated into the calibrated APEX model to estimate annual grain sorghum yields for the representative farm; c) federal crop insurance premiums, indemnities, and loss ratios are constructed based on the simulated grain sorghum yields for the farm.

The Coupled Model Intercomparison Project (CMIP) provides a standard protocol for climate change groups from around the world to collaborate for the next several years (Taylor, Stouffer, and Meehl 2012). It is developed by the World Climate Research Programme (WCRP), and is followed by more than 20 modeling groups (Brekke, Thrasher, and Pruitt 2013).

A set of climate projections is generated by climate modeling groups under the CMIP. The climate projections are released through the Intergovernmental Panel on Climate Change (IPCC) Assessment. For example, the IPCC Fourth and Fifth Assessment released the climate projections generated by the CMIP phase 3 (CMIP3) and 5 (CMIP5), respectively. Considering that the CMIP5 has more models and higher-spatial-resolution models (Taylor, Stouffer, and Meehl 2012), climate models proposed by CMIP5 are used in this chapter.

Previous studies found that multi-model ensembles are better than a single-model forecast, especially for regional studies (e.g., Palmer et al. 2005). For example, Tebaldi and Knutti (2007) discuss the sources of model uncertainty and the benefits of using multi-model ensembles for regional studies. Asseng et al. (2013) found that multi-model ensembles are preferred for crop yields simulation under climate change because a single model cannot adequately describe the uncertainty in climate change. Therefore, rather than using a single model, multi-model ensembles are used in the study to generate climate projections. Table 56 lists the models used in this chapter and the institutions where the models are developed. Model names, modeling centers, mainly developed institutions, and major reference are listed in the table. Detailed differences among these models are not discussed in this chapter due to the objective of this chapter.

Table 56. The List of Climate Models Used in this Chapter

Model	Modeling Center	Institution	Reference
ACCESS1.0	CSIRO-BOM	CSIRO (Commonwealth Scientific and Industrial Research Organisation, Australia), and BOM (Bureau of Meteorology, Australia)	Collier, Mark and Peter Uhe(2012)
BCC-CSM1.1	BCC	Beijing Climate Center, China Meteorological Administration	Wu et al.(2010);Xiao-Ge et al.(2013)
CanESM2	CCCma	Canadian Centre for Climate Modelling and Analysis	Chylek et al.(2011)
CCSM4	NCAR	National Center for Atmospheric Research	Danabasoglu et al.(2012);Meehl et al.(2012)
CESM1(BGC)	NSF-DOE-NCAR	National Science Foundation, Department of Energy, National Center for Atmospheric Research	Long et al.(2013);Lindsay et al.(2014)
CNRM-CM5	CNRM-CM5	Centre National de Recherches Meteorologiques / Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique	Voldoire et al.(2013);Oueslati et al.(2013)
CSIRO-Mk3.6.0	CSIRO-QCCCE	Commonwealth Scientific and Industrial Research Organisation in collaboration with the Queensland Climate Change Centre of Excellence	Collier et al.(2011)
GFDL-CM3.1			Massonnet et al.(2012)
GFDL-ESM2G	NOAA GFDL	Geophysical Fluid Dynamics Laboratory	Dunne et al.(2013);T Kuhlbrodt and JM Gregory(2012)
GFDL-ESM2M			Ng et al.(2014)
INM-CM4.1	INM	Institute for Numerical Mathematics	Volodin et al. (2010)
IPSL-CM5A-LR	IPSL	Institute Pierre-Simon Laplace	Dufresne et al.(2013);Persechino et al.(2013)

Table 56. Continued.

Model	Modeling Center	Institution	Reference
IPSL-CM5A-MR			Smith et al.(2013)
MIROC-ESM	MIROC	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	Watanabe et al.(2011)
MIROC-ESM-CHEM		University of Tokyo	Guilyardi et al.(2012)
MIROC5	MIROC	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	Watanabe et al.(2010);Hirota et al.(2011)
MPI-ESM-LR	MPI-M	Max Planck Institute for Meteorology (MPI-M)	Ilyina et al.(2013)
MPI-ESM-MR			Giorgetta et al.(2013)
MRI-CGCM3	MRI	Meteorological Research Institute	Yukimoto et al.(2012)
NorESM1-M	NCC	Norwegian Climate Centre	Tjiputra et al.(2012); Bentsen et al.(2013)

Source: Friedlingstein et al. 2014, World Climate Research Program. Available at: http://cmip-pcmdi.llnl.gov/cmip5/availability.html, and updated by author.

The CMIP5 also proposed four Representative Concentration Pathways (RCPs) which characterize “radiative forcing of the atmosphere by 2100 relative to preindustrial levels, expressed in units of W m^{-2}: RCP2.6, 4.5, 6.0, and 8.5” (Field et al. 2014; Vuuren et al. 2012). The four RCP scenarios are independently designed by climate modeling groups based on variables that are relevant to climate change, such as greenhouse gas emissions and concentrations, social-economic characteristics, technological development, and land-cover change projections (Vuuren et al. 2011). The four scenarios are used as a basis for modeling experiments across the world. More detailed information for the four scenarios is listed in table 60. Figure 38 presents the different projections across the four RCPs, such as population, gross domestic product (GDP), and main greenhouse gasses. Figure 41 shows the projected changes in the 20-year return value of annual minimum and maximum daily surface air temperatures (2081 – 2100), compared with the recent past (1986 – 2005) (Wuebbles et al. 2014).

Table 57. Information on Individual RCPs

RCPs	Institution	Information	Reference
RCP 2.6	Netherlands Environmental Assessment Agency (NEAA)	The emission pathway is representative for scenarios in the literature leading to very low greenhouse gas concentration levels. It is a so-called "peak" scenario: its radiative forcing level first reaches a value around 3.1 W/m2 mid-century, returning to 2.6 W/m2 by 2100. In order to reach such radiative forcing levels, greenhouse gas emissions (and indirectly emissions of air pollutants) are reduced substantially over time. The final RCP is based on the publication by Van Vuuren et al. (2007).	Van Vuuren et al. (2007).
RCP 4.5	Pacific Northwest National Laboratory's Joint Global Change Research Institute (JGCRI)	It is a stabilization scenario where total radiative forcing is stabilized before 2100 by employment of a range of technologies and strategies for reducing greenhouse gas emissions.	Wise et al (2009).
RCP 6.0	National Institute for Environmental Studies (NIES)	It is a stabilization scenario where total radiative forcing is stabilized after 2100 without overshoot by employment of a range of technologies and strategies for reducing greenhouse gas emissions.	Fujino et al. (2006) and Hijioka et al. (2008).
RCP 8.5	International Institute for Applies Systems Analysis (IIASA)	The RCP 8.5 is characterized by increasing greenhouse gas emissions over time representative for scenarios in the literature leading to high greenhouse gas concentration levels.	Riahi et al. (2007).

Source: Vuuren et al. 2011, Chaturvedi et al. 2012; Bernie, Lowe, and Smith 2013; and RCP Database, available at: http://tntcat.iiasa.ac.at:8787/RcpDb/dsd?Action=htmlpage&page=welcome

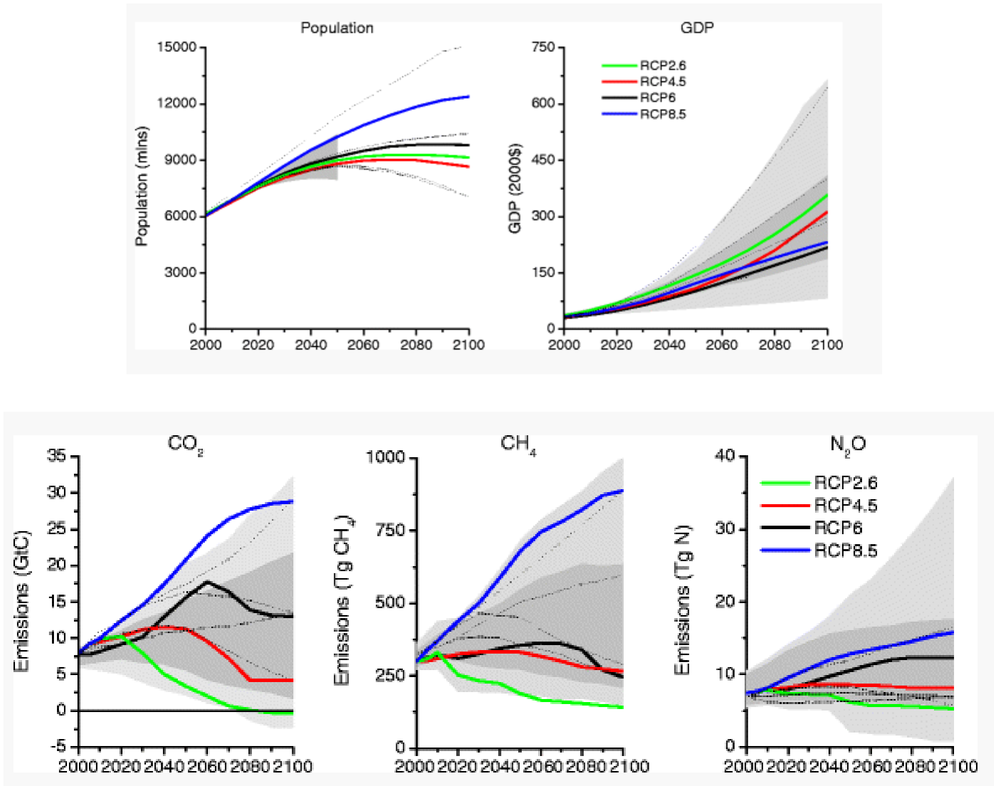

Figure 41. Population, GDP, Emissions of Main Greenhouse Gases Projections

Source: Wayne 2013.

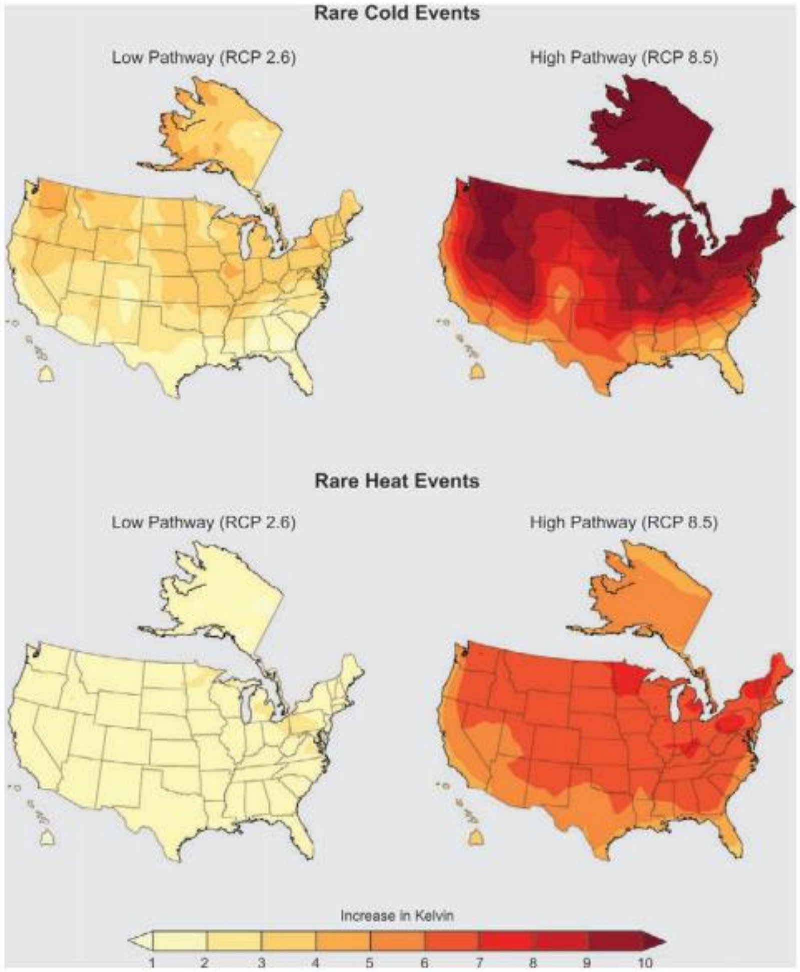

Figure 42. Projected Changes (°C) in the Daily Surface Air Temperature

Source: Wuebbles et al. 2014.

