Title Page

The names of the authors:

1) Mukesh Dev Bhattarai¹, 2) Silvia Secchi^{*2}, and 3) Justin Schoof²

Title of the article:

Projecting Corn and Soybeans Yields Under Climate Change in a Corn Belt Watershed

Abstract

Climate change may have positive or negative effects on agricultural yields depending on location and mitigation and adaptation practices. This research investigates future corn and soybean yields in the Raccoon watershed, in the US Corn Belt, using projected climate data. We used the Environmental Policy Integrated Climate (EPIC) model to estimate the impact of climate change for 2015-2099 with data downscaled from eight atmosphere-ocean general circulation models (AOGCMs) with three emissions pathways reflecting low, medium and high greenhouse gas emissions scenarios. Soil properties were gathered from the Soil Survey Geographic Database and data on crop rotations was derived from CropScape, a geospatial cropland data layer product of the US National Agricultural Statistics Service (NASS). Our findings indicate that 20-year mean yields of both corn and soybean for 2080-2099 simulated in EPIC using all eight AOGCMs under low and medium carbon scenarios will increase in comparison to the 20-year mean yields for 2015-2034. However, under the high carbon scenario, 20-year means of both corn and soybean yields for 2080-2099 will decline in comparison to the 20-year mean yields for 2015-2034, pointing to the effects of climate change. We also examined the possible impact of carbon fertilization on yields. Our results show that carbon fertilization of soybean, a C_3 plant, may contribute to an increase in yield of 2% to 20% while its contribution to the growth of corn, a C_4 plant, will be much lower.

Keywords:

Climate Change, Environment, Crop Yields, Carbon Fertilization, Climate Models, Downscaling

1 - Introduction

Agricultural crops are grown in a variety of regions with diverse climatic conditions, their success depending on many factors such as soil quality, fertilizers, and seed technology and quality (Adams et al., 1998; Reddy and Hodges, 2000). As climate plays a determining role in agriculture, climate change may adversely affect global agricultural productivity, though some areas and crops may benefit from the change (Challinor et al., 2009; Li et al., 2011; Niu et al., 2009; Southworth et al., 2000). The net effect of climate change on agricultural productivity and the environmental impacts of agricultural activities will depend on the possible alteration of many properties of the climate and weather, such as the length of the growing season, water availability, rate of carbon fertilization, and the effects of weeds, insects and diseases among other factors (Bayer et al., 2015; Desjardins et al., 2007; Reilly et al., 2003; Wang et al., 2014). A number of crop simulation models are now being widely used to incorporate the impact of climate change on various ecosystem services together with the biophysical aspects of crops (Adams et al., 1998; Bryant et al., 2000; Challinor et al., 2009; Rosenzweig and Parry, 1994; Roudier et al., 2011). Although many modeling approaches have been attempted to simulate yields using climate projections derived from coupled atmosphere-ocean general circulation models (AOGCMs), fewer researchers have used downscaled data to estimate impacts on agricultural yields over a watershed. The use of downscaled data, coupled with high-resolution land use and soil data, can help policy makers and land managers better understand spatial and temporal impacts of climate change on yields. Fine-grained impact assessments are also important in understanding reactive individual adaptations, which are widespread in agriculture, and their spatial patterns. For example, differential yield impacts on C₄ and C₃ plants may affect crop profitability and alter farmers' crop choices. Here, we present a systematic approach to

projecting agricultural yields under various climate scenarios by integrating the Environment Policy Integrated Climate (EPIC) model with field level data and downscaled 21st century climate data. The novelty of this approach is that it combines very detailed land use and soil data with downscaled climate scenarios. Therefore, it provides a much richer set of results than models relying on coarser spatial resolutions, which may underestimate effects on soils at the tails of the distribution. Since the results are spatially explicit, they can also be useful in outreach activities with farmers, and can be linked with watershed level water quantity and quality models.

Climate change may have different impacts on plants depending on climate zones and types of plants. A number of researchers have indicated that agriculture may benefit from climate change, particularly in the temperate zone, due to increased CO₂ concentrations in the atmosphere, a phenomenon termed the carbon fertilization effect (Heimann and Reichstein, 2008; McGrath and Lobell, 2013). It has also been predicted that the southern hemisphere may suffer more adverse consequences of climate change than the northern hemisphere due to differences in carbon concentrations in the atmosphere. Carbon fertilizer effects are different for C₃ and C₄ plants. The productivity gain is generally greater for plants with the C₃ photosynthetic pathway compared to plants with the C₄ pathway (Adams et al., 1998; Kimball et al., 2002; Long et al., 2005; Rosenzweig and Iglesias, 1998; Thomson et al., 2005). Therefore, given crop production patterns, climate change may have more effects on C₃ plants than C₄ plants. This could affect global food security as many plants that are sources of staple foods in developing countries in the southern hemisphere such as wheat, rice, and beans are C₃ plants. This may create upward pressure on intensive agriculture in the northern hemisphere if demand for food grains were to

grow. Hence, the inclusion of carbon fertilization effects on C₃ and C₄ plants in our research provides insights for future mitigation and adaptation endeavors at the watershed scale, where more interaction and outreach with farmers occur, but our results can be contextualized at a global scale as well.

2 - Materials and Methods

2.1 - Selection of Crops and Study Area

Since agricultural production involves thousands of crops and practices worldwide, to reduce the simulations to a manageable size, a set of representative crops and an appropriate study area were chosen. Corn and soybeans were selected for the study as these two crops combined cover almost 53 % of the United States' total agricultural land (USDA NASS, 2016). Among U.S. states, Iowa is the largest producer of corn and ethanol and one of the largest producers of soybeans (USDA NASS, 2016). Within Iowa, the Raccoon watershed was chosen as a representative region of the US Corn Belt because of its highly productive and intensive agriculture.

