Impacts of Climate Change on Federal Crop Insurance Loss Ratios

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ABSTRACT

This study builds and demonstrates a methodology to evaluate the impacts of climate change on the FCIP for a representative grain sorghum farm in Sherman County, Texas. The results indicate that the approved APH yields and federal yield protection (YP) 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.

Key words: crop insurance, premium subsidies, demand

JEL classification: G22, Q54, Q18

INTRODUCTION

Farming is risky due to the impacts of climate conditions, especially in rain-fed agricultural regions. 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. Studies show that climate change is inevitable and climate variability increases with global warming (Thornton et al. 2014). As a result, farming would be riskier and historical yield patterns would be less reliable for the estimation of future production. However, the impacts of climate change on the FCIP received very little attention in the literature.

Figure 1 displays the national crop insurance loss ratios for all crops, all plans and all coverages. Relatively large lose ratios (indemnity/gross premium) occurred in 1988 at 2.45, 1993 at 2.19, 2002 at 1.39 and 2012 at 1.58 and these losses were mainly due to weather extremes. Figure 2 shows corn and soybean production in the U.S. during 1985-2015. The drought in 1988 was nationwide and costed $15.6 billion in losses of agriculture (Riebsame et al. 1991). 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 3 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.

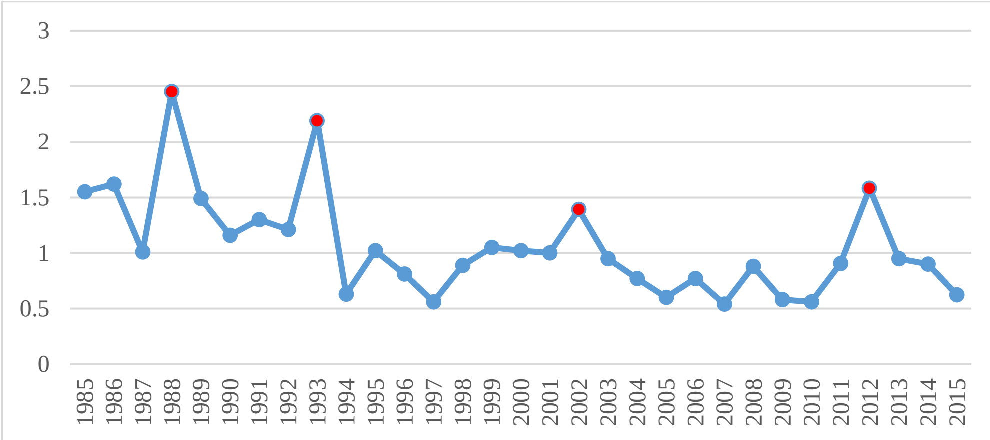

Figure 1. National Crop Insurance Loss Ratios

Source: USDA, RMA, Summary of Business Reports

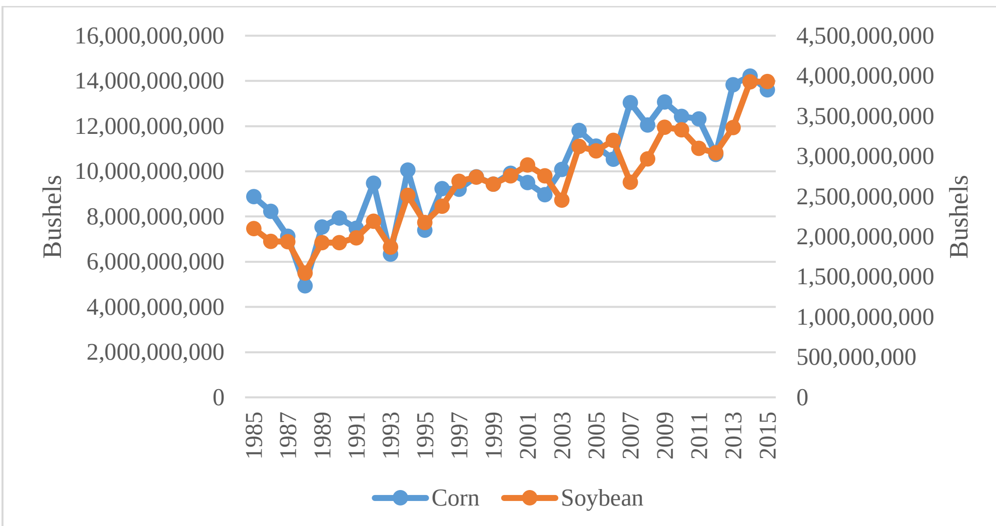

Figure 2. Corn Production in the U.S.