The climate projections generated by global climate models (GCMs) normally have grid scales range from 1° - 6° (approximately 111km – 666km) (see Appendix IV for detailed resolution for each model). Although the climate projections provide valuable information for global climate change studies, large errors have been found at fine scales for regional studies (Hewitson and Crane 1996). To solve the low resolution problem, Bureau of Reclamation, Climate Analytics Group, Climate Central, Lawrence Livermore National Laboratory, Santa Clara University, Scripps Institution of Oceanography, U.S. Army Corps of Engineers, U.S. Geological Survey, and National Center for Atmospheric Research collaboratively developed the downscaled CMIP3 and CMIP5 climate projections (Brekke et al. 2013). The downscaled climate projections are available on the "Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections" website (DCHP website) at http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/ for requests. At the monthly level, downscaled monthly total precipitation and monthly mean daily temperature are available on the DCHP website. Daily precipitation, minimum and maximum temperatures can also be simulated by the DCHP based on requests.

Table 61 shows the 132 weather projections generated by the 20 models and RCP scenarios available in the DCHP. 20 Climate models (table 60) are used to generate daily downscaled weather projections for Sherman County, Texas under CMIP5. Three RCP scenarios are selected: RCP2.6, RCP4.5, and RCP8.5 because few runs are available under the RCP6.0 scenario (table 60). Daily precipitation (mm/day), minimum surface air temperature (°C), maximum surface air temperature (°C) from 2017 - 2040 are generated and saved into three data sets (three NetCDF files) by the DCHP, respectively.

Table 58. Weather Projection Generation

Climate Models:	Emissions Path: RCP2.6	Emissions Path: RCP4.5	Emissions Path: RCP6.0	Emissions Path: RCP8.5
access1-0	☐☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	☐☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐
bcc-csm1-1	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐
bnu-esm	☐☐☐☐☐☐☐☐☐☐☐☐	☐☐☐☐☐☐☐☐☐☐☐☐	☐☐☐☐☐☐☐☐☐☐☐☐	☐☐☐☐☐☐☐☐☐☐☐☐
canesm2	✔✔✔✔✔☐☐☐☐☐☐☐	✔✔✔✔✔☐☐☐☐☐☐☐	☐☐☐☐☐☐☐☐☐☐☐☐	✔✔✔✔✔☐☐☐☐☐☐☐
ccsm4	✔✔☐☐☐☐☐☐☐☐☐☐	✔✔☐☐☐☐☐☐☐☐☐☐	✔✔☐☐☐☐☐☐☐☐☐☐	✔✔☐☐☐☐☐☐☐☐☐☐
cesm1-bgc	☐☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	☐☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐
cnrm-cm5	☐☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	☐☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐
csiro-mk3-6-0	✔✔✔✔✔✔✔✔✔✔☐☐	✔✔✔✔✔✔✔✔✔✔☐☐	☐☐☐☐☐☐☐☐☐☐☐☐	✔✔✔✔✔✔✔✔✔✔☐☐
gfdl-cm3	✔☐☐☐☐☐☐☐☐☐☐☐	☐☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐
gfdl-esm2g	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐
gfdl-esm2m	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐
inmcm4	☐☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	☐☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐
ipsl-cm5a-lr	✔✔✔☐☐☐☐☐☐☐☐☐	✔✔✔✔☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔✔✔✔☐☐☐☐☐☐☐☐
ipsl-cm5a-mr	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐
miroc-esm	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐
miroc-esm-chem	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐
miroc5	✔✔✔☐☐☐☐☐☐☐☐☐	✔✔✔☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔✔✔☐☐☐☐☐☐☐☐☐
mpi-esm-lr	✔✔✔☐☐☐☐☐☐☐☐☐	✔✔✔☐☐☐☐☐☐☐☐☐	☐☐☐☐☐☐☐☐☐☐☐☐	✔✔✔☐☐☐☐☐☐☐☐☐
mpi-esm-mr	✔☐☐☐☐☐☐☐☐☐☐☐	✔✔✔☐☐☐☐☐☐☐☐☐	☐☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐
mri-cgcm3	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐
noresm1-m	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐	✔☐☐☐☐☐☐☐☐☐☐☐

Source: http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/

In this chapter, the 132 weather trails generated by the DCHP (table 60) are grouped into four scenarios based on the RCP values, and are referred to as RCP2.6, 4.5, 6.0, and 8.5 scenarios in this section. Twenty climate models (indicated in table 60) are used to generate daily weather characteristics. However, not all of the 20 models are used in each RCP scenario, and more than one trial could be generated by one model under a RCP scenario. For example, under the RCP2.6 scenario, no weather projection is generated by the model "cesm1-bgc," while five trials are generated by the model "canesm2" (table 60). Because only 13 weather trials are generated by RCP6.0 scenario, weather trials created under the RCP6.0 scenario are not included in this study. Overall, 119 weather trails which are generated for three RCP scenarios and 20 models are used so simulate grain sorghum yields.

The downscaled weather trails are saved in three NetCDF files (requested from the DCHP). The first NetCDF file includes date and daily precipitation information. More specifically, for each day (a row in the NetCDF file), there are 119 precipitation projections generated by the 119 weather trials. Therefore, the dimension of the pricipitation data set is 8760 (number of days) * 120 (119 weather trials plus date). Similarly, the second and the third NetCDF file contians daily minimum and maximum temperature, and its dimention is 8760 * 120, respectively.

The weather information saved in the three NetCDF files are reorganized to better fit the research objectives. 119 weather files are genreated by using the open-source R project based on the weather information saved in the three NetCDF files. Each of the 119 weather files contains the daily precipitation, minimum and maximum temperatures which are generated by one weather trail (see table 60 for the 119 weather trails). Therefore, there are 36 weather files under the RCP2.6 scenario, 42 weather files under the RCP4.5 scenario, 41 weather files under the RCP8.5 scenario. Figure 43 shows the first 10 observations of a weather file which is generated by the model “ACCESS1.0” under the RCP4.5 scenario.

2017	1	1	3.21	-9.38	0.08
2017	1	2	5.82	-3.59	0.13
2017	1	3	10.24	-0.89	0.01
2017	1	4	13.3	-6.4	0
2017	1	5	13.79	-5.19	0
2017	1	6	16.44	-5.4	0
2017	1	7	18.62	-1.66	0
2017	1	8	20.87	2.92	0
2017	1	9	13.37	-0.93	6.22
2017	1	10	8.78	-4.9	0

Figure 43. An Example of Weather Projections

Because the APEX model has a strict requirement for the data format, the format of the 119 weather projection files are further revised to fit the model. Daily precipitation, minimum and maximum temperatures are generated directly from the DCHP. Other weather information, such as solar radiation, relative humidity, and wind speed are generated by the APEX model. It is programmed in Python (version 3.3.0) to automatically change weather projections in the APEX database, revise APEX model’s parameters, run the model to simulate grain sorghum yields for 2017 - 2040, and save the simulated yield results. Figure 44 shows the trend of simulated grain sorghum yields from 2017 – 2040 in the three RCP scenarios (RCP2.6, 4.5, and 8.5). Summary statistics of the simulated grain sorghum yields are listed in table 62.

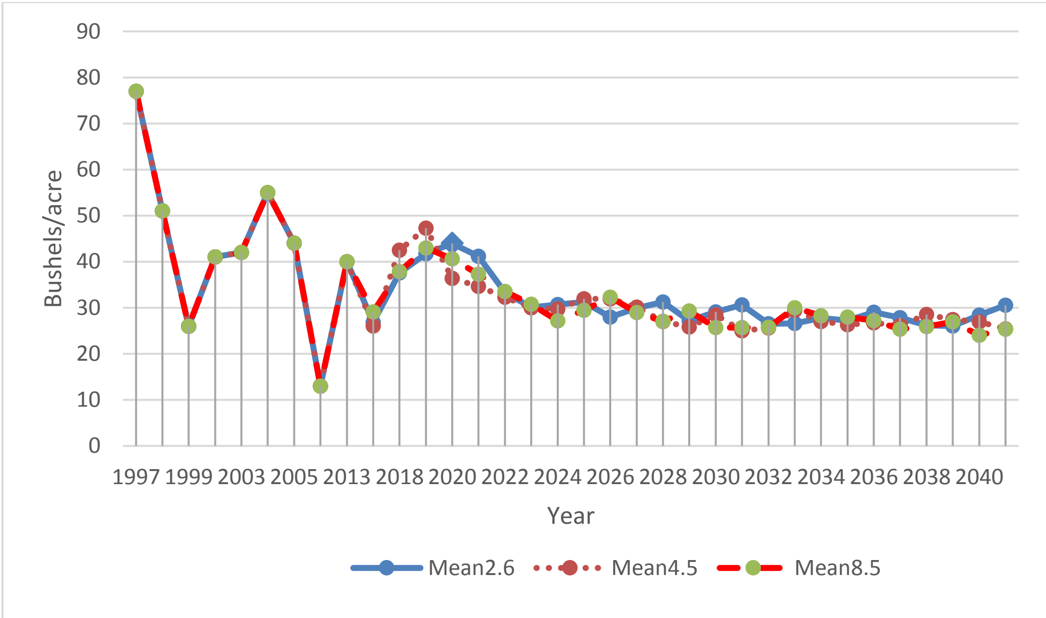

Figure 44. Average Simulated Grain Sorghum Yields (RCP2.6, 4.5, and 8.5)

Table 59. Summary Statistics of Simulated Grain Sorghum Yields

		2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Mean	RCP2.6	43.98	41.17	33.31	30.05	30.67	31.25	27.99	29.95	31.28	27.13	29.09
	RCP4.5	36.42	34.62	32.28	30.00	29.70	31.97	31.95	30.13	26.98	25.83	28.49
	RCP8.5	40.64	37.27	33.55	30.74	27.18	29.45	32.27	28.98	27.10	29.27	25.66
Standard Deviation	RCP2.6	18.79	14.82	15.56	11.09	11.93	11.15	11.47	11.08	11.34	13.37	11.31
	RCP4.5	15.94	14.44	10.32	12.28	13.08	14.34	10.19	12.19	12.62	10.40	11.41
	RCP8.5	19.88	17.75	13.12	14.75	10.97	12.41	12.20	11.79	12.90	10.81	10.26
Coefficient of Variation	RCP2.6	42.72	36.00	46.70	36.92	38.89	35.69	40.98	37.01	36.26	49.29	38.88
	RCP4.5	43.77	41.71	31.97	40.93	44.04	44.85	31.88	40.47	46.79	40.24	40.06
	RCP8.5	48.92	47.62	39.11	47.99	40.37	42.15	37.80	40.67	47.61	36.93	39.99

		2031	2032	2033	2034	2035	2036	2037	2038	2039	2040
Mean	RCP2.6	30.60	26.52	26.57	27.77	27.25	29.05	27.86	26.20	26.04	28.40
	RCP4.5	36.42	34.62	32.28	30.00	29.70	31.97	31.95	30.13	26.98	25.83
	RCP8.5	40.64	37.27	33.55	30.74	27.18	29.45	32.27	28.98	27.10	29.27
Standard Deviation	RCP2.6	12.71	12.33	9.15	12.19	9.22	11.80	13.14	11.89	10.35	10.34
	RCP4.5	15.94	14.44	10.32	12.28	13.08	14.34	10.19	12.19	12.62	10.40
	RCP8.5	19.88	17.75	13.12	14.75	10.97	12.41	12.20	11.79	12.90	10.81
Coefficient of Variation	RCP2.6	41.53	46.51	34.44	43.89	33.84	40.64	47.16	45.40	39.73	36.40
	RCP4.5	36.27	41.26	39.17	40.39	41.19	46.04	43.98	35.91	44.69	39.28
	RCP8.5	48.92	47.62	39.11	47.99	40.37	42.15	37.80	40.67	47.61	36.93

The simulated grain sorghum yields for the representative farm tend to decrease from 2020 to 2040 under the three RCP scenarios (table 61). The mean yield over the representative farm's nine-year history is 43.22 bushels/acre, and the mean simulated yield in 2020 over 36 climate models is 43.98 bushels/acre in the RCP2.6 scenario, and it decreaseS to 28.40 bushels/acre in 2040 (table 61). The coefficients of variation are presented in figure 45, and the historical coefficient of variation is 39.08.