2.2 – Description of the EPIC model

The EPIC model (version 0509) was used to simulate the yield response of corn and soybeans to various climate change scenarios. The EPIC model simulates both the impact of climate change on specific crops and on the environmental indicators associated with the crop's production, including a host of characteristics such as soil quality, weather parameters, management practices and landscape type (Izaurrealde et al., 2006; Williams et al., 1984; Williams et al., 1983). EPIC calculates plant biomass by simulating carbon fixation through photosynthesis and

respiration for maintenance and growth (Stockle et al., 1992). The model can estimate the effects of climate, soil and management decisions on soil, water, nutrients and pesticides and then predict their accumulated impacts in terms of variables such as yields, SOC (Soil Organic Carbon), soil erosion and water quality (Izaurrealde et al., 2006; Williams et al., 1984; Williams et al., 1983). EPIC is an extensively tested model (Izaurrealde et al., 2006; Williams et al., 1984). Researchers in the US and all over the world have used this model for various types of simulations, and the model has been successfully validated (Balkovič et al., 2013; Causarano et al., 2008; Chavas et al., 2009; Chung et al., 1999; Izaurrealde et al., 2006). EPIC has been also used to research climate change impacts on several crops world-wide (Dhakhwa et al., 1997; Liu et al., 2007; Priya and Shibasaki, 2001; Tingem and Rivington, 2009).

2.3 - Development of Baseline Field Data

We used CropScape, an online visualization portal of the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (USDA), to generate historical Geospatial Cropland Data Layers (CDL) for the Raccoon Watershed to identify field data with an appropriate geo-reference to soil data and management practices (USDA NASS Research and Development Division, 2016). The data was then processed in an ArcGIS environment to identify land use land cover (LULC) for multiple years. This procedure enabled us to identify a total of 2481 unique land use areas (ULUAs) including crop fields, forests, pastures, and urban areas in the Raccoon Watershed (Teshager et al., 2016). These ULUAs were then processed to identify their soils. Out of 2481 ULUAs, 2045 spatially explicit crop fields were identified together with their geo-references to soil map units. Similarly, crop rotations for each field for the three years between 2008 and 2010 were also identified using the procedure. We used four

crop rotation choices: i) Corn-Soybean-Corn (CSC), ii) Corn-Corn-Soybean or Soybean-Soybean-Corn (CCS or SSC), iii) continuous Corn (CC) and iv) others, that include pastures, forests, urban areas and water. According to the results of the ArcGIS processing procedure, 56% of the Raccoon Watershed was under the CSC rotation, 19% was under CCS or SSC, 10% was under CC, and 15% was under “others”, as shown in Figure 1.

In general, three main tillage categories are practiced in US agriculture: conventional, conservation and no-till (Horowitz et al., 2010). The conventional tillage system leaves less than 15% crop residue on the ground. The system involves often multiple operations with implements such as mold board, disk and/or chisel plow. Conservation tillage systems are methods of soil tilling which leave a minimum of 30% of crop residue on the soil surface so as to reduce soil erosion. Soil loss through water erosion is greatly reduced when crop residue is left on the soil surface and soil drainage, organic matter, and moisture content are improved. Conservation tillage also reduces air pollution, sequesters carbon, improves water quality and creates wildlife habitat. No-till is a subcategory of conservation tillage in which plows, disk etc. are never used, and it aims for 100% ground cover. The harvested crop’s stalk and roots remain in the ground. No-till is considered the most environmentally friendly tillage method.

We used the CDL data, together with USDA’s Agriculture Resource Management Survey (ARMS) data (USDA Economic Research Service, 2015), to calculate the percentages of tillage categories (conventional tillage, conservational tillage, and no-till) associated with crop rotations. Although the corn-soybean rotation has traditionally been the most important crop rotation in the US Corn Belt, continuous corn has become a common option to meet the

increasing demand for corn (Stern et al., 2012). Demand for corn drives up the planting of corn after corn and simultaneously increases conventional tillage, since less intensive tillage practices negatively impact corn yields in continuous corn systems (Vetsch and Randall, 2002), and increased fertilizer applications may partly compensate yield drags from continuous corn (Katsvairo and Cox, 2000; Lehmann et al., 2013). We assumed that 90% of continuous corn is under conventional tillage on the basis of the ARMS data (USDA Economic Research Service, 2015), a review of the literature (Blanco-Canqui and Lal, 2008; Stern et al., 2012), and materials from Iowa State University's Extension Office (Duffy, 2013). In the cases of other rotations including CSC, and CSS/SCC, we assumed that such rotations are 30% no-till, 40% conservation tillage and 30% conventional tillage, as farmers make their management decisions based on host of factors including yield expectation, their beliefs, financial constraints, slope and field areas.

Nitrogen fertilization is important for corn production. The rates of application of N-fertilizer depend on a host of factors such as types of crops, soil, and rotation practices among others. According to USDA, an average of 158 kg ha⁻¹ of N-fertilizer was applied for corn production in Iowa (USDA NASS, 2016). For this research, we used 202 kg ha⁻¹ N-fertilizer for continuous corn and 135 kg ha⁻¹ for the corn-soybean rotation. Iowa – like most of the Corn Belt - enjoys plenty of rainfall and hence irrigation in general is not a common practice, therefore irrigation was assumed to be absent.

All soil parameters including slope and slope length required as input for EPIC were derived from the US Soil Survey Geographic (SSURGO) database using soil map units already geo-

referenced with individual fields (USDA Natural Resources Conservation Service, 2016). All 2045 ULUAs were linked through ten weather stations in and around the Raccoon Watershed.

2.4 - Forecasting Crop Yields with Future Climate Scenarios in Iowa

In order to meaningfully compare the various 21st century emissions pathways, the concept of Representative Concentration Pathways, or RCPs (Moss et al., 2010), which are based on radiative forcing, has been adopted as part of Phase 5 of the Coupled Model Intercomparison Project (CMIP5) (Taylor et al., 2012), the coordinated modeling experiment that informed the 5th Assessment Report of the Intergovernmental Panel on Climate Change (IPCC). RCPs were distinguished and identified according to target levels of radiative forcing for 2100. They are RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5, corresponding to 2.6, 4.5, 6.0 and 8.5 W m⁻² of radiative forcing at the end of the century, respectively. In general terms, RCP 2.6 represents a low carbon scenario, RCP 4.5 and RCP 6.0 represent midlevel carbon scenarios and RCP 8.5 represents a high carbon scenario. For this research, we chose RCP 2.6, RCP 4.5 and RCP 8.5. The CMIP5 data archive, available at http://cmip-pcmdi.llnl.gov/cmip5/data_portal.html, includes results from more than 20 AOGCMs simulating the climate of the recent past as well as 21st century projections. The AOGCMs used in this study are identified in Table 1 and are restricted to those with daily output for the historical period and 21st century projections for all of the required variables. To facilitate direct comparison, output from all of the models was interpolated to a common 2.5° × 2.5° grid using a triangle-based linear interpolation. Although coarse-resolution AOGCMs can provide realistic simulations on a seasonal time scale and a continental-to-hemispheric spatial scale, additional information is required for watershed level

applications. We therefore applied a downscaling technique to derive each of the above-mentioned variables as explained below.