Source: USDA, NASS

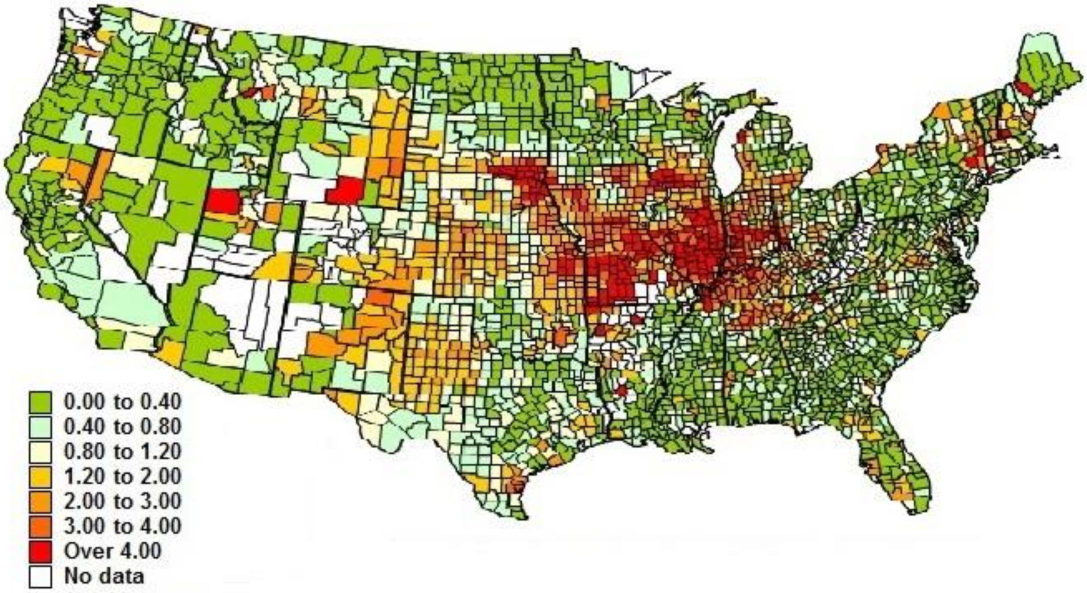

Figure 3. 2012 Crop Insurance Loss Ratios by County

Source: Schnitkey 2015

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 4 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.

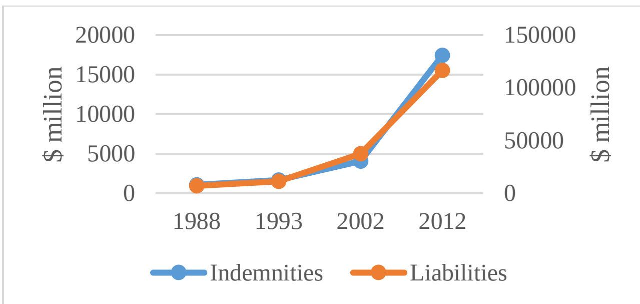

Figure 4. National Crop Insurance Indemnities and Liabilities

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

The purpose of this study is to test the ability of the APEX model to be used for climate change analysis in a crop insurance setting. The Agricultural Policy Environmental eXtender (APEX) model is built on the Environmental Policy Integrated Climate (EPIC) model (Williams et al. 20005) 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 et al. 1998; Bryant et al., 1992; Edwards et al., 1994; Wang et al. 2012). This 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 study is constructed as the followings. In the first part, the crop and soil productivity simulation model (APEX) is parameterized and calibrated to estimate grain sorghum yields for a representative 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.

PARAMETERIZATION AND CALIBRATION OF THE APEX MODEL

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 1 lists the summary statistics of annual yields of non-irrigated grain sorghum for the selected farm.

Table 1. 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.

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.

In this study, two interfaces (ArcAPEX and APEXeditor) of the APEX model were 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. Each subarea is related to a channel for routing (Shukla 2011). 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 parameterize 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 5.