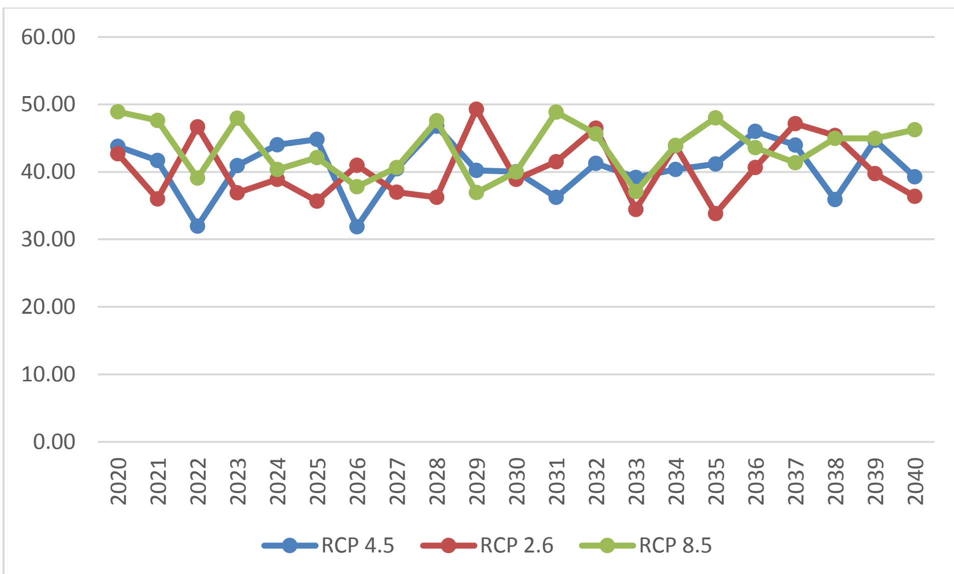

Figure 45. Coefficients of Variation (CV) for Simulated Grain Sorghum Yields

In this section, individual federal grain sorghum Yield Protection (YP) insurance policy is simulated at the 65% coverage level with a 100% price level coverage. The calculations of YP premiums and indemnities are independently constructed for each RCP scenario (RCP2.6, 4.5, and 8.5). The transitional yield (T-yield) and the projected price are assumed to be 20 bushels and $3.75/bushel across the period (2017 – 2040).

An empirical distribution is defined for each year from 2017 to 2040 by using the simulated grain sorghum yields generated by the APEX model based on the weather projections. For example, under the RCP4.5 scenario, 42 daily weather trails are generated by 20 models (table 60) for each year (2017 – 2040). Therefore, 42 grain sorghum yield simulations are generated from the APEX model based on the 42 weather trails. The 42 grain sorghum yield simulations are further used to construct an empirical probability distribution for the representative farm at each year. The empirical probability distributions are different from year to year because the grains sorghum yields simulated by the APEX model are different. For each year, the empirical distribution is used to simulate stochastic grain sorghum yields for the representative farm. The constructions of the empirical distributions and the generations of stochastic grain sorghum yields are implemented by using Simetar© (Richardson, Schuman, and Feldman 2006). The simulated stochastic grain sorghum yields are used for future calculations of the farm's actual production history (APH) yields, premiums, and indemnities, and are referred as realized yields.

The APH Yield Calculation

Following RMA's rules, the 60% of the T-yield (20 * 60% = 12 bushels) is used to substitute annual grain sorghum yields which are lower than the substitution (USDA, RMA). According to the federal crop insurance premium calculations, the APH yield is calculated as the average of previous four to ten years' yields with the 60% of T-yield substitution. For example, to calculate the representative farm's APH yield in year 2020, three years of stochastic grain sorghum yields (2017 – 2019) generated from the empirical probability distributions and seven years of observed grain sorghum yields are used. For year 2027, previous ten years simulated stochastic grain sorghum yields (2010 – 2026) are used to construct the APH yield. Figure 46 - 48 show the fan graphs for APH yields over 2020 – 2040 to illustrate the changes of the representative farm's APH yields under the three scenario (RCP2.6, 4.5, and 8.5).

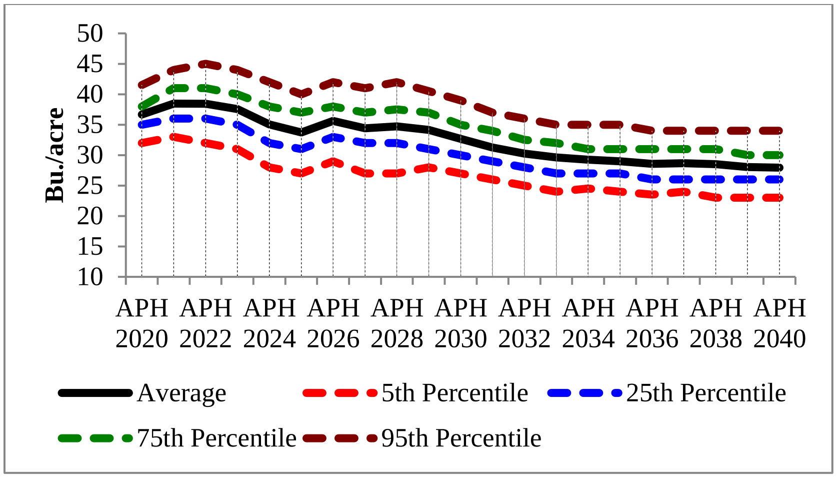

Figure 46. Fan Graph for APH Yields under the RCP2.6 Scenario

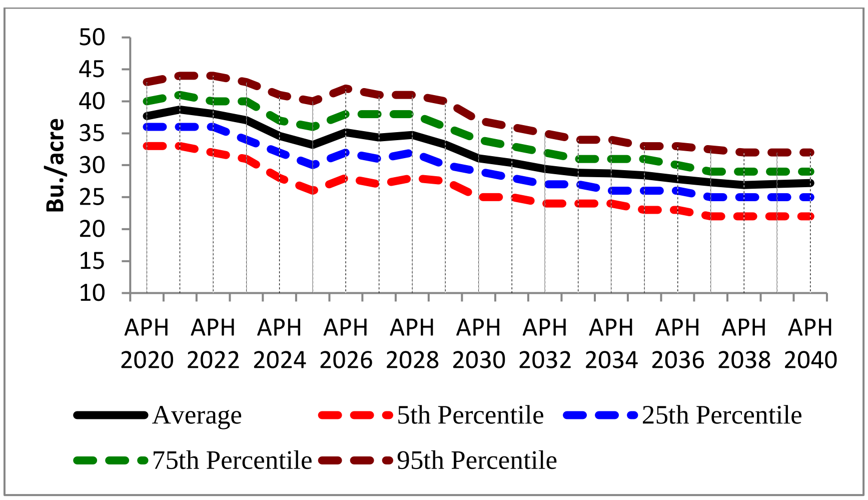

Figure 47. Fan Graph for APH Yields under the RCP4.5 Scenario

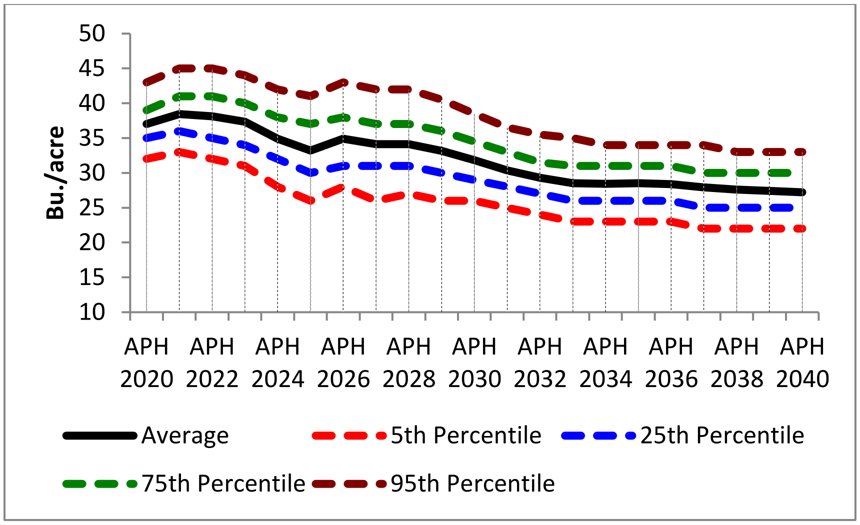

Figure 48. Fan Graph for APH Yields under the RCP8.5 Scenario

Table 62 shows the summary statistics of the simulated APH yields under each scenario. Overall, the APH yields decrease through 2020 – 2040. For example, under the RCP2.6 scenario, the simulated APH yield is 36.64 and 32.69 in year 2020 and 2040, respectively; and under the RCP4.5 scenario, the simulated APH yield decreases from 37.69 (in year 2020) to 31.30 (in year 2040). Since the guaranteed yield of the individual YP insurance at the 65% coverage level is calculated as 65% of the APH yield, the decreasing APH yields will result in lower yield guarantees and lower net premiums (details are discussed in the "Federal Crop Insurance Premium Calculation" below).