2.5 - Downscaling of AOGCMs climate data

The use of continental level climatic data with low resolution land use data may not be sufficient for assessing spatial and temporal impacts of climate change on yields and to appreciate reactive adaptations for policy making endeavors. Therefore, we used downscaled climate data with high resolution land use and soil data. The term downscaling describes a mechanism that involves a range of methods applied to infer climate information at regional or local scale from coarsely resolved AOGCMs. Downscaling can be conducted using dynamical approaches (i.e., regional climate modeling) or using statistical models, and has been the subject of several review papers (Schoof, 2013; Wilby and Wigley, 1997). The computational cost of dynamical downscaling is prohibitive for applications utilizing a large number of emissions pathways and AOGCMs. Therefore, this work adopts a statistical approach to derive high resolution climate information from the coarsely resolved AOGCMs.

Downscaling was conducted separately for the precipitation and non-precipitation variables, namely, daily maximum and minimum temperature ($T_{\max}$, $T_{\min}$), relative humidity, wind speed, and solar radiation. For precipitation, we used a scaling technique well established in the literature (Schoof and Pryor, 2014; Wilks, 1999). For $T_{\max}$, $T_{\min}$, relative humidity and wind speed, regression equations were developed to relate monthly means and standard deviations to large scale values of circulation and thermodynamic properties (air temperature and specific humidity) derived from NCEP-NCAR reanalysis data (Kalnay et al., 1996). The regression

equations were then applied to output from the AOGCMs listed in Table 1 to derive monthly means and standard deviations of the required variables at the local scale. For all variables (other than solar radiation), the downscaling produced descriptors of the time series that could then be used with a stochastic weather generator to produce daily time series for each variable compatible with EPIC (Schoof, 2013; Schoof et al., 2007). Solar radiation was then estimated using maximum and minimum temperature (as a surrogate for cloud cover) and geographic location information (Bristow and Campbell, 1984).

3 - Results and Discussion

3.1 - Calibration of EPIC

The EPIC users' guide (Williams et al., 1983) provided a number of steps for the performance of crop yield calibrations and validations. Since yield data are reported by county, for calibration, we used data for Guthrie County, which lies completely within the Raccoon Watershed. We identified the ULUAs within Guthrie County and run the EPIC simulations for those ULUAs only. The results reported at the county level are a weighted average of those simulations. We ran the simulations for corn and soybean crop yields from 1974 to 1992, using historic climate data. The simulated results were then compared with the estimated yields of corn and soybean in Guthrie County as published by USDA-NASS (USDA NASS, 2016). We adjusted heat units, plant population, and plant stress levels, depending on soil, weather and management practices in Iowa based on reports of Iowa State University's Extension (Duffy, 2013) and USDA (USDA NASS, 2016). We then selected three crop parameters for adjustment during the calibration process. They were the Harvest Index (HI), the biomass-energy ratio (WA) $\text{kg ha}^{-1} \text{MJ}^{-1}$, and the Maximum Potential Leaf Area Index (MXLA). The final values were 0.55 for corn HI and 0.3

for soybeans, 45 for corn WA and 25 for soybeans, and 6 for corn MXLA and 5 for soybeans. We verified that the final values of these parameters lay within acceptable ranges and were comparable to published data. HI values that had been adjusted in the model approximated values reported in the literature (Causarano et al., 2008; Kiniry et al., 2004). The WA was also close to the parameters reported in previous research (Kiniry et al., 2004; Lindquist et al., 2005). Similarly, MXLA values for both corn and soybean closely approximated the values reported by Causarano et al. (2008).

For calibration purposes, we used CDL data for the crop rotation practices of Guthrie County in 2008-2010. It is important to identify rotation practices as the sequence of crops in the rotations has some influence on crop yield and management practices. For example, the corn-soybean rotation has higher corn yields with reduced cost (Katsvairo and Cox, 2000). The EPIC model simulates yields taking into account the crop rotation. In Guthrie, we found that for the calibration period, almost 70% of crop ULUAs were cropped under the corn-soybean (CS) rotation, 18% of crop ULUAs were cropped using corn-soybean-soybean (CSS)/soybean-soybean-corn (SSC), and 12% were in continuous corn (CC). Although this pattern of crop rotation may not be fixed either in the past or the future, since it depends on a variety of economic and technological factors, we assumed that the pattern did not change to allow for comparability of the results. As noted above, for nitrogen input, another important variable, we assumed the same application rates across the watershed: 202 kg ha⁻¹ for Continuous Corn and 135 kg ha⁻¹ for the other rotations based on the reports of Iowa State University's Extension (Duffy, 2013) and USDA (USDA NASS, 2016). For both calibration and validation, the first year results were excluded from the analysis that follows.

The calibration results of the EPIC model showed that out of 18 runs for the 1975-1992 calibration period, 15 produced corn yields within 20% of the NASS estimates, which has been considered as an acceptable range (Causarano et al., 2008). Similarly, out of 18 runs for the same period, 14 runs produced a soybean yield within 20% of the NASS estimates (Supplementary Table 1). The Coefficient of Determination (R^2) for the calibration period was 0.73 for corn and 0.70 for soybean (Figures 2 and 3). The mean annual yield of corn from the EPIC simulations for 1975-1993 was 4.8% higher than the mean annual yield from the NASS database for the calibration period. In the case of soybeans, the mean annual yields produced by the EPIC simulations for the same period was 10.8% lower than the mean annual yields reported by NASS. The variance of the NASS estimates across the years for corn was $2.088 \text{ mg}^2 \text{ ha}^{-2}$, while the EPIC estimates' variance was higher, $3.742 \text{ mg}^2 \text{ ha}^{-2}$. For soybeans, the NASS estimates' variance was $0.086 \text{ mg}^2 \text{ ha}^{-2}$ and the EPIC simulations' was $0.261 \text{ mg}^2 \text{ ha}^{-2}$.