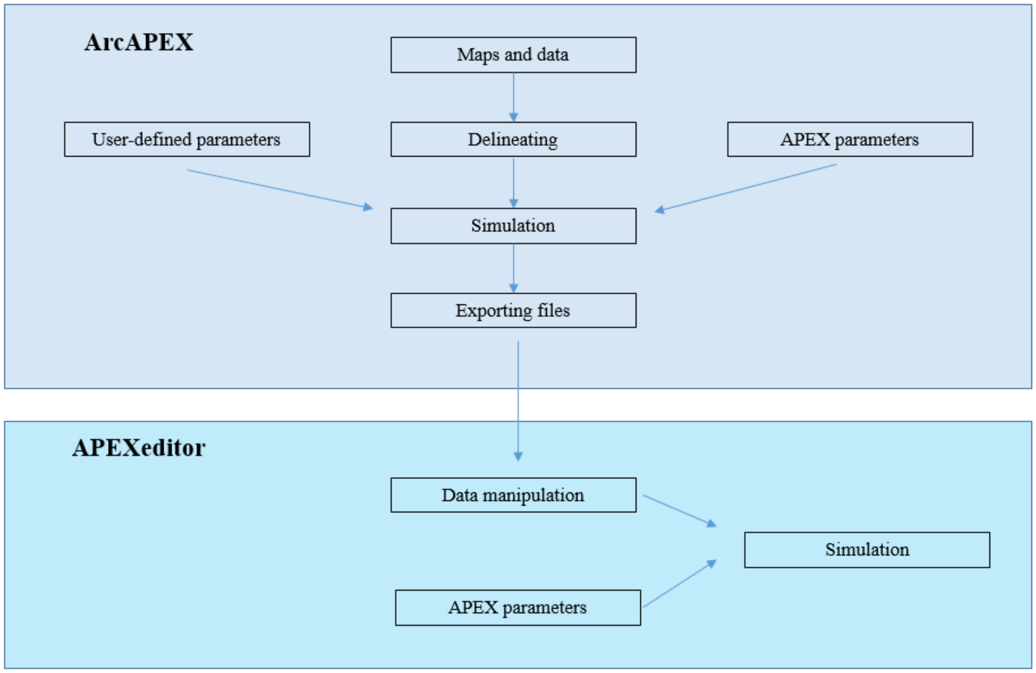

Figure 5. The Flowchart of ArcAPEX and APEXeditor

Table 2 lists the sources of data which were used in the APEX model parameterization. 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. A projection of the DEM is generated by using tools in ArcMap (figure 6). A single-flow direction algorithm available in ArcMap is used to generate required flow information for subarea delineation (figure 8).

Table 2. Input Used in the APEX Model Set Up to Define Parameters for the Study Subarea

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		
Precipitation	Daily		
Solar radiation, relative humidity and wind	Daily	Climate Forecast System Reanalysis (CFSR)	1/1/1979 - 7/31/2014

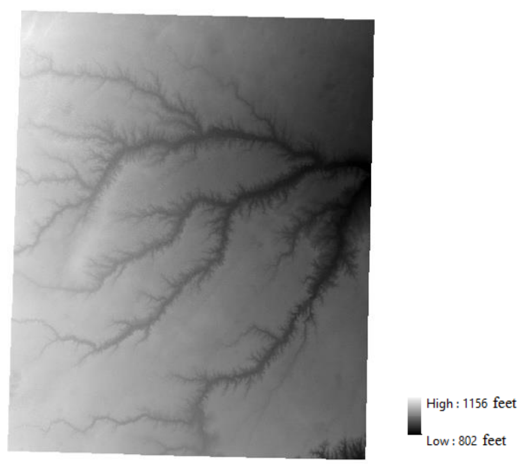

Figure 6. A DEM-based Projection of Sherman, Texas

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

An outlet is manually added on a randomly selected channel, and then a subarea associated with the outlet is automatically delineated by ArcAPEX. 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.

Soil information for Sherman County, Texas is extracted from the Harmonized World Soil Database (HWSD). Instead of using the HSWD Viewer to manually query the dataset, the HWSD is accessed and queried in the open-source R project (Rossiter, 2014). The latitude of Sherman County, Texas ranges from 36.055 to 36.501, and the longitude ranges from -101.623 to -102.163. 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 7) 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. There are three soil layers in the subarea, and all the three layers are loam. Detailed soil information is listed in Appendix I.