Table 60. Summary Statistics of the APH Simulation

		2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Mean	RCP2.6	36.64	38.43	38.44	37.55	35.04	33.74	35.62	34.43	34.74	34.13	32.69
	RCP4.5	37.69	38.71	38.05	37.06	34.58	33.19	35.14	34.32	34.75	33.22	31.10
	RCP8.5	37.00	38.45	38.11	37.33	34.89	33.23	34.89	34.12	34.13	33.17	31.84
Standard Deviation	RCP2.6	2.96	3.46	3.70	3.97	4.04	4.23	4.31	4.38	4.25	3.97	3.74
	RCP4.5	2.90	3.28	3.58	3.65	3.83	4.06	4.30	4.30	4.28	3.94	3.61
	RCP8.5	3.07	3.61	3.89	4.11	4.35	4.52	4.65	4.71	4.61	4.40	3.92
Coefficient of Variation	RCP2.6	8.08	8.99	9.64	10.57	11.51	12.53	12.09	12.72	12.23	11.63	11.43
	RCP4.5	7.70	8.47	9.42	9.86	11.08	12.23	12.23	12.54	12.30	11.87	11.61
	RCP8.5	8.29	9.39	10.20	11.02	12.46	13.62	13.32	13.80	13.52	13.26	12.32

		2031	2032	2033	2034	2035	2036	2037	2038	2039	2040
Mean	RCP2.6	31.24	30.23	29.59	29.23	28.96	28.55	28.67	28.52	28.02	27.94
	RCP4.5	30.35	29.41	28.80	28.73	28.44	27.79	27.31	26.90	27.05	27.21
	RCP8.5	30.36	29.28	28.50	28.44	28.54	28.40	27.92	27.60	27.42	27.22
Standard Deviation	RCP2.6	3.44	3.35	3.35	3.34	3.30	3.32	3.25	3.32	3.36	3.27
	RCP4.5	3.46	3.29	3.24	3.15	3.12	3.05	3.10	3.01	3.00	3.06
	RCP8.5	3.70	3.52	3.59	3.33	3.42	3.44	3.47	3.40	3.41	3.44
Coefficient of Variation	RCP2.6	11.01	11.10	11.32	11.42	11.38	11.64	11.35	11.64	12.00	11.71
	RCP4.5	11.41	11.18	11.25	10.98	10.98	10.98	11.36	11.19	11.10	11.24
	RCP8.5	12.19	12.04	12.59	11.72	11.97	12.12	12.44	12.33	12.44	12.63

The Federal Crop Insurance Premium Calculation

According to the RMA's "Actuarial Documentation of Multiple Peril Crop Insurance Ratemaking Procedures", the basic formula to calculate the federal crop insurance premium is

Premium = liability * premium rate * adjustment factor

and

Liability = acres planted * APH yield * coverage level * base price * price election percentage

The planted acre is assumed as one acre to simplify calculations. Because the farm's federal crop insurance liabilities are closely related to APH yields, decreasing APH yields will result in lower liabilities over time (assuming the base price is constant over time).

The detailed calculations of individual YP insurance premiums for grain sorghum follows the RMA rules, and are generated by using the premium calculator programmed by AFPC. The federal crop insurance subsidy rate is 59% at the 65% coverage level for basic and optional units, which means producers only pay for the 41% of the gross premiums. The net premiums (producers paid premiums) are calculated based on the stochastic APH yields of the representative farm simulated by APEX. Figure 49 – 51 show the simulated net premiums ($/acre) under each scenario (RCP2.6, 4.5, and 8.5).

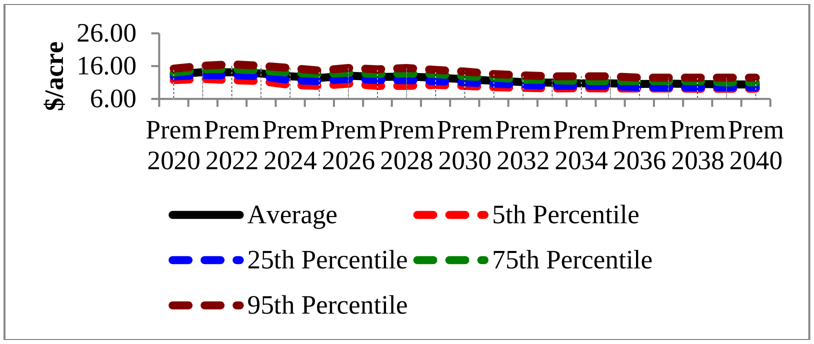

Figure 49. Fan Graph for Net Premiums under the RCP2.6 Scenario

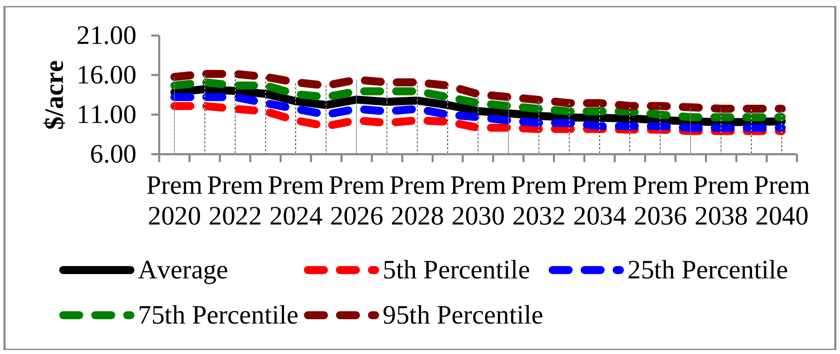

Figure 50. Fan Graph for Net Premiums under the RCP4.5 Scenario

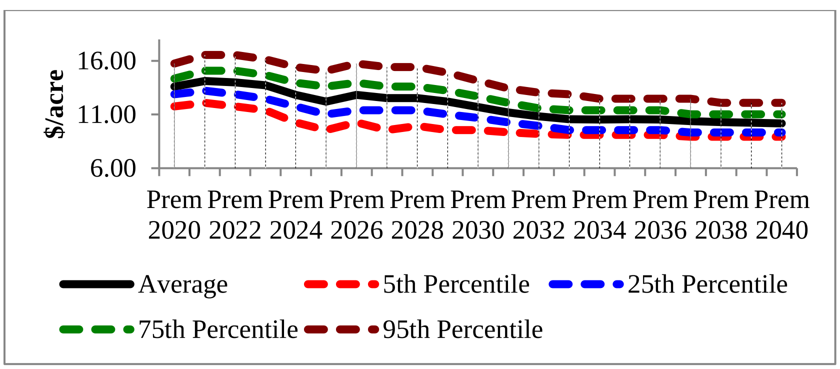

Figure 51. Fan Graph for Net Premiums under the RCP8.5 Scenario

Table 64 presents the summary statistics of the simulated federal YP insurance premiums. The Student's-t test and the F-test are used to test the three series of the simulated federal YP insurance premiums (generated for three RCP scenarios) in year 2020, 2030, and 2040 (table 64 – 66). The null hypotheses assume that the averages and variances of the premium simulations are the same across the three RCP scenarios. In year 2020 (table 64), the Student's-t test rejects the null hypothesis that the means of the premiums for RCP2.6 and RCP4.5 scenarios are equal at the 95% confidence level. According to the Student's-t tests, the means of the premiums are statistically equal between RCP2.6 and RCP8.5 scenarios, but they are statistically different between RCP4.5 and RCP8.5 scenarios (table 64). The F tests fail to reject the null hypothesis that the variances of premiums are equal among RCP2.6, RCP4.5, and RCP8.5 scenarios at the 95% confidence level.

In year 2030, the means of simulated grain sorghum YP insurance premiums are statistically different between RCP2.6 and RCP4.5 scenarios, as well as between RCP2.6 and RCP8.5 scenarios at the 95% confidence level (table 65). But, according to the results of the Student's t-test in table 66, the means of the simulated YP insurance premiums between RCP4.5 and RCP8.5 in year 2030 are statistical equal. Similarly as 2020, the F-tests show that the variances of simulated premiums are equal among the three RCP scenarios (table 65).

In year 2040, the means of the simulated grain sorghum YP insurance premiums are statistically different for RCP2.6 and RCP4.5 based on the Student's t-test (table 66) at the 95% confidence level. Similarly, the means of the simulated grain sorghum YP insurance premiums are statistically different between RCP2.6 and RCP8.5 scenarios (table 66). The variances of the premium simulations are statistically equal between RCP2.6 and RCP4.5, and RCP4.5 and RCP8.5 in year 2040 (table 66). But the variances of premium simulations are statistically different in year 2040 for RCP2.6 and RCP8.5 (table 66) at the 95% confidence level.

As discussed above, the simulated federal grain sorghum YP insurance premiums decrease as the simulated APH yields decrease over time. For example, the simulated mean premium is $13.59/acre at the 65% coverage level for 2020, and it decreases to $10.17/acre under the RCP8.5 scenario. Farmers are expected to pay less for the same crop insurance coverage level over time due to the impacts of climate change on the yields of grain sorghum.

Table 61. Summary Statistics of Simulated YP Net Premiums

		2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Mean	RCP2.6	13.46	14.12	14.12	13.80	12.88	12.40	13.09	12.66	12.77	12.54	12.02
	RCP4.5	13.85	14.22	13.98	13.61	12.70	12.20	12.91	12.62	12.77	12.21	11.45
	RCP8.5	13.59	14.12	14.00	13.71	12.82	12.22	12.82	12.54	12.55	12.19	11.71
Standard Deviation	RCP2.6	1.09	1.27	1.36	1.46	1.48	1.54	1.58	1.59	1.55	1.45	1.35
	RCP4.5	1.07	1.20	1.32	1.34	1.41	1.48	1.58	1.57	1.56	1.43	1.28
	RCP8.5	1.13	1.33	1.43	1.51	1.59	1.64	1.70	1.72	1.68	1.60	1.43
Coefficient of Variation	RCP2.6	8.10	8.98	9.62	10.56	11.48	12.40	12.04	12.57	12.17	11.57	11.24
	RCP4.5	7.70	8.46	9.42	9.86	11.07	12.12	12.20	12.44	12.22	11.71	11.20
	RCP8.5	8.31	9.39	10.19	11.01	12.44	13.46	13.29	13.67	13.42	13.12	12.17

		2031	2032	2033	2034	2035	2036	2037	2038	2039	2040
Mean	RCP2.6	11.49	11.14	10.91	10.79	10.70	10.56	10.60	10.56	10.40	10.38
	RCP4.5	11.19	10.86	10.65	10.62	10.52	10.31	10.17	10.05	10.08	10.14
	RCP8.5	11.19	10.82	10.57	10.53	10.58	10.54	10.39	10.28	10.23	10.17
Standard Deviation	RCP2.6	1.23	1.18	1.16	1.14	1.11	1.11	1.09	1.10	1.07	1.04
	RCP4.5	1.21	1.11	1.09	1.06	1.03	0.97	0.96	0.90	0.91	0.94
	RCP8.5	1.30	1.20	1.17	1.09	1.11	1.11	1.09	1.05	1.04	1.02
Coefficient of Variation	RCP2.6	10.68	10.56	10.60	10.57	10.41	10.48	10.27	10.40	10.26	10.01
	RCP4.5	10.81	10.26	10.23	10.02	9.84	9.40	9.41	8.99	9.04	9.23
	RCP8.5	11.66	11.06	11.09	10.32	10.51	10.51	10.45	10.18	10.17	10.05

Table 62. Comparison Results of the Distributions of Net Premiums (2020)

Distribution Comparison of RCP2.6 & RCP4.5				
Confidence Level		95.00%		
	Test Value	Critical Value	P-Value	
2 Sample t Test	-5.65	2.24	0.000	*Reject the Ho that the Means are Equal*
F Test	1.05	1.16	0.303	*Fail to Reject the Ho that the Variances are Equal*
Distribution Comparison of RCP2.6 & RCP8.5				
Confidence Level		95.00%		
	Test Value	Critical Value	P-Value	
2 Sample t Test	-1.88	2.24	0.061	*Fail to Reject the Ho that the Means are Equal*
F Test	1.07	1.16	0.216	*Fail to Reject the Ho that the Variances are Equal*
Distribution Comparison of RCP4.5 & RCP8.5				
Confidence Level		95.00%		
	Test Value	Critical Value	P-Value	
2 Sample t Test	3.65	2.24	0.000	*Reject the Ho that the Means are Equal*
F Test	1.12	1.16	0.096	*Fail to Reject the Ho that the Variances are Equal*