3.2 – EPIC Model Validation

We validated the model for the entire Raccoon watershed for 1993-2010 against NASS estimates. As for calibration, the first year's EPIC results were not considered in the analysis. Since the watershed covers 14 counties, we used the mean yields reported by NASS for these 14 counties to calculate the estimate for the watershed as a whole. During this 17-year period, 16 out of 17 simulation runs produced corn yields within a range of 20% of the NASS mean yields while for the same period, 15 simulation runs out of 17 produced soybean yields within a range of 20% of the NASS estimate. The Coefficient of Determination (R^2) for the validation period was 0.71 for corn and 0.70 for soybeans (Figure 2 and 3). The mean annual yields generated by the EPIC simulations for 1993-2010 were 0.35% and 5.51% higher than the NASS estimations

for the same period for corn and soybean respectively. For the validation period, the NASS estimates for corn had a higher variance across years ($1.234 \text{ mg}^2 \text{ ha}^{-2}$), that that computed from the EPIC simulations ($1.825 \text{ mg}^2 \text{ ha}^{-2}$). For soybeans, the variance was $0.182 \text{ mg}^2 \text{ ha}^{-2}$ for the NASS estimates and $0.331 \text{ mg}^2 \text{ ha}^{-2}$ for the EPIC simulations.

A number of factors could explain the differences between the calibration and the validation results, including crop rotations, tillage practices, amount and number of fertilizer applications among others. Crop rotation practices were based on the 2008-2010 CDL data. Though there is a long list of rotation practices that are prevalent in the Racoon Watershed, to facilitate the simulation run the list was shortened to include only three categories, corn-soybean (CS), corn-corn-soybean (CCS)/soybean-soybean-corn (SSC), and continuous corn (CC). Based on 2008-2010 CDL data, we assumed the pattern of these rotations practices to be constant for the entire simulation period. However, the rotation practices fluctuated over the period of 1974 to 2010. Stern et al. (2012) pointed out in their research that crop rotation practices have indeed fluctuated, primarily due to change in corn prices. Similarly, tillage practices and fertilizers applications, which we assumed to be fixed, likely fluctuated as well. For example, there is evidence that the use of no till has increased (Horowitz et al., 2010).

3.3 - Climate Model Performance

We tested the performance of data derived from the eight AOGCMs by comparing the corn and soybean yields simulated by EPIC using each model with the NASS corn and soybean yields for the period 1974-2003. We used three statistical standards that are commonly used for model

comparisons, namely, the Coefficient of Determination (R^2), the Root Mean Square Error (RMSE) and the Mean Absolute Error (MEA):

$$R^2 = \left[\frac{\frac{1}{n} \sum_{m=1}^n (x_o - \mu_o)(x_m - \mu_m)}{\sigma_{x_o} * \sigma_{x_m}} \right]^2, \text{RMSE} = \sqrt{\frac{\sum_{m=1}^n (x_o - x_m)^2}{n}}, \text{MAE} = \frac{\sum_{m=1}^n |x_o - x_m|}{n}$$

Where x_o is the observed data, x_m is the model output, σ is the standard deviation and n is the sample size. Also, o stands for “observed variable”, m for “model variable”, and μ stands for mean of values of observed variable or model variable. Table 2 shows the results of the analysis of all eight models’ outputs in terms of the three statistical standards. The performances of all of the models very closely approximated the NASS estimates.

3.4 - Yields projections of corn and soybean

We examined the outcomes of EPIC simulations using the downscaled weather data of all eight models for the period 2015-2099 for corn and soybean yields in all three RCPs. Figure 4 shows the mean yield growth pattern of corn and soybean for the research period (2015-2099) as simulated by each of the eight models used as EPIC input. The figure suggests that yield for corn and soybeans would increase by the end of the century in both the RCP 2.6 and RCP 4.5, but projections decreased for both crops in the RCP 8.5 (Figure 4).

We compared simulated mean yields between the periods 2080-2099 and 2015-2034 for corn and soybeans. Figure 5 shows that, when comparing 20-year mean crop yields in the latter part of the century to the 20-year mean of the base period of 2015-2034, yields increased under RCP 2.6 and RCP 4.5 whereas under RCP 8.5 they decreased. In the case of corn, the 20-year mean corn yield increased by 4.2% under RCP 2.6, while the increase was 5.5% under RCP 4.5. In the case of RCP 8.5, the mean 20-year corn yields registered a decline of 6.4% as compared to the base

period. In the case of soybeans, Figure 5 shows the same pattern as for corn. Mean crop yields in the period 2080-2099 compared to the 20-year mean in the base period of 2015-2034 increased under RCP 2.6 and RCP 4.5 while they were lower under RCP 8.5. Under RCP 2.6, the increase in the 20-year mean soybean yields was 8.9%, while for RCP 4.5 the increase was 11.1%. For RCP 8.5, the mean 20-year soybean yields registered a decline, however this reduction was smaller than for corn (3.6%). This raises the possibility that high emission levels may have adverse effects on overall agricultural productivity and ultimately on global food security. It is important to note that yields consistently remain very close to across all RCPs until the middle of the century under all the AOGCMs used in the simulations, while towards the end of century the yields within the three RCP scenarios started to diverge.

It is important to note that we report mean crop yields projections (ensemble) of eight models under three different RCPs. This could potentially mask the variability due to responses of different AOGCMs. At the lead times considered here, uncertainty in the climate projections arises from both the models and the emissions pathways and, to a lesser extent, internal climate system variability (Hawkins and Sutton, 2009). Figure 6 shows the range of yield growth patterns for both corn and soybean under RCP 2.6 and RCP 8.5 using the simulated outcomes of all eight AOGCMs. The figure indicates that till the middle of century, observed variation could be attributed solely to model response uncertainty, underscoring the lagging effect of climate change, while after the middle of the century the ranges of yields projections under RCP 2.6 and RCP 8.5 start to deviate, suggesting there is an impact of climate change on crop yields.

To formally test this hypothesis, we also used t-tests to compare projected yields of corn and soybeans under RCP 2.6 and RCP 8.5. The summary results of the t-tests are shown in Table 3. We used the t-tests to compare projected yields for four different periods: i) the whole simulation period of 2015-2099, ii) the initial simulation period, defined as 2015-2042, iii) the middle period, 2043-2070, and iv) the final period, 2071-2099. The p-values for 2015-2042 suggest that there is no significant difference between the crop yields for both corn and soybeans, underscoring the lagging effects of climate change. In contrast, for the latter two periods, the p-values indicate that the differences between crop yields are highly significant, pointing to the impact of climate change on crop yields.

Figure 6 also suggests that the corn yields have a wider range than soybean yields at the beginning of the century. Such a wide range may be the reason why the ensemble mean yields of corn are different for the three RCPs even in the initial simulation period, when the differences in the impact of climate change are small across the three RCPs.