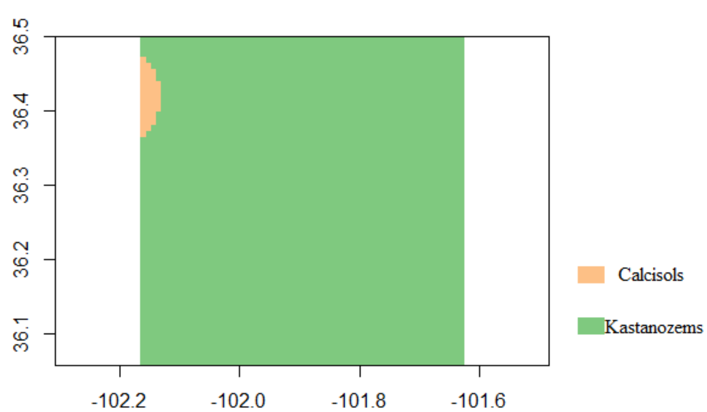

Figure 7. Soil Classes in Sherman County, Texas

Source: HWSD

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. The units in the SWCP are changed to metric unit to match with units in the APEX model.

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.

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 Global Weather Database, 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 were projected on an ArcGIS map, and station 2 is significant 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.

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.

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 estimated yields and historical yields for non-irrigated grain sorghum are presented in table 55. The estimated yields are converted to bushel per acre to match with the units in the original yield dataset.

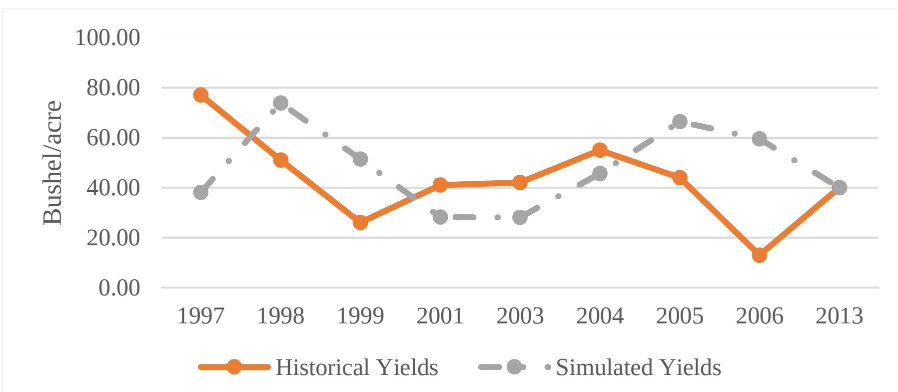

Figure 8. Historical Farm Yields and Simulated Yields

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). Table 3 shows the selected parameters for the calibration process.

Table 3. 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)

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. 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. However, changing weather information and adjusting sensitive parameters did not improve the accuracy of the APEX model.

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.

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 farms' 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.

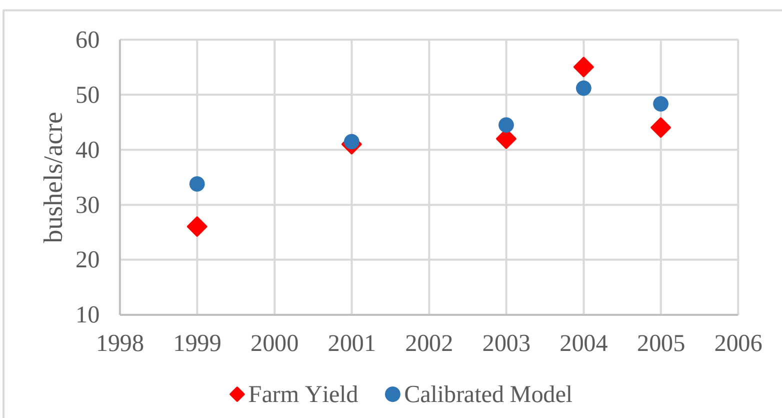

Figure 9. Comparisons of Grain Sorghum Yields

The Student's t-test and F-test are used to test the simulated grain sorghum yields generated by the calibrated APEX model. 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.

YIELD SIMULATION UNDER DIFFERENT WEATHER SCENARIOS

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 et al. 2013). A set of climate projections is generated by climate modeling groups under the CMIP, and 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, Knutti and Tebaldi (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.