Table 63. Comparison Results of the Distributions of Net Premiums (2030)

Distribution Comparison of RCP2.6 & RCP4.5				
Confidence Level		95.00%		
	Test Value	Critical Value	P-Value	
2 Sample t Test	6.89	2.24	0.000	*Reject the Ho that the Means are Equal*
F Test	1.11	1.16	0.120	*Fail to Reject the Ho that the Variances are Equal*
Distribution Comparison of RCP2.6 & RCP8.5				
Confidence Level		95.00%		
	Test Value	Critical Value	P-Value	
2 Sample t Test	3.58	2.24	0.000	*Reject the Ho that the Means are Equal*
F Test	1.11	1.16	0.119	*Fail to Reject the Ho that the Variances are Equal*
Distribution Comparison of RCP4.5 & RCP4.5				
Confidence Level		95.00%		
	Test Value	Critical Value	P-Value	
2 Sample t Test	0.00	2.24	1.000	*Fail to Reject the Ho that the Means are Equal*
F Test	1.00	1.16	0.500	*Fail to Reject the Ho that the Variances are Equal*

Table 64. Comparison Results of the Distributions of Net Premiums (2040)

	Test Value	95.00% Critical Value	P-Value	
Distribution Comparison of RCP2.6 & RCP4.5				
Confidence Level		95.00%		
2 Sample t Test	3.81	2.24	0.000	*Reject the Ho that the Means are Equal*
F Test	1.23	1.16	0.010	*Reject the Ho that the Variances are Equal*
Distribution Comparison of RCP2.6 & RCP8.5				
Confidence Level		95.00%		
2 Sample t Test	3.09	2.24	0.002	*Reject the Ho that the Means are Equal*
F Test	1.03	1.16	0.370	*Fail to Reject the Ho that the Variances are Equal*
Distribution Comparison of RCP4.5 & RCP8.5				
Confidence Level		95.00%		
2 Sample t Test	-0.59	2.24	0.554	*Fail to Reject the Ho that the Means are Equal*
F Test	1.19	1.16	0.024	*Reject the Ho that the Variances are Equal*

Federal crop insurance indemnities for the representative farm at the 65% coverage level of individual YP are simulated based on the stochastic grain sorghum yields. If the realized grain sorghum yield is below the guaranteed yield (65% of the APH yield), the federal YP insurance indemnity is triggered, and the farmer is paid by the federal government based on the projected price and the corresponding yield loss:

If realized yield < yield guarantee:

Federal Crop Insurance Indemnity = price election percentage * projected price * (yield guarantee – realized yield);

Else:

Federal Crop Insurance Indemnity = 0

Federal YP indemnities ($/acre) are calculated for the representative farm following the formula. For example, under the RCP2.6 scenario, the simulated indemnities range from 0 to $50/acre over 500 iterations for 2020. Under the RCP2.6 scenario, the maximum indemnity is $88.67/acre in year 2022. Figure 52 – 54 are the fan graphs of the simulated indemnities of federal YP insurance for the representative farm under the three scenarios (RCP2.6, 4.5, and 8.5).

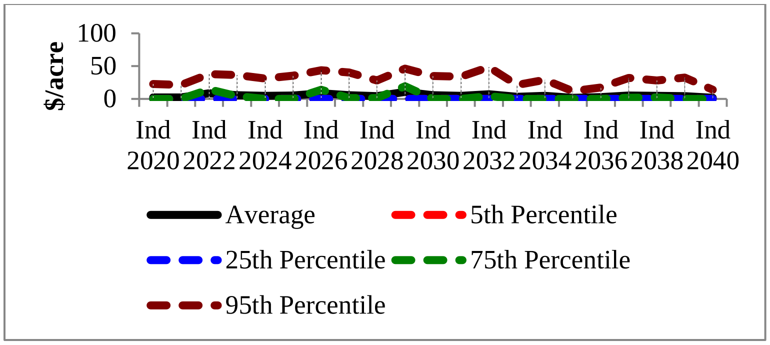

Figure 52. Fan Graph for Indemnities under the RCP2.6 Scenario

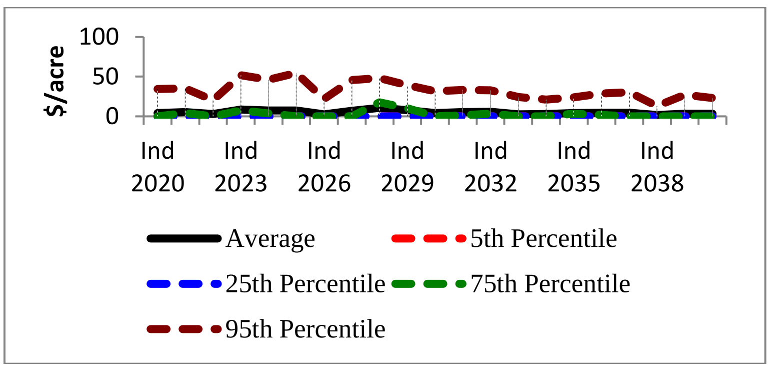

Figure 53. Fan Graph for Indemnities under the RCP4.5 Scenario

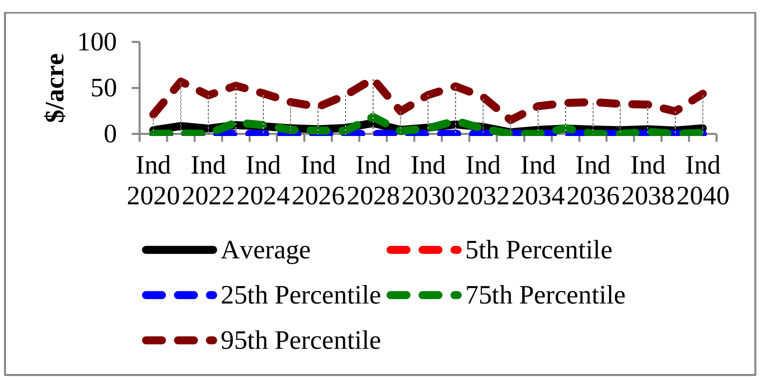

Figure 54. Fan Graph for Indemnities under the RCP8.5 Scenario

Corresponding federal YP insurance loss ratios are calculated as the ratios of indemnities to net premiums, and are illustrated in fan graphs (figure 55 – 57). Table 65 shows the summary statistics of simulated loss ratios for each RCP scenario during 2020 – 2040. In year 2020, the expected loss ratio across 500 iterations is 0.17, 0.28, and 0.28 for RCP2.6, 4.5, and 8.5, respectively. The highest loss ratio across 500 iterations is 3.2, 4.0, and 5.9 for RCP2.6, 4.5, and 8.5, respectively, in year 2020. In year 2020, 2030, and 2040, the highest loss ratio is 5.9, 5.5, and 5.2 and the three highest loss ratios all occur under the RCP8.5 scenario.

The Student's t-test and F-test are used to test the distributions of the three series of loss ratios for RCP2.6, 4.5, and 8.5 scenarios (Appendix VIII). The null hypotheses for equal means and equal variances are rejected at the 95% confidence level between RCP2.6 and RCP4.5 scenarios, and between RCP2.6 and RCP8.5 scenarios in year 2020, which implies that the means and variances of the simulated loss ratios for RCP2.6 and RCP4.5 are statistically different, and the means and variances of the simulated loss ratios for RCP2.6 and RCP8.5 are statistically different. In year 2030, both the means and variances of the simulated federal crop insurance loss ratios are statistically different between RCP4.5 and RCP8.5. In year 2040, all the means and variances null hypotheses are rejected by tests. Therefore, in year 2040, the means of the simulated loss ratios are different across the three RCP scenarios, and the variances of the simulated loss ratios are statistically different across the three RCP scenarios also.

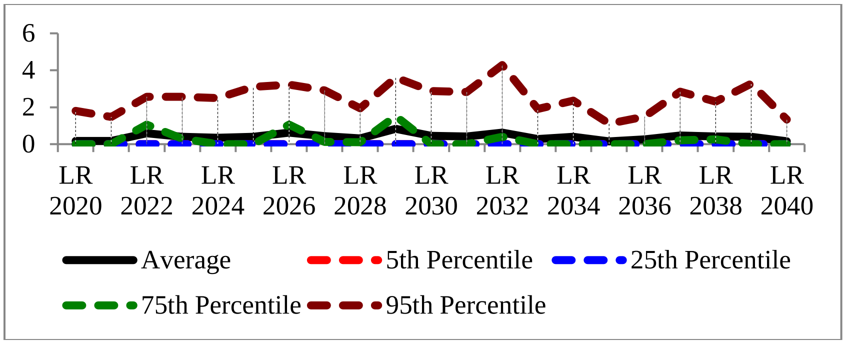

Figure 55. Fan Graph for Net Loss Ratios under the RCP2.6 Scenario

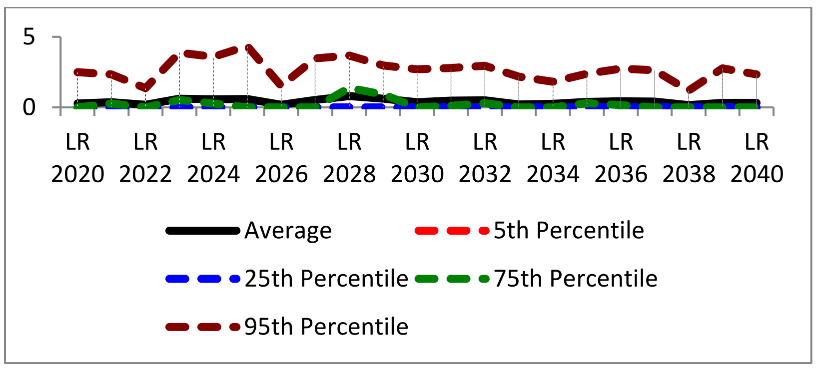

Figure 56. Fan Graph for Net Loss Ratios under the RCP4.5 Scenario

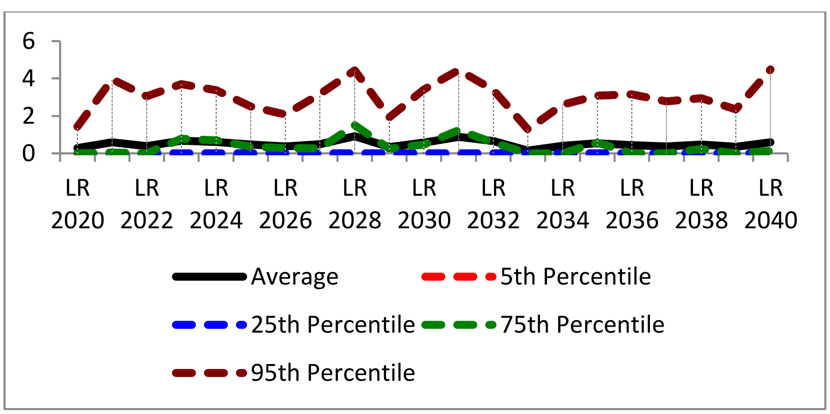

Figure 57. Fan Graph for Net Loss Ratios under the RCP8.5 Scenario

Table 65. Summary Statistics of Simulated Net Loss Ratios

		2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Mean	RCP2.6	0.17	0.17	0.59	0.40	0.34	0.40	0.62	0.43	0.31	0.83	0.44
	RCP4.5	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28
	RCP8.5	0.28	0.59	0.39	0.67	0.62	0.48	0.36	0.48	0.92	0.33	0.57
Standard Deviation	RCP2.6	0.56	0.48	1.00	0.88	0.80	1.05	1.03	0.93	0.65	1.21	0.96
	RCP4.5	0.81	0.75	0.52	1.22	1.21	1.39	0.53	1.18	1.31	1.06	0.90
	RCP8.5	0.78	1.29	1.06	1.21	1.14	1.08	0.73	1.04	1.60	0.65	1.12
Coefficient of Variation	RCP2.6	332.48	284.14	170.67	218.65	233.53	262.58	166.03	216.75	212.94	146.32	217.01
	RCP4.5	285.88	209.28	266.08	198.85	211.98	238.03	269.58	221.44	162.86	171.81	248.17
	RCP8.5	279.77	219.93	269.62	179.55	185.61	225.82	200.86	215.52	174.36	200.15	195.35