It is also important to note that we are reporting results at the watershed level. However, the raw yield data is available by ULUAs, and can be mapped. This could provide an important outreach tool to local farmers, since they would be able to visualize both spatial and temporal variability of yields at a very fine scale. Figure 7 shows the impact of climate change on crop yields for each ULUA. We compared the differences between 20 years mean yields between the end of the century (2080-2099) and the early portion of the century (2015-2034) for both corn and soybean for each of ULUAs in the RCP 8.5. Fine-grained spatially explicit maps like the one in Figure 7 could be helpful, for example, in identifying areas where to focus adaptation efforts to reduce

yield losses. Further statistical analysis could be used to correlate yield losses with soil and topographic characteristics, in order to generalize results.

3.5 - Effects of Carbon Fertilization

The increased concentration of CO₂ in the atmosphere may have direct effects on plants, as it reduces stomatal conductance and hence enhances water-use efficiency (Acock, 1990; Rosenberg, 1981). More specifically, direct stimulation of photosynthesis at ca 550 ppm could be translated to yield increases of +20% for soybean, a C₃ plant and about +6% for corn, a C₄ plant (Long et al., 2005). A review of 770 experimental observations for a variety of crops suggested that doubling of the CO₂ level may cause an average yield increase of 34% for C₃ plants, whereas the average yield growth for C₄ plants was 14% (Acock, 1990; Patterson and Flint, 1980). Similarly, based on review of hundreds of experimental studies, Kimball (1983) reported that doubling of atmospheric CO₂ concentrations resulted in an average of 33% yield increase of C₃ plants (Kimball, 1983). Other studies that examined the direct stimulation of photosynthesis at CO₂ concentrations at ca 550 ppm reported impacts of +21% for soybean and +6% for corn (Rosenzweig and Iglesias, 1998), +29% for soybean and +8% for corn (Adams et al., 1998), and +10% for corn (Dhakhwa et al., 1997).

To analyze the relationship between carbon fertilization and the mean crop yields of corn and soybean in the Raccoon Watershed, we ran the EPIC model with a fixed atmospheric CO₂ concentration of 350 ppm for all three RCPs using the projected data given by all eight models. We derived the 350 ppm concentration as an approximate average of atmospheric concentrations of CO₂ for the period of 1974-2010 as taken from the published data of the Mauna Loa, Hawaii measuring station, available at <http://www.esrl.noaa.gov/gmd/ccgg/trends/>.

We examined the outcomes of the EPIC simulations for corn and soybean yields in all three RCPs with a constant CO₂ concentration of 350 ppm using the downscaled weather data of all eight models for the period 2015-2099. The results are reported in Figure 8. The mean model yields projection figures show that, as in case of dynamic CO₂ atmospheric concentration, corn and soybean yields will continue to grow throughout the century in RCP 2.6 and RCP 4.5 and decline towards the end of century in case of RCP 8.5, although at different rates.

We also compared the 20-year mean model yields of corn and soybean generated by the EPIC simulations under dynamic atmospheric CO₂ concentration with the constant atmospheric CO₂ concentration of 350 ppm to gauge the effect of carbon fertilization on corn and soybean yields. Figure 9 shows the 20-yr mean model yields increments of corn and soybean under the three RCPs used towards the end of century.

The exercise reveals that carbon fertilization has very little impact on corn yields in our study area. It also suggests that soybeans are more sensitive to carbon fertilization. The difference between the 20-yr model mean yield of soybean under dynamic atmospheric CO₂ and fixed atmospheric CO₂ concentration of 350 ppm under RCP 2.6 category is 2%, whereas the difference is 11% and 20% for category RCP 4.5 and RCP 8.5 respectively. The results also suggest that although carbon fertilization has positive effects on soybean yields, it cannot compensate completely for the negative effects of climate change as overall soybean yields decrease in the higher carbon category due to changes in magnitude, timing, and frequency of precipitation and increased temperature together with extreme weather patterns during the

growing season. This result may have important implications for agricultural adaptation in the Corn Belt.

4 - Conclusions

The crop yield decline rate in RCP 8.5, which corresponds to a high carbon scenario, may raise a concern that climate change, if not contained, could have detrimental effects on the sustainability of the agricultural industry and eventually on food security as yield growth in temperate zones may not be able to compensate for possible losses in tropical areas. This illustrates how climate change is a global phenomenon, but its impacts are local. If climate change will more adversely affect tropical zones, there may be a significant reduction in global corn and soybean production. If this turns out to be the case, corn and soybean will likely still remain lucrative crops for farmers in the Racoon watershed despite the possibility of yield loss if high carbon emissions are realized as unmet demand for corn may exert upward pressures on corn and soybean prices. Commodity crop prices are determined by global market forces but they have large local economic impacts. Using fine-grained data and models to better understand local agronomic and economic impacts may help local adaptation efforts.

Acknowledgments

This work was supported by the National Science Foundation (Award 1009925). We thank Awoke D. Teshager for his help with the figures. We acknowledge the World Climate Research Programme's Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modeling groups (listed in Table 1 of this paper) for producing and making available their model output. For CMIP the U.S. Department of Energy's Program for Climate

453 Model Diagnosis and Intercomparison provides coordinating support and led development of
454 software infrastructure in partnership with the Global Organization for Earth System Science
455 Portals.