The CMIP5 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" (IPCC 2014). 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 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 4 shows the 132 weather projections generated by the 20 models and RCP scenarios available in the DCHP. 20 Climate models 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. 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 4. 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/

A Python program is coded to automatically adjust the format of the weather information to fit in the APEX model, run the grain sorghum model to simulate yields for years 2017 – 2040, and export the simulated yields in separated files. Figure 10 shows the trend of simulated grain sorghum yields from 2017 – 2040 in the three RCP scenarios (RCP2.6, 4.5, and 8.5).

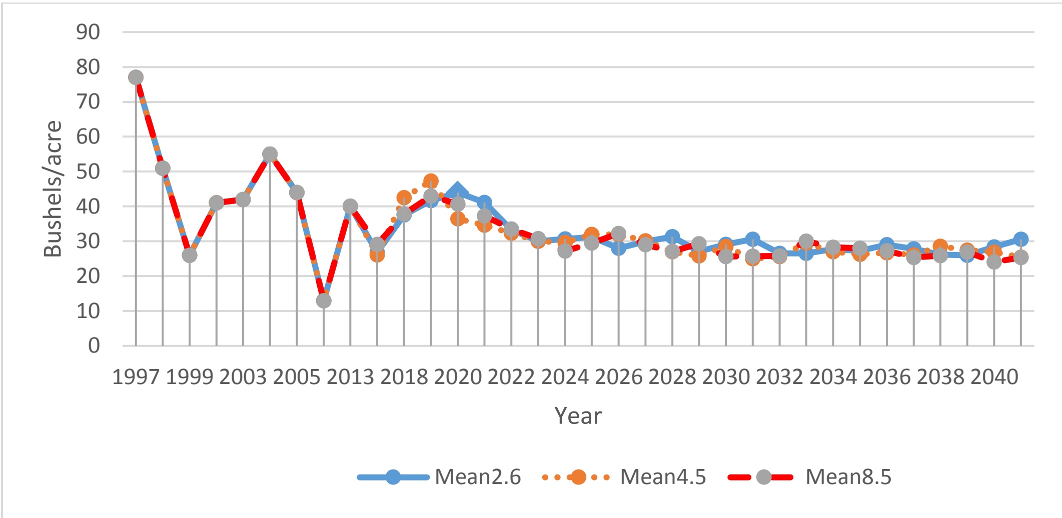

Figure 10. Average Grain Sorghum Yields Simulated for the Three RCP Scenarios (RCP2.6, 4.5, and 8.5)

The simulated grain sorghum yields for the representative farm tend to decrease from 2020 to 2040 under the three RCP scenarios (figure 10). The mean yield over the representative farm's nine-year history is 43.22 bushels/acre, and the mean simulated yieldin 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 (figure 10).

Federal Crop Insurance Loss Ratios

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 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.

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 (USDA, RMA). Figures 11 - 13 show the fan graphs for APH yields over 2020 – 2040 to illustrate the changes of the representative farm's APH yields under the three scenarios (RCP2.6, 4.5, and 8.5).