		2031	2032	2033	2034	2035	2036	2037	2038	2039	2040
Mean	RCP2.6	0.41	0.63	0.28	0.40	0.15	0.26	0.46	0.42	0.40	0.16
	RCP4.5	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28
	RCP8.5	0.89	0.66	0.15	0.40	0.54	0.44	0.38	0.46	0.34	0.59
Standard Deviation	RCP2.6	0.98	1.33	0.65	0.96	0.64	0.78	1.02	0.96	0.99	0.55
	RCP4.5	1.00	1.00	0.78	0.66	0.79	0.94	1.04	0.49	0.89	0.78
	RCP8.5	1.58	1.28	0.49	0.92	1.10	1.09	1.12	1.00	0.88	1.31
Coefficient of Variation	RCP2.6	238.34	211.15	231.78	242.11	424.75	300.74	219.61	232.04	246.92	337.02
	RCP4.5	208.18	198.91	354.30	251.63	201.19	217.19	253.08	302.95	269.77	245.64
	RCP8.5	177.69	194.03	334.42	227.83	203.75	249.42	297.59	215.40	255.03	224.34

Summary

Chapter III develops the methodology to estimate the impacts of climate change on the federal crop insurance APH yields, premiums, indemnities, and loss ratios. A representative grain sorghum farm in Sherman County, Texas is used to illustrate the methodology. The ensembles of multiple climate models are used to generate local weather projections to better describe the uncertainties in climate change. Specifically, 119 weather trials are generated based on climate model ensembles and three RCP scenarios (2.6, 4.5, and 8.5). The downscaled daily weather information in the 119 weather trials are incorporated in the APEX model to simulate annual grain sorghum yields through 2040 to evaluate the representative farm's yield risks. In each RCP scenario, an empirical yield distribution is constructed for each year based on the simulated grain sorghum yields by the APEX model. Stochastic grain sorghum yields are generated based on the empirical distributions to calculate the federal YP insurance premiums, indemnities, and loss ratios at the 65% coverage level with the 60% of T-yield substitution.

Simulated results show that climate change will result in lower grain sorghum yields (2020 – 2040) in each climate change scenario for the representative farm in Sherman County, Texas. As the realized grain sorghum yields decrease, the approved APH yields will decrease. Crop insurance premium costs will also decrease with the lower APH yields.

The study finds that the current APH formula which uses the average crop yields in previous ten years with the 60% of T-yield substitution will accommodate the gradual change in crop yields as climate change continuous. Although the simulated grain sorghum yields decrease from 2020 to 2040 as climate change continues, there is no extreme decrease occurs in the simulated yields based on the climate change forecasts. Therefore, the efficiency of the current APH formula will not be negated by climate change.

The study also finds that the simulated federal crop insurance loss ratios and premiums are statistically different across the three climate change scenarios (RCP2.6, 4.5, and 8.5) in year 2020, 2030, and 2040. Student's t-test and F-test show that the means and variances of simulated insurance loss ratios are statistically different at the 95% confidence level across the three climate change scenarios in year 2020, 2030, and 2040 (table 64 – 66). Therefore, which climate scenario is used in the analysis of the impacts of climate change on the FCIC would affect the conclusions.

Due to the time constraint, the methodology is only applied for one crop (non-irrigated grain sorghum) and one farm (in Sherman County, Texas). A more comprehensive analysis using the methodology can be undertaken for multiple crops and regions. The results can provide a better overview of the impacts of climate changes on the FCIP.

CHAPTER V

CONCLUSIONS

The FCIP helps farmers to manage production and/or price risks. It is a vital part of the farm safety net under the 2014 Farm Bill. However, the FCIP has been subject to problems and criticisms, such as being an expensive government subsidized program (Glauber 2004), with disparities across regions (Woodard et al. 2012), and potential impacts of climate change on the federal crop insurance loss ratios. The purpose of this dissertation is to evaluate the demand for crop insurance and design and test a methodology to estimate the impacts of climate change on the FCIP. In particular, the first chapter discusses the demand for federal corn insurance (both yield and revenue insurance policies) at each coverage level and in each major production region. The second chapter estimated the demand for federal wheat insurance at each coverage level for three major production regions. The third chapter develops the methodology to estimate the potential impacts of climate change on federal crop insurance premiums, indemnities, and loss ratios.

In the first chapter, the elasticities of demand for corn yield and revenue insurance are estimated at each coverage level among four major production regions (the Corn Belt, Lake States, Northern Plains, and Southern Plains). The results find that the elasticities of demand for federal corn insurance are different across insurance plans (yield and revenue), coverage levels, and regions. At the 80% coverage level, the elasticity of demand for corn yield insurance with respect to net premium is -0.230, -0.158, and -0.259 in the Corn Belt, Lake States, and Northern Plains, respectively. At the 75% coverage level, the elasticity of demand for corn yield insurance with respect to net premium is -0.654 in the Southern Plains (the 80% coverage level was not offered to the majority of counties in the Southern Plains back to 1998 and 2002). The elasticity of demand for corn revenue insurance with respect to net premium is -0.200, -0.208 in the Corn Belt and Lake States, respectively, while the elasticity of demand for corn revenue insurance is -0.670 at the 75% coverage level in the Southern Plains. The study also evaluates the CRS Report R43951, which suggests the government reduce subsidy rates by 10 percentage points at each coverage level. Results find that given a 10 percentage points reduction in premium subsidy rates, corn producers in the Corn Belt would reduce their demand for federal corn yield and revenue insurance by 4.792% and 4.167%, respectively, at the 80% coverage level; while corn producers in the Southern Plaisn are expected to reduce their corn yield and revenue insurance demand by 11.891% and 12.182%, respectively, at the 75% coverage level. More importantly, the results find that, with the suggested 10 percentage points reduction, the expected demand change will contradict the major objective of the 2000 ARPA, which intended to encourage greater federal crop insurance demand among high coverage levels.

The second chapter examines the demand for federal wheat insurance at each coverage level in three major wheat production regions (Pacific Northwest, Northern Plains, and Southern Plains). At the 75% coverage level, the elasticity of demand for federal wheat yield insurance with respect to net premium in the Southern Plains (-0.264) is about twice of the elasticity of demand for federal wheat yield insurance with respect to net premium in the Northern Plains (-0.145). In the Northern Plains, wheat farmers are expected to reduce their demand for federal wheat yield insurance by 2.636%, 4.800%, and 7.211% at the 70%, 75%, and 80% coverage level, respectively, given a 10 percentage points cut on the subsidy rates. In the Southern Plains, the demand for wheat yield insurance is expected to be reduced by 3.153% and 2.636% at the 70% and 75% coverage level, respectively with the proposed reduction in the subsidy rates.

The third chapter develops and demonstrated a methodology to estimate the potential impacts of climate change on federal crop insurance in terms of approved APH yields, federal insurance premiums, indemnities, and loss ratios for a representative grain sorghum farm in Sherman County, Texas. Twenty climate change models and three climate scenarios (RCP2.6, 4.5, and 8.5) are used to generate weather projections for 2017 - 2040. Downscaled daily weather information based on the ensembles of climate models and climate change scenarios are incorporated in used the APEX model to simulate annual grain sorghum yields for a representative Texas grain sorghum farm. In each climate change scenario, the simulated non-irrigated grain sorghum yields from APEX are used to construct empirical probability distributions for each year (2017 -2040). The stochastic grain sorghum yields simulated from the empirical probability distributions are used to calculate federal crop insurance APH yields, premiums, indemnities, and loss ratios, following RMA's rules. The results find that climate change will result in lower APH yields and cheaper federal YP insurance premiums. The study also found that since no extreme yield change occurs based on the climate forecasts, the current APH formula using the previous ten years' average yields with a T-yield substitution policy will accommodate the gradual change in crop yields over 2020 – 2040 period. Moreover, statistical tests show that the loss ratios of federal YP insurance are statistically different for each climate scenario. Therefore, which climate scenario is used in the analysis of the impacts of climate change on the FCIP matters.

Overall, the three essays answer the questions about possible responses to lower federal crop insurance subsidy rates and climate change. With lower federal crop insurance subsidy rates, farmers would bear more costs of federal crop insurance and reduce their demand for federal crop insurance different across coverage levels, insurance policies, and regions. Under each of the three climate change scenarios (RCP2.6, 4.5, and 8.5), farmers will pay lower crop insurance premiums as the actual and approved APH yields decrease. The current APH formula will accommodate gradual changes in crop yields since climate change does not result in dramatic changes for the representative farm. Moreover, the study finds which climate change scenario is used in the analysis affects the evaluation of the impacts of climate change on the FCIC with RCP2.6 has the largest mean loss ratios in year 2020 and RCP8.5 has the largest mean loss ratios in year 2030, and 2040.