456 **References**

- 457 Acock, B., 1990. Effects of Carbon Dioxide on Photosynthesis, Plant Growth, and Other
458 Processes 1, in: Kimball, B.A. (Ed.), *Impact of Carbon Dioxide, Trace Gases, and Climate*
459 *Change on Global Agriculture*. American Society of Agronomy, Crop Science Society of
460 America, and Soil Science Society of America, Madison, WI, pp. 45-60.
- 461 Adams, R.M., Hurd, B.H., Lenhart, S., Leary, N., 1998. Effects of global climate change on
462 agriculture: an interpretative review. *Climate Research* 11, 19-30.
- 463 Balkovič, J., van der Velde, M., Schmid, E., Skalský, R., Khabarov, N., Obersteiner, M.,
464 Stürmer, B., Xiong, W., 2013. Pan-European crop modelling with EPIC: Implementation, up-
465 scaling and regional crop yield validation. *Agricultural Systems* 120, 61-75.
- 466 Bayer, A.D., Pugh, T.A.M., Krause, A., Arneth, A., 2015. Historical and future quantification of
467 terrestrial carbon sequestration from a Greenhouse-Gas-Value perspective. *Global*
468 *Environmental Change* 32, 153-164.
- 469 Blanco-Canqui, H., Lal, R., 2008. No-Tillage and Soil-Profile Carbon Sequestration: An On-
470 Farm Assessment *Soil Science Society of America Journal* 72, 693-701.
- 471 Bristow, K.L., Campbell, G.S., 1984. On the relationship between incoming solar radiation and
472 daily maximum and minimum temperature. *Agricultural and Forest Meteorology* 31, 159-166.
- 473 Bryant, C.R., Smit, B., Brklacich, M., Johnston, T.R., Smithers, J., Chjotti, Q., Singh, B., 2000.
474 *Adaptation in Canadian Agriculture to Climatic Variability and Change*. *Climatic Change* 45,
475 181-201.
- 476 Causarano, H.J., Doraiswamy, P.C., McCarty, G.W., Hatfield, J.L., Milak, S., Stern, A.J., 2008.
477 EPIC Modeling of Soil Organic Carbon Sequestration in Croplands of Iowa *Journal of*
478 *Environmental Quality* 37, 1345-1353.
- 479 Challinor, A.J., Ewert, F., Arnold, S., Simelton, E., Fraser, E., 2009. Crops and climate change:
480 progress, trends, and challenges in simulating impacts and informing adaptation. *Journal of*
481 *Experimental Botany* 60, 2775-2789.
- 482 Chavas, D.R., Izaurralde, R.C., Thomson, A.M., Gao, X., 2009. Long-term climate change
483 impacts on agricultural productivity in eastern China. *Agricultural and Forest Meteorology* 149,
484 1118-1128.
- 485 Chung, S.W., Gassman, P.W., Kramer, L.A., Williams, J.R., Gu, R., 1999. Validation of EPIC
486 for Two Watersheds in Southwest Iowa. *Journal of Environmental Quality* 28, 971-979.
- 487 Desjardins, R.L., Sivakumar, M.V.K., de Kimpe, C., 2007. The contribution of agriculture to the
488 state of climate: Workshop summary and recommendations. *Agricultural and Forest*
489 *Meteorology* 142, 314-324.
- 490 Dhakhwa, G.B., Campbell, C.L., LeDuc, S.K., Cooter, E.J., 1997. Maize growth: assessing the
491 effects of global warming and CO₂ fertilization with crop models. *Agricultural and Forest*
492 *Meteorology* 87, 253-272.
- 493 Duffy, M., 2013. *Estimated Costs of Crop Production in Iowa - 2013 FM-1712*. Iowa State
494 University Extension.
- 495 Hawkins, E., Sutton, R., 2009. The Potential to Narrow Uncertainty in Regional Climate
496 Predictions. *Bulletin of the American Meteorological Society* 90, 1095-1107.
- 497 Heimann, M., Reichstein, M., 2008. Terrestrial ecosystem carbon dynamics and climate
498 feedbacks. *Nature* 451, 289-292.
- 499 Horowitz, J., Ebel, R., Ueda, K., 2010. No- till farming is a growing practice. *Economic*
500 *Information Bulletin No. 70*. Washington, DC: USDA Economic Research Service.

501 Izaurrealde, R.C., Williams, J.R., McGill, W.B., Rosenberg, N.J., Jakas, M.C.Q., 2006.
 502 Simulating soil C dynamics with EPIC: Model description and testing against long-term data.
 503 Ecological Modelling 192, 362-384.
 504 Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., Iredell, M., Saha,
 505 S., White, G., Woollen, J., Zhu, Y., Leetmaa, A., Reynolds, R., Chelliah, M., Ebisuzaki, W.,
 506 Higgins, W., Janowiak, J., Mo, K.C., Ropelewski, C., Wang, J., Jenne, R., Joseph, D., 1996. The
 507 NCEP/NCAR 40-Year Reanalysis Project. Bulletin of the American Meteorological Society 77,
 508 437-471.
 509 Katsvairo, T.W., Cox, W.J., 2000. Tillage x rotation x management interactions in corn.
 510 Agronomy Journal 92, 493-500.
 511 Kimball, B.A., 1983. Carbon Dioxide and Agricultural Yield: An Assemblage and Analysis of
 512 430 Prior Observations. Agronomy Journal 75, 779-788.
 513 Kimball, B.A., Kobayashi, K., Bindi, M., 2002. Responses of Agricultural Crops to Free-Air
 514 CO₂ Enrichment, in: Sparks, D.L. (Ed.), Advances in Agronomy. Academic Press., pp. 293-368.
 515 Kiniry, J.R., Bean, B., Xie, Y., Chen, P.-y., 2004. Maize yield potential: critical processes and
 516 simulation modeling in a high-yielding environment. Agricultural Systems 82, 45-56.
 517 Lehmann, N., Finger, R., Klein, T., Calanca, P., Walter, A., 2013. Adapting crop management
 518 practices to climate change: Modeling optimal solutions at the field scale. Agricultural Systems
 519 117, 55-65.
 520 Li, X., Takahashi, T., Suzuki, N., Kaiser, H.M., 2011. The impact of climate change on maize
 521 yields in the United States and China. Agricultural Systems 104, 348-353.
 522 Lindquist, J.L., Arkebauer, T.J., Walters, D.T., Cassman, K.G., Dobermann, A., 2005. Maize
 523 radiation use efficiency under optimal growth conditions. Agronomy Journal 97, 72-78.
 524 Liu, J., Williams, J.R., Zehnder, A.J.B., Yang, H., 2007. GEPIC – modelling wheat yield and
 525 crop water productivity with high resolution on a global scale. Agricultural Systems 94, 478-493.
 526 Long, S.P., Ainsworth, E.A., Leakey, A.D.B., Morgan, P.B., 2005. Global food insecurity.
 527 Treatment of major food crops with elevated carbon dioxide or ozone under large-scale fully
 528 open-air conditions suggests recent models may have overestimated future yields. Philosophical
 529 Transactions of the Royal Society B: Biological Sciences 360, 2011-2020.
 530 McGrath, J., M., Lobell, D., B., 2013. Regional disparities in the CO₂ fertilization effect and
 531 implications for crop yields. Environmental Research Letters 8, 014054.
 532 Moss, R.H., Edmonds, J.A., Hibbard, K.A., Manning, M.R., Rose, S.K., van Vuuren, D.P.,
 533 Carter, T.R., Emori, S., Kainuma, M., Kram, T., Meehl, G.A., Mitchell, J.F.B., Nakicenovic, N.,
 534 Riahi, K., Smith, S.J., Stouffer, R.J., Thomson, A.M., Weyant, J.P., Wilbanks, T.J., 2010. The
 535 next generation of scenarios for climate change research and assessment. Nature 463, 747-756.
 536 Niu, X., Easterling, W., Hays, C.J., Jacobs, A., Mearns, L., 2009. Reliability and input-data
 537 induced uncertainty of the EPIC model to estimate climate change impact on sorghum yields in
 538 the U.S. Great Plains. Agriculture, Ecosystems & Environment 129, 268-276.
 539 Patterson, D.T., Flint, E.P., 1980. Potential effects of global atmospheric CO₂ enrichment on the
 540 growth and competitiveness of C₃ and C₄ weed and crop plants. Weed Science 28, 71-75.
 541 Priya, S., Shibasaki, R., 2001. National spatial crop yield simulation using GIS-based crop
 542 production model. Ecological Modelling 136, 113-129.
 543 Reddy, K.R., Hodges, H., 2000. Climate change and global crop productivity. CABI.
 544 Reilly, J., Tubiello, F., McCarl, B., Abler, D., Darwin, R., Fuglie, K., Hollinger, S., Izaurrealde,
 545 C., Jagtap, S., Jones, J., Mearns, L., Ojima, D., Paul, E., Paustian, K., Riha, S., Rosenberg, N.,