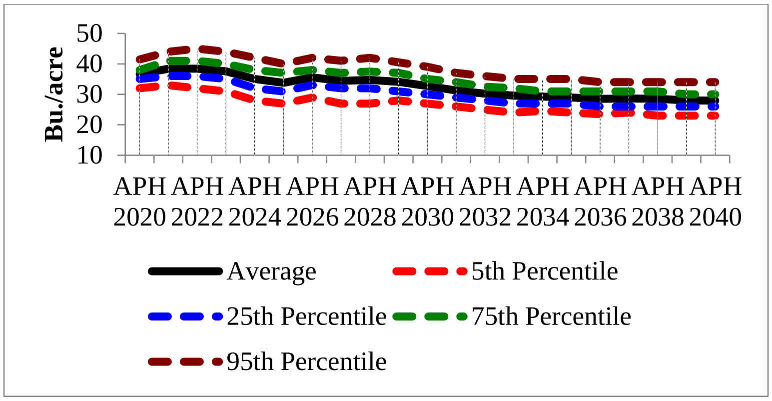

Figure 11. Fan Graph for APH Yields under the RCP2.6 Scenario

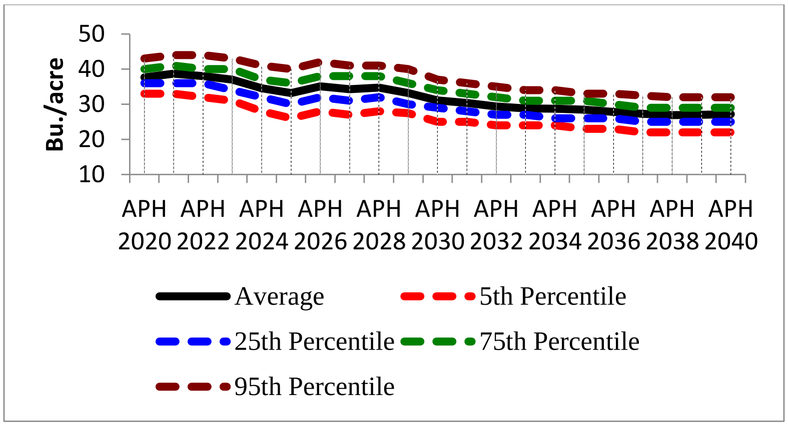

Figure 12. Fan Graph for APH Yields under the RCP4.5 Scenario

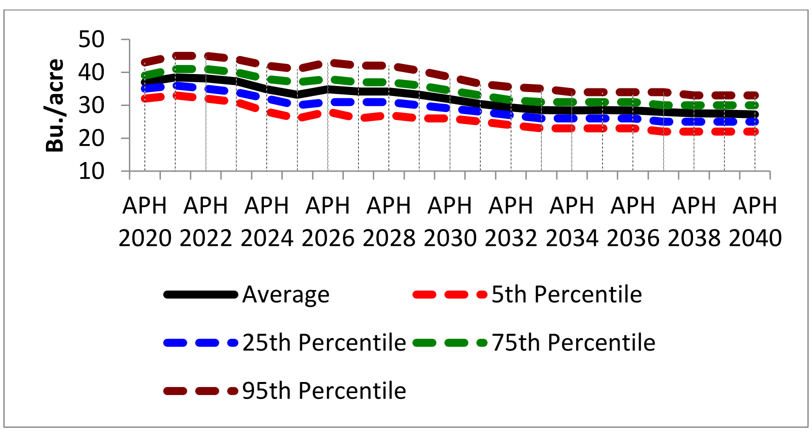

Figure 13. Fan Graph for APH Yields under the RCP8.5 Scenario

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 at 2020 and 2040, respectively; and under the RCP4.5 scenario, the simulated APH yield decreases from 37.69 (at 2020) to 31.30 (at 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.

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 net premiums (producers paid premiums) are calculated based on the stochastic APH yields of the representative farm simulated by APEX. Figures 14 – 16 show the simulated net premiums ($/acre) under each scenario (RCP2.6, 4.5, and 8.5).