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APPENDIX I CORN USUAL PLANTING AND HARVESTING DATES

State	1996 Harvested Acres (000)	Usual Planting Dates			Usual Harvesting Dates		
		Begin	Most Active	End	Begin	Most Active	End
AL	280	Mar 5	Mar 25 - Apr 25	May 18	Jul 21	Aug 11 - Sep 20	Nov 2
AZ	40	Mar 15	Apr 1 - May 15	Jun 1	Sep 1	Oct 1 - Nov 1	Dec 1
AR	230	Apr 3	Apr 10 - May 18	May 25	Aug 16	Aug 27 - Sep 18	Oct 11
CA	220	Mar 15	Apr 1 - Jul 1	Jul 15	Sep 1	Oct 1 - Nov 15	Dec 1
CO	940	Apr 15	May 1 - May 15	Jun 1	Oct 1	Oct 15 - Nov 10	Dec 1
DE	150	Apr 19	Apr 30 - May 16	May 28	Sep 10	Sep 20 - Oct 15	Nov 5
FL	112	Mar 1	Mar 15 - Apr 15	Apr 25	Jul 15	Aug 1 - Sept 10	Oct 1
GA	525	Mar 1	Mar 20 - Apr 15	May 5	Jul 25	Aug 15 - Sep 5	Oct 10
ID	40	Apr 21	May 5 - May 26	Jun 9	Sep 29	Oct 20 - Nov 10	Nov 24
IL	10,800	Apr 22	Apr 30 - May 18	May 28	Sep 24	Oct 9 - Nov 3	Nov 19
IN	5,450	Apr 25	May 5 - May 20	Jun 10	Sep 20	Oct 10 - Nov 25	Dec 10
IA	12,450	Apr 22	May 2 - May 16	Jun 3	Sep 17	Oct 7 - Oct 31	Nov 17
KS	2,350	Apr 10	Apr 25 - May 15	May 25	Sep 5	Sep 20 - Oct 20	Nov 10
KY	1,200	Apr 12	Apr 21 - May 18	Jun 8	Sep 8	Sep 22 - Oct 20	Nov 15
LA	523	Mar 10	Mar 19 - Apr 4	Apr 28	Jul 29	Aug 13 - Sep 1	Sep 16
MD	465	Apr 20	Apr 30 - May 20	Jun 7	Sep 9	Sep 22 - Oct 22	Nov 17
MI	2,300	May 1	May 10 - May 21	May 31	Oct 3	Oct 23 - Nov 17	Dec 3
MN	6,950	Apr 24	May 3 - May 22	Jun 8	Sep 29	Oct 15 - Nov 12	Nov 28
MS	605	Mar 27	Mar 31 - Apr 28	Jun 11	Aug 12	Sep 1 - Oct 6	Oct 22
MO	2,650	Apr 5	Apr 20 - May 25	Jun 10	Sep 1	Sep 20 - Oct 30	Dec 1
MT	15	Apr 19	May 1 - May 25	Jun 8	Sep 15	Sep 20 - Oct 5	Oct 15
NE	8,300	Apr 21	May 3 - May 19	Jun 1	Sep 21	Oct 11 - Nov 6	Dec 1
NJ	94	May 7	May 28 - Jun 20	Jun 28	Oct 1	Oct 30 - Nov 10	Nov 28
NM	84	Apr 15	Apr 20 - May 10	May 20	Sep 25	Oct 1 - Oct 30	Nov 20
NY	630	Apr 25	May 5 - May 25	Jun 5	Oct 10	Oct 20 - Nov 20	Dec 1
NC	900	Apr 1	Apr 10 - Apr 25	May 20	Aug 20	Sep 10 - Oct 7	Nov 7
ND	720	May 3	May 13 - May 26	Jun 5	Sep 29	Oct 10 - Oct 27	Nov 9
OH	2,750	Apr 22	May 1 - May 30	Jun 12	Sep 25	Oct 15 - Nov 14	Nov 25
OK	170	Mar 25	Apr 18 - May 4	May 15	Aug 25	Sep 8 - Oct 1	Oct 20
OR	33	Apr 20	May 20 - Jun 1	Jun 15	Oct 10	Nov 1 - Nov 20	Dec 15
PA	1070	Apr 30	May 10 - May 25	Jun 15	Sep 25	Oct 15 - Nov 20	Dec 10
SC	380	Mar 10	Mar 20 - Apr 20	May 15	Jul 25	Aug 20 - Sep 25	Oct 10
SD	3,700	May 1	May 9 - May 25	Jun 11	Sep 24	Oct 10 - Nov 6	Nov 30
TN	680	Apr 5	Apr 15 - May 1	Jun 1	Sep 1	Sep 20 - Oct 15	Nov 10
TX	1,800	Feb 28	Mar 20 - Apr 29	May 15	Jul 16	Aug 6 - Sep 24	Nov 1
UT	21	Apr 15	Apr 30 - May 20	Jun 5	Sep 25	Oct 10 - Oct 30	Dec 10
VA	310	Apr 5	Apr 20 - May 20	Jun 5	Aug 25	Sep 5 - Oct 25	Nov 20
WA	120	Apr 15	May 1 - May 20	Jun 5	Oct 5	Oct 20 - Nov 20	Dec 1
WV	40	Apr 25	May 1 - Jun 1	Jun 15	Sep 10	Sep 20 - Oct 25	Nov 25
WI	3,000	Apr 25	May 1 - Jun 5	Jun 10	Oct 1	Oct 15 - Nov 15	Nov 30
WY	50	Apr 22	May 3 - May 21	Jun 10	Sep 24	Oct 11 - Nov 9	Dec 5

Source: Available at http://swat.tamu.edu/media/90113/crops-typicalplanting-harvestingdates-by-states.pdf

APPENDIX II R CODE FOR QUERYING SOIL DATA FROM HWSD

```
rm(list=ls())
long2UTM <- function(long) {
  return(floor((long + 180)/6) + 1) %% 60
}
##### function to extract and format one rectangular window
extract.one <- function(bbox, name="window")
{
  print(paste("Area name: ", name, "; bounding box:
            [",paste(bbox,collapse=", "),"]", sep=""))
  # extract the window
dir.create(paste("C:\\Users\\jacky\\Dropbox\\research\\climate3\\hwsd\\HWSD_RASTE
R\\window",name,sep=""), showWarnings = FALSE)
setwd(paste("C:\\Users\\jacky\\Dropbox\\research\\climate3\\hwsd\\HWSD_RASTER\\
window",name,sep=""))
  hwsd.win <- crop(hwsd, extent(bbox))
  # find the zone for the centre of the box
  print(paste("Central meridian:", centre <- (bbox[1]+bbox[2])/2))
  utm.zone <- long2UTM(centre)
  print(paste("UTM zone:", utm.zone))
  # make a UTM version of the window
  hwsd.win.utm <- projectRaster(hwsd.win,
                          crs=(paste("+proj=utm +zone=",utm.zone,
                                "+datum=WGS84    +units=m    +no_defs    +ellps=WGS84
+towgs84=0,0,0",
                                sep="")), method="ngb")
  print(paste("Cell dimensions:",
            paste((cell.dim <- res(hwsd.win.utm)),
                collapse=", ")))
  # write the raster images to disk
  eval(parse(text=paste("writeRaster(hwsd.win, file='HWSD_", name,
                   "', format='EHdr', overwrite=TRUE)",sep="")))
  eval(parse(text=paste("writeRaster(hwsd.win.utm, file='HWSD_", name,
                   "_utm', format='EHdr', overwrite=TRUE)",sep="")))
  # extract attributes for just this window
  dbWriteTable(con, name="WINDOW_TMP",
             value=data.frame(smu_id=unique(hwsd.win)), overwrite=TRUE)
  records <- dbGetQuery(con, "select T.* from HWSD_DATA as T
                   join WINDOW_TMP as U on T.mu_global=u.smu_id
                   order by su_sym90")
  dbRemoveTable(con, "WINDOW_TMP")
```

```
  # convert to factors as appropriate
  for (i in names(records)[c(2:5,8:15,17:19,28,45)])
    eval(parse(text=paste("records$",i," <- as.factor(records$",i,")", sep="")))
  # remove all-NA fields
  fields.to.delete <- NULL
  for (i in 1:length(names(records)))
    if (all(is.na(records[,i])))
    { fields.to.delete <- c(fields.to.delete, i) }
  if (length(fields.to.delete > 1))
    records <- records[,-fields.to.delete]
  print(paste("Dimensions of attribute table: ",
            paste(dim(records), collapse=", "),
            " (records, fields with data)", sep=""))
  # write attribute table in CSV formats
  eval(parse(text=paste("write.csv(records,
                    file='./HWSD_", name, ".csv')",sep="")))
  # make a spatial polygons dataframe, add attributes
  print(system.time(hwsd.win.poly <-
                  rasterToPolygons(hwsd.win, n=4, na.rm=TRUE, dissolve=TRUE)))
  # transform to UTM for correct geometry
  hwsd.win.poly.utm <- spTransform(hwsd.win.poly,
                             CRS(proj4string(hwsd.win.utm)))
  m <- match(hwsd.win.poly.utm$value,
           records$MU_GLOBAL); hwsd.win.poly.utm@data <- records[m,]
  # plot the map unit ID
  print(paste("Number of legend categories in the map:",
            lvls <- length(levels(hwsd.win.poly.utm$MU_GLOBAL))))
  p1 <- spplot(hwsd.win.poly.utm, zcol="MU_GLOBAL",
             col.regions=terrain.colors(lvls), main=paste("HWSD SMU code"),
             sub=paste("UTM zone", utm.zone), scales=list(draw = TRUE))

eval(parse(text=paste("pdf(file='C:\\Users\\jacky\\Dropbox\\research\\climate3\\hwsd\\H
WSD_RASTER\\HWSD_", name, "_SMU_CODE.pdf')",sep="")))
  print(p1); dev.off()
  setwd("C:\\Users\\jacky\\Dropbox\\research\\climate3\\hwsd\\HWSD_RASTER")
} # end extract.one
##################################################################
## read in HWSD raster database, assign CRS
require(sp)
require(raster)
setwd("C:\\Users\\jacky\\Dropbox\\research\\climate3\\hwsd\\HWSD_RASTER")
hwsd                                                                    <-
raster("C:\\Users\\jacky\\Dropbox\\research\\climate3\\hwsd\\HWSD_RASTER\\hwsd.bi
l")
```

```
#test<-raster("hwsd.bil")
#ncol(test)
save(hwsd,file="C:\\Users\\jacky\\Dropbox\\research\\climate3\\hwsd\\hwsd.RData")
ncol(hwsd)
nrow(hwsd)
projection(hwsd)#generate a projection for the raster database

require(rgdal)
proj4string(hwsd) <-"+proj=longlat +datum=WGS84 +ellps=WGS84 +towgs84=0,0,0"
## establish connection to attribute database
require(RSQLite)
m <- dbDriver("SQLite")
con <- dbConnect(m, dbname="HWSD.sqlite")
## other packages to be used in the function
require(rgeos)
## call the function for each window we want to extract
extract.one(c(-102.163303, -101.623466, 36.055131,36.500684), "SHERMAN COUNTY")

################################
hwsd.sherman<-crop(hwsd, extent(c(-102.163303, -101.623466, 36.055131,36.500684)))
nrow(hwsd.sherman)
ncol(hwsd.sherman)
bbox(hwsd.sherman)
#show the uique values in a raster for Sherman
unique(hwsd.sherman)
plot(hwsd.sherman,col=bpy.colors(length(unique(hwsd.sherman))))

hwsd.sherman2<-(hwsd.sherman%/%10)
freq(hwsd.sherman2)
require(RColorBrewer)
plot(hwsd.sherman2,col=brewer.pal(length(unique(hwsd.sherman2)), "Accent"))
plot(hwsd.sherman2,col=bpy.colors(length(unique(hwsd.sherman2))))

#create a projection
print(paste("UTM zone:",
        utm.zone <-  floor((sum(bbox(hwsd.sherman2)[1, ])/2 + 180)/6) + 1))

proj4string.utm14 <-paste("+proj=utm +zone=", utm.zone,
                "+datum=WGS84 +units=m +no_defs +ellps=WGS84 +towgs84=0,0,0",
sep="")

hwsd.sherman.utm <- projectRaster(hwsd.sherman2,
crs=proj4string.utm14,method="ngb")
```

```
unique(hwsd.sherman.utm)

(cell.dim<-res(hwsd.sherman.utm))

paste("Cell N dimension is ", round(((cell.dim[2]/cell.dim[1]) - 1)*100,1),
    "% larger than cell dimension E", sep="")
plot(hwsd.sherman.utm,col=brewer.pal(6,"Accent"),asp=1)
#grid()

#compute the area coverd by each code
(cell.area<-cell.dim[1]*cell.dim[2]/10^4)
(tmp<-cbind(freq(hwsd.sherman.utm)[,1],freq(hwsd.sherman.utm)[,2]*cell.area/10^2))

ix<-which(is.na(tmp[,1]))
sum(tmp[-ix,2])
#rm(cell.dim,cell.area,tmp,ix)
######################################################
require(RSQLite)
m<-dbDriver("SQLite")
con<-dbConnect(m,dbname="HWSD.sqlite")
dbListTables(con)
dbGetQuery(con,"pragma table_info(HWSD_DATA)")$name
dbGetQuery(con, "select count(*) as grid_total from HWSD_DATA")
```