546 Rosenzweig, C., 2003. U.S. Agriculture and Climate Change: New Results. *Climatic Change* 57,
547 43-67.

548 Rosenberg, N.J., 1981. The increasing CO₂ concentration in the atmosphere and its implication
549 on agricultural productivity. *Climatic Change* 3, 265-279.

550 Rosenzweig, C., Iglesias, A., 1998. The use of crop models for international climate change
551 impact assessment, in: Tsuji, G.Y., Hoogenboom, G., Thornton, P.K. (Eds.), *Understanding*
552 *Options for Agricultural Production*. Springer Netherlands, Dordrecht, pp. 267-292.

553 Rosenzweig, C., Parry, M.L., 1994. Potential impact of climate change on world food supply.
554 *Nature* 367, 133-138.

555 Roudier, P., Sultan, B., Quirion, P., Berg, A., 2011. The impact of future climate change on West
556 African crop yields: What does the recent literature say? *Global Environmental Change* 21,
557 1073-1083.

558 Schoof, J.T., 2013. Statistical Downscaling in Climatology. *Geography Compass* 7, 249-265.

559 Schoof, J.T., Pryor, S.C., 2014. Assessing the fidelity of AOGCM-simulated relationships
560 between large-scale modes of climate variability and wind speeds. *Journal of Geophysical*
561 *Research: Atmospheres* 119, 9719-9734.

562 Schoof, J.T., Pryor, S.C., Robeson, S.M., 2007. Downscaling daily maximum and minimum
563 temperatures in the midwestern USA: a hybrid empirical approach. *International Journal of*
564 *Climatology* 27, 439-454.

565 Southworth, J., Randolph, J.C., Habeck, M., Doering, O.C., Pfeifer, R.A., Rao, D.G., Johnston,
566 J.J., 2000. Consequences of future climate change and changing climate variability on maize
567 yields in the midwestern United States. *Agriculture, Ecosystems & Environment* 82, 139-158.

568 Stern, A.J., Doraiswamy, P.C., Raymond Hunt, J.E., 2012. Changes of crop rotation in Iowa
569 determined from the United States Department of Agriculture, National Agricultural Statistics
570 Service cropland data layer product. *Journal of Applied Remote Sensing* 6, 063590-063590.

571 Stockle, C.O., Williams, J.R., Rosenberg, N.J., Jones, C.A., 1992. A method for estimating the
572 direct and climatic effects of rising atmospheric carbon dioxide on growth and yield of crops:
573 Part I—Modification of the EPIC model for climate change analysis. *Agricultural Systems* 38,
574 225-238.

575 Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2012. An Overview of CMIP5 and the Experiment
576 Design. *Bulletin of the American Meteorological Society* 93, 485-498.

577 Teshager, A.D., Gassman, P.W., Secchi, S., Schoof, J.T., Misgna, G., 2016. Modeling
578 Agricultural Watersheds with the Soil and Water Assessment Tool (SWAT): Calibration and
579 Validation with a Novel Procedure for Spatially Explicit HRUs. *Environmental Management* 57,
580 894-911.

581 Thomson, A.M., Brown, R.A., Rosenberg, N.J., Izaurrealde, R.C., Benson, V., 2005. Climate
582 Change Impacts for the Conterminous USA: An Integrated Assessment. *Climatic Change* 69, 43-
583 65.

584 Tingem, M., Rivington, M., 2009. Adaptation for crop agriculture to climate change in
585 Cameroon: Turning on the heat. *Mitigation and Adaptation Strategies for Global Change* 14,
586 153-168.

587 USDA Economic Research Service, 2015. Agricultural Resource Management Survey, in:
588 United States Department of Agriculture, E.R.S. (Ed.). United States Department of Agriculture,
589 Economic Research Service, Washington, DC.

590 USDA NASS, 2016. Quick Stats: U.S. & All States Data – Crops

591 USDA NASS Research and Development Division, 2016. Cropland Data Layer.

USDA Natural Resources Conservation Service, 2016. Soil Survey Geographic (SSURGO) Database.

Vetsch, J.A., Randall, G.W., 2002. Corn production as affected by tillage system and starter fertilizer. *Agronomy Journal* 94, 532-540.

Wang, X., Peng, L., Zhang, X., Yin, G., Zhao, C., Piao, S., 2014. Divergence of climate impacts on maize yield in Northeast China. *Agriculture, Ecosystems & Environment* 196, 51-58.

Wilby, R.L., Wigley, T.M.L., 1997. Downscaling general circulation model output: a review of methods and limitations. *Progress in Physical Geography* 21, 530-548.

Wilks, D.S., 1999. Multisite downscaling of daily precipitation with a stochastic weather generator. *Climate Research* 11, 125-136.

Williams, J.R., Jones, C.A., Dyke, P.T.I., 1984. A modeling approach to determining the relationship between erosion and soil productivity. *Transactions of the ASAE* 27, 129-0144.