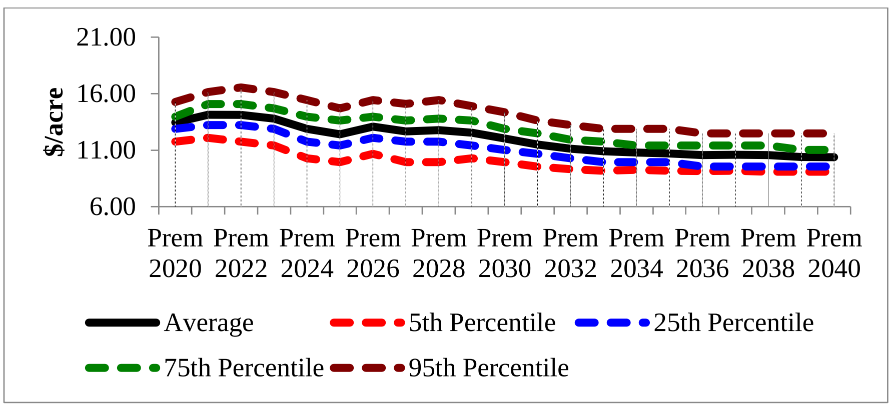

Figure 14. Fan Graph for Net Premiums under the RCP2.6 Scenario

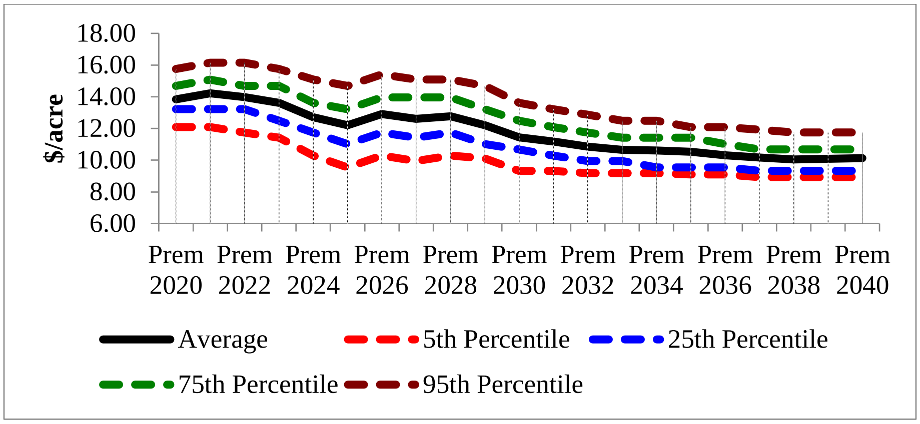

Figure 15. Fan Graph for Net Premiums under the RCP4.5 Scenario

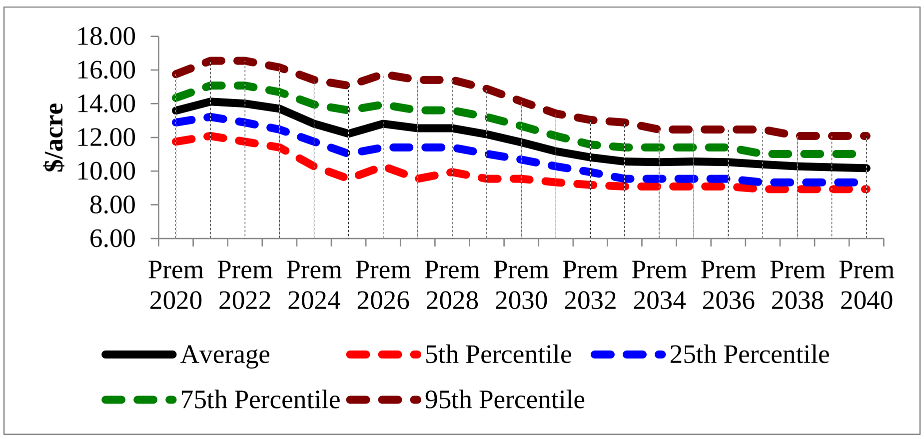

Figure 16. Fan Graph for Net Premiums under the RCP8.5 Scenario

The Student's-t test and the F-test were used to test the three series of the simulated federal YP insurance premiums (generated for three RCP scenarios) in year 2020, 2030, and 2040. The null hypotheses assume that the averages and variances of the premium simulations are the same across the three RCP scenarios. In year 2020, 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. 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. But 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.

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 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. The variances of the premium simulations are statistically equal between RCP2.6 and RCP4.5, and RCP4.5 and RCP8.5 at 2040. But the variances of premium simulations are statistically different at 2040 for RCP2.6 and RCP8.5 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.

Corresponding federal YP insurance loss ratios are calculated as the ratios of indemnities to net premiums, and are illustrated in fan graphs (figure 17 – 19). At 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, at 2020. At 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. The null hypotheses for equal means are rejected at the 95% confidence level between RCP2.6 and RCP4.5 scenarios, and between RCP4.5 and RCP8.5 scenarios in year 2020, which implies that the means of the simulated loss ratios for RCP2.6 and RCP4.5 are statistically different, and the means of the simulated loss ratios for RCP2.6 and RCP4.5 are statistically different. But the variances of the simulated loss ratios are statistically equal to each other across the three RCP scenarios in year 2020. In year 2030, both the means and variances of the simulated federal crop insurance loss ratios are statistically different between RCP4.5 and RCP4.5. In year 2040, all the means and variances null hypotheses are rejected by tests. Therefore, at 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.