APPENDIX III HWSD FOR SHERMAN COUNTY, TEXAS

Coverage	DSMW		
Soil Mapping Unit	4821		
Dominant Soil Group	KS - Kastanozems		
Sequence	1	2	3
Share in Soil Mapping Unit (%)	60	20	20
Database ID	43914	43916	43915
Soil Unit Symbol (FAO 74)	Kl	Kk	Kh
Soil Unit Name (FAO74)	Luvic Kastanozems	Calcic Kastanozems	Haplic Kastanozems
Soil Unit Symbol (FAO 85)	-	-	-
Soil Unit Name (FAO 85)	-	-	-
Soil Unit Symbol (FAO 90)	-	-	-
Soil unit Name (FAO 90)	-	-	-
Topsoil Texture	Medium	Medium	Medium
Reference Soil Depth (cm)	100	100	100
PHASE1	-	-	-
PHASE2	-	-	-
Obstacles to Roots (ESDB) (cm)	-	-	-
Impermeable Layer (ESDB) (cm)	-	-	-
Soil Water Regime (ESDB)	-	-	-
Drainage class (0-0.5% slope)	Moderately Well	Moderately Well	Moderately Well
AWC (mm)	150	150	150
Gelic Properties	No	No	No
Vertic Properties	No	No	No
Petric Properties	No	No	No
Topsoil Sand Fraction (%)	36	32	34
Topsoil Silt Fraction (%)	41	43	45
Topsoil Clay Fraction (%)	23	25	21
Topsoil USDA Texture Classification	loam	loam	loam
Topsoil Reference Bulk Density (kg/dm3)	1.38	1.36	1.39
Topsoil Bulk Density (kg/dm3)	1.2	1.26	1.29
Topsoil Gravel Content (%)	8	8	8
Topsoil Organic Carbon (% weight)	1.27	1.44	1.28
Topsoil pH (H2O)	7.3	8.1	7.4
Topsoil CEC (clay) (cmol/kg)	66	60	81
Topsoil CEC (soil) (cmol/kg)	23	19	21

Topsoil Base Saturation (%)	100	100	100
Topsoil TEB (cmol/kg)	18.4	18.4	18.4
Topsoil Calcium Carbonate (% weight)	4.5	5	5.4
Topsoil Gypsum (% weight)	0	0	0
Topsoil Sodicity (ESP) (%)	3	3	1
Topsoil Salinity (ECe) (dS/m)	0.1	1.1	1.6
Database ID	43914	43916	43915
Subsoil Sand Fraction (%)	29	30	36
Subsoil Silt Fraction (%)	42	46	43
Subsoil Clay Fraction (%)	29	24	21
Subsoil USDA Texture Classification	clay loam	loam	loam
Subsoil Reference Bulk Density (kg/dm3)	1.33	1.36	1.39
Subsoil Bulk Density (kg/dm3)	1.18	1.22	1.42
Subsoil Gravel Content (%)	5	5	5
Subsoil Organic Carbon (% weight)	0.57	0.57	0.51
Subsoil pH (H2O)	7.9	8.1	7.9
Subsoil CEC (clay) (cmol/kg)	68	78	97
Subsoil CEC (soil) (cmol/kg)	24	18	19
Subsoil Base Saturation (%)	100	100	100
Subsoil TEB (cmol/kg)	21.1	21.1	19.1
Subsoil Calcium Carbonate (% weight)	10	14.3	10.4
Subsoil Gypsum (% weight)	0	0	0
Subsoil Sodicity (ESP) (%)	3	3	3
Subsoil Salinity (ECe) (dS/m)	3.6	2.5	2.2

APPENDIX IV RESOLUTIONS OF CMIP5 CLIMATE MODELS

Model	Atmospheric Grid	
	Latitude	**Longitude**
ACCESS1.0	1.25	1.875
ACCESS1.3	1.25	1.875
BCC-CSM1.1	2.7906	2.8125
BCC-CSM1.1(m)	2.7906	2.8125
BNU-ESM	2.7906	2.8125
CCSM4	0.9424	1.25
CESM1(BGC)	0.9424	1.25
CNRM-CM5	1.4008	1.40625
CNRM-CM5-2	1.4008	1.40625
CSIRO-Mk3.6.0	1.8653	1.875
CSIRO-Mk3L-1-2	3.1857	5.625
CanESM2	2.7906	2.8125
INM-CM4	1.5	2
IPSL-CM5A-LR	1.8947	3.75
IPSL-CM5A-MR	1.2676	2.5
IPSL-CM5B-LR	1.8947	3.75
MIROC-ESM	2.7906	2.8125
MIROC-ESM- CHEM	2.7906	2.8125
MIROC5	1.4008	1.40625
MPI-ESM-LR	1.8653	1.875
MPI-ESM-MR	1.8653	1.875
MPI-ESM-P	1.8653	1.875
MRI-CGCM3	1.12148	1.125
MRI-ESM1	1.12148	1.125
NorESM1-M	1.8947	2.5

Source: available at https://verc.enes.org/data/enes-model-data/cmip5/resolution

APPENDIX V NUMBER OF OBSERVATIONS

		50%	55%	60%	65%	70%	75%	80%	85%
Corn Yield Insurance	Corn Belt	399	141	225	456	376	363	98	73
	Lake States	283	170	186	286	180	153	39	-
	Northern Plains	288	103	131	335	239	241	64	38
	Southern Plains	111	31	39	143	54	35	-	-
Corn Revenue Insurance	Corn Belt	182	91	187	422	363	330	163	143
	Lake States	141	57	128	240	148	126	55	28
	Northern Plains	177	78	157	319	250	226	97	76
	Southern Plains	61	16	44	85	54	27		
Wheat Yield Insurance	Pacific Northwest	41	-	25	51	33	52	-	-
	Northern Plains	300	99	147	398	256	333	66	31
	Southern Plains	228	74	90	266	121	89	-	-

APPENDIX VI. SUMMARY STATISTICS OF WEATHER DATA

Variable	Max Temperature	Min Temperature	Precipitation	Wind	Relative Humidity	Solar
Mean	22.672	9.068	1.199	4.549	0.444	18.633
StDev	11.142	9.953	4.152	1.567	0.192	7.301
CV	49.145	109.757	346.44	34.455	43.257	39.181
Min	-16.361	-23.578	0	0.905	0.048	0.709
Median	23.502	8.985	0	4.319	0.412	18.311
Max	47.18	29.417	87.104	11.902	0.991	32.904
Skewness	-0.352	-0.198	7.415	0.722	0.595	-0.034
Kurtosis	-0.674	-0.789	83.909	0.41	-0.279	-0.874

APPENDIX VII. Selected Parameters for APEX Yield Calibration

Parameter	Symbol	Unit	Model Default Set Value	Recommended Range	Reference
Harvest Index	HI	-	0.5	0.45 - 0.60	Akarsh, Patel, and Kumar (2013)
Maximum Potential Leaf Area Index	DMLA	-	5.5	5.0 - 6.0	Doraiswamy et al. (2003)
Potential Heat Units	PHU	°C	2200	1200 - 2400	Kiniry, Benson , and Williams (1991); Akarsh, Patel, and Kumar (2013)
Water Stress	PARM(3)	Percentage	0.5	0 - 1	Steglich an and Williams (2013)
Initial Organic Nitrogen Concentration	WN	g N/Mg or ppm)	N/A	100-5000	Steglich an and Williams (2013)
Initial organic P Concentration	WPO	g/t	N/A	50 - 1000	Steglich an and Williams (2013)
Fertilizer	-	kg/ha	-	-	Experts' Opinions
Plant Population	OPV5	plants/m^2	8	-	Experts' Opinions
Beginning Year of Simulation	IYR	-	-	-	Experts' Opinions
Planting Date	-	-	-	-	Experts' Opinions
Harvest Date	-	-	-	-	Experts' Opinions
Potential Evapotranspiration	IET	-	0	0 - 5	Wang et al. (2012)

APPENDIX VIII. Comparison Results of Net Loss Ratios (2020, 2030, and 2040)

Distribution Comparison of RCP2.6 & RCP4.5 (2020)				
Confidence Level		95.00%		
	Test Value	Critical Value	P-Value	
2 Sample t Test	-2.67	2.25	0.008	*Reject the Ho that the Means are Equal*
F Test	2.14	1.16	0.000	*Reject the Ho that the Variances are Equal*

Distribution Comparison of RCP2.6 & RCP8.5 (2020)				
Confidence Level		95.00%		
	Test Value	Critical Value	P-Value	
2 Sample t Test	-2.62	2.25	0.009	*Reject the Ho that the Means are Equal*
F Test	1.98	1.16	0.000	*Reject the Ho that the Variances are Equal*

Distribution Comparison of RCP4.5 & RCP8.5 (2020)				
Confidence Level		95.00%		
	Test Value	Critical Value	P-Value	
2 Sample t Test	0.10	2.24	0.918	*Fail to Reject the Ho that the Means are Equal*
F Test	1.08	1.16	0.186	*Fail to Reject the Ho that the Variances are Equal*

APPENDIX VIII. Continued.

Distribution Comparison of RCP2.6 & RCP4.5 (2030)

Confidence Level	Test Value	95.00% Critical Value	P-Value	
2 Sample t Test	1.39	2.24	0.165	*Fail to Reject the Ho that the Means are Equal*
F Test	1.15	1.16	0.060	*Fail to Reject the Ho that the Variances are Equal*

Distribution Comparison of RCP2.6 & RCP8.5 (2030)

Confidence Level	Test Value	95.00% Critical Value	P-Value	
2 Sample t Test	-1.97	2.24	0.049	*Fail to Reject the Ho that the Means are Equal*
F Test	1.36	1.16	0.000	*Reject the Ho that the Variances are Equal*

Distribution Comparison of RCP4.5 & RCP8.5 (2030)

Confidence Level	Test Value	95.00% Critical Value	P-Value	
2 Sample t Test	-3.30	2.24	0.001	*Reject the Ho that the Means are Equal*
F Test	1.56	1.16	0.000	*Reject the Ho that the Variances are Equal*

APPENDIX VIII. Continued.

Distribution Comparison of RCP2.6 & RCP4.5 (2040)				
Confidence Level		95.00%		
	Test Value	Critical Value	P-Value	
2 Sample t Test	-3.65	2.25	0.000	*Reject the Ho that the Means are Equal*
F Test	2.04	1.16	0.000	*Reject the Ho that the Variances are Equal*

Distribution Comparison of RCP2.6 & RCP8.5 (2040)				
Confidence Level		95.00%		
	Test Value	Critical Value	P-Value	
2 Sample t Test	-6.65	2.25	0.000	*Reject the Ho that the Means are Equal*
F Test	5.78	1.16	0.000	*Reject the Ho that the Variances are Equal*

Distribution Comparison of RCP4.5 & RCP8.5 (2040)				
Confidence Level		95.00%		
	Test Value	Critical Value	P-Value	
2 Sample t Test	-3.92	2.25	0.000	*Reject the Ho that the Means are Equal*
F Test	2.84	1.16	0.000	*Reject the Ho that the Variances are Equal*