Williams, J.R., Renard, K.G., Dyke, P.T., 1983. EPIC: A new method for assessing erosion's effect on soil productivity. *Journal of Soil and Water Conservation* 38, 381-383.

Table 1 Description of the CMIP5 AOGCMs used in this study. Models are referenced by the ID throughout the paper

Model	Institution	Resolution (Longitude × Latitude)	References
BCC-CSM1.1	Beijing Climate Center – China Meteorological Administration	$2.8125^{\circ} \times 2.8125^{\circ}$	Wu, 2012; Xin et al., 2012
BNU-ESM	Beijing Normal University, China	$2.8125^{\circ} \times 2.8125^{\circ}$	Ji et al., 2014
Can-ESM2	Canadian Centre for Climate Modelling and Analysis, Canada	$2.8125^{\circ} \times 2.8125^{\circ}$	Arora et al., 2011; von Salzen et al., 2013
CNRM-CM5	National Center for Meteorological Research, France	$1.4^{\circ} \times 1.4^{\circ}$	Voldoire et al., 2012
IPSL-CM5A-LR	Institut Pierre Simon Laplace, France	$3.75^{\circ} \times 1.9^{\circ}$	Dufresne et al., 2013
MPI-ESM-LR	Max Planck Institute for Meteorology, Germany	$1.875^{\circ} \times 1.6^{\circ}$	Stevens et al., 2013
MRI-CGCM3	Meteorological Research Institute, Japan	$1.125^{\circ} \times 1.125^{\circ}$	Yukimoto et al., 2012
NorESM1-M	Norwegian Climate Center, Norway	$2.5^{\circ} \times 1.9^{\circ}$	Iverson et al., 2013

Table 2 Performance of All Eight Models in Terms of Statistical Standards

	Yields		
Models	R^2	RMSE	MAE
BCC-CSM1.1	0.91	1.33	0.94
BNU-ESM	0.90	1.49	1.08
Can-ESM2	0.84	1.59	1.08
CNRM-CM5	0.91	1.29	0.94
IPSL-CM5A-LR	0.82	1.54	1.02
MPI-ESM-LR	0.84	1.51	1.06
MRI-CGCM3	0.90	1.29	0.93
NorESM1-M	0.88	1.36	0.98

Table 3: t-Test: Yields Under RCP 2.6 & RCP 8.5

Corn Yields				
Period	2015-2099	2015-2042	2043-2070	2071-2099
t Stat	10.3939	1.3006949	9.21722	18.624301
P(T<=t) two-tail	9.5E-17	0.2043554	7.92E-10	2.6071E-17
t Critical two-tail	1.98861	2.0518305	2.051831	2.04840714
Soybean Yields				
Period	2015-2099	2015-2042	2043-2070	2071-2099
t Stat	10.6765	1.6329382	10.34556	16.2705794
P(T<=t) two-tail	2.6E-17	0.1140914	6.82E-11	8.403E-16
t Critical two-tail	1.98861	2.0518305	2.051831	2.04840714

Figure Captions

Figure 1. Distribution of Crop Rotation Practices in the Raccoon Watershed for 2008-2010

Figure 2. Mean Corn Yields Comparison of EPIC and NASS in Guthrie County for the calibration period (1975-1992) and the whole Raccoon watershed for the validation period (1994-2010).

Figure 3. Mean Soybean Yields Comparison of EPIC and NASS in Guthrie County for the calibration period (1975-1992) and the whole Raccoon watershed for the validation period (1994-2010).

Figure 4. Mean Corn and Soybean Annual Yield Projections Using Downscaled Outputs of Eight Models for the Period 2015-2099

Figure 5. Comparison of Simulated 20-yr Mean Yields for Corn and Soybeans

Figure 6. Range of Crop Yields under a) RCP 2.6 (grey area) with Mean Yields (green line) and b) RCP 8.5 (magenta area) with Mean Yields (black line). The brown area is the overlap of ranges under the two RCPs

Figure 7. Impact of climate change on corn yields (a) and soybean yields (b) for each ULUA. Percentage change depicts differences of 20 years mean crop yields for initial (2015-2033) and end-century period (2080-2099) in the RCP 8.5. Blank ULUAs are non-crop areas for corn yields map (a). In case of map (b), blank ULUAs are either non-crop areas or non-soybean crop (continuous corn) areas.

Figure 8. Mean Corn and Soybean Annual Yield Projections Using Downscaled Outputs of Eight Models for the Period 2015-2099 with Fixed CO₂ Atmospheric Concentrations

Figure 9. Difference between 20-yr Mean Crop Yields Increments under Dynamic CO₂ Concentrations and 20-yr Mean Crop Yields Increments under Fixed 350 PPM CO₂ Concentration

Figure 1. Distribution of Crop Rotation Practices in the Raccoon Watershed for 2008-2010

Figure 2. Mean Corn Yields Comparison of EPIC and NASS in Guthrie County for the calibration period (1975-1992) and the whole Raccoon watershed for the validation period (1994-2010).

Figure 3. Mean Soybean Yields Comparison of EPIC and NASS in Guthrie County for the calibration period (1975-1992) and the whole Raccoon watershed for the validation period (1994-2010).

Figure 4. Mean Corn and Soybean Annual Yield Projections Using Downscaled Outputs of Eight Models for the Period 2015-2099

Figure 5. Comparison of Simulated 20-yr Mean Yields for Corn and Soybeans

Figure 6. Range of Crop Yields under a) RCP 2.6 (grey area) with Mean Yields (green line) and b) RCP 8.5 (magenta area) with Mean Yields (black line). The brown area is the overlap of ranges under the two RCPs

Figure 7. Impact of climate change on corn yields (a) and soybean yields (b) for each ULUA. The percentage change is for differences of 20 years mean crop yields between the initial (2015-2033) and end-century period (2080-2099) in the RCP 8.5. The blank ULUAs are non-crop areas for the corn yields map (a). In map (b), the blank ULUAs are either non-crop areas or non-soybean crop (continuous corn) areas.

Figure 8. Mean Corn and Soybean Annual Yield Projections Using Downscaled Outputs of Eight Models for the Period 2015-2099 with Fixed CO₂ Atmospheric Concentrations

Figure 9. Difference between 20-yr Average Crop Yields Increments under Dynamic CO₂ Concentrations and 20-yr Average Crop Yields Increments under Fixed 350 PPM CO₂ Concentration