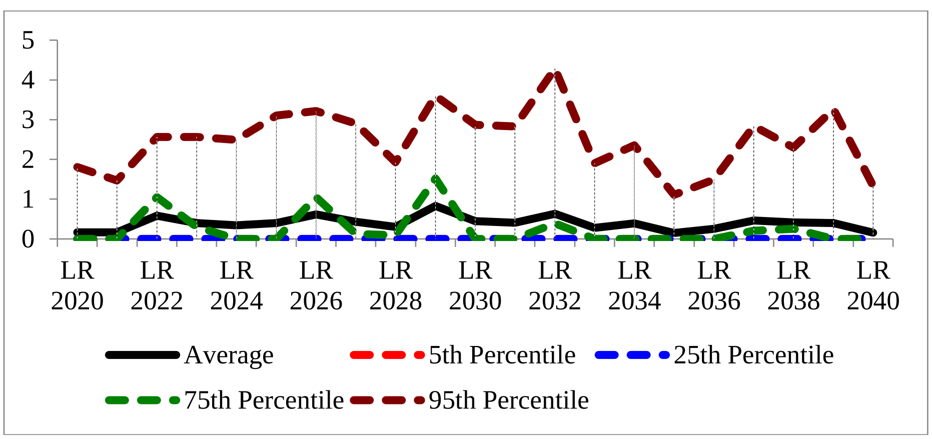

Figure 17. Fan Graph for Loss Ratios under the RCP2.6 Scenario

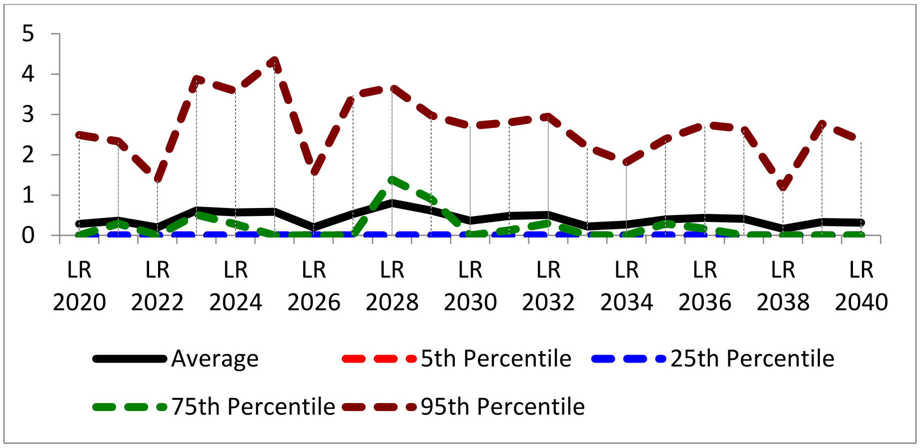

Figure 18. Fan Graph for Loss Ratios under the RCP4.5 Scenario

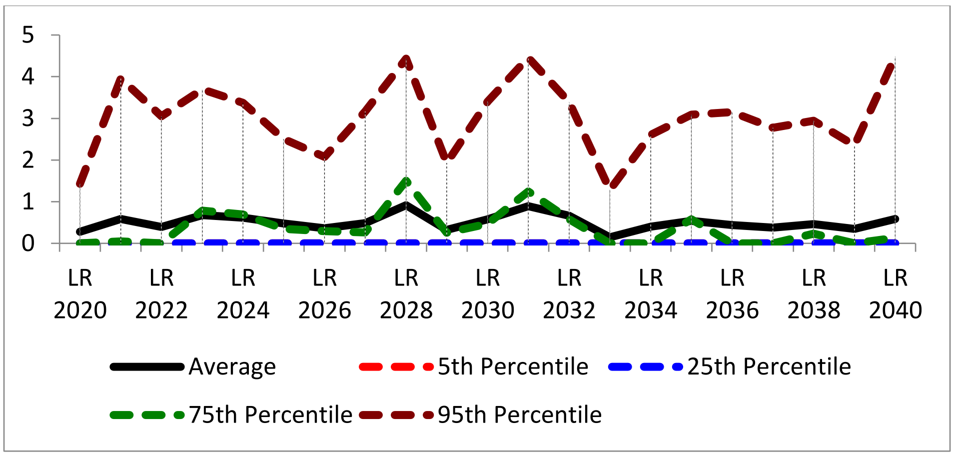

Figure 19. Fan Graph for Loss Ratios under the RCP8.5 Scenario

SUMMARY

This study 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. Althought 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 cliamte 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. 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.

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