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IMPACT OF CLIMATE CHANGE ON CORN YIELDS IN ALABAMA

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Abstract

The study used calibrated Crop Environment Resource Synthesis (CERES) maize (corn) model to simulate maize (corn) physiological growth processes and yields under 2045 and 2075 projected climate change scenarios for six representative counties in Alabama. The future climatologies for two emission scenarios Representative Concentration Pathway (RCP) 4.5 (medium) and RCP 8.5 (high) were developed based on the IPSL-CM5A-MR high resolution climate model. Average yield decreases of 19.5% and 37.3% were, respectively, projected under RCP 4.5 and RCP 8.5 for 2045, and average yield decreases of 32.5% and 77.8% were, respectively, projected under RCP 4.5 and RCP 8.5 for 2075. These yield decreases were largely influenced by increasing temperatures as evidenced by the shortening of various development stages such as anthesis and maturity, which are important determinants of the final grain yield and number. Corn production in Autauga County was projected to be highly vulnerable to climate change, while production in Limestone County was least vulnerable. Corn crops in Alabama appear to be sensitive to climate change and will require adaptation strategies.

Keywords: Climate Change, CERES-Maize model, General Circulation Model (GCM), Representative Concentration Pathway (RCP) emission scenarios.

Introduction

The Earth's climate is projected to undergo marked changes over the 21st Century due to natural processes and anthropogenic factors (IPCC, 2014). Agriculture is possibly the most climate sensitive sector of the economy. The potential impacts of climate change on food security (Porter et al., 2014) and the need for 60% more food by 2050 (FAO, 2012) has attracted global attention. Given the central role of crop production in food security and, the projected unprecedented change in climate (IPCC, 2014), there is the need to assess possible responses of crop yields to climate change. Corn (Maize) is of key focus because it remains among the world's top staple foods (FAO, 2015); therefore climate change impacts on its production could have broad and global repercussions on food security.

Global circulation models and process-based crop models such as Crop Environment Resource Synthesis (CERES)-Maize (Corn) have been used in different studies assessing the potential impacts of climate change on crop production. The unique ability of process-based crop simulation models to capture specific relationships between air temperature, rainfall and plant growth and development, allow these models to give a more precise simulation of expected corn responses to future climate scenarios (Alexandrov and Hoogenboom, 2000; Southworth et al., 2000; Tubiello et al., 2002; Guo et al., 2010; Bianca et al., 2013).

The coarse resolution of general circulation models limit the predictions of these dynamic process-based crop simulation models (Jones and Thornton, 2003). In this study, MarkSim DSSAT Weather File Generator, a software that not only downscales but also generates daily weather from general circulation models is used to overcome the coarse resolution of general circulation models (Jones and Thornton, 2013). The generated daily weather data characteristic of future climate scenarios was used to drive the CERES-Maize (Corn) model. These methods were applied to selected counties in the State of Alabama, where approximately 95.8% of the 2.7 million acres under cropland is rain fed (ALFA, 2015).

Over the last half century, corn yields in Alabama have been fluctuating as a result of changing climate and extreme weather events (ACES, 2015; USDA-NASS, 2015). Climate change could, therefore, have significant impacts on corn production in Alabama. The downscaling software is used for the generation of future daily weather data at the county scale (Jones and Thornton, 2013) thus, creating an opportunity to study local contrasts in crop responses to climate change. It is, however, noted that there are other states, such as within the corn belt that are major corn producers compared to Alabama, and all these states contribute to making the U.S. the world's largest producer and exporter of corn (Schlenker and Roberts, 2009;USDA-NASS, 2015). Consequently, significant impacts of climate change on corn production in any of these states would have broad implications on global food security. As such, over the years, several studies have been conducted to assess these impacts on corn yields in different regions of the U.S. (Southworth et al., 2000; Rosenzweig et al., 2002;Tubiello et al.,2002; Tsvetsinskaya et al., 2003; Mera et al., 2006; Schlenker and Roberts, 2009). From these studies, it is likely that climate change will improve yields in some regions; reduce them in others, or have little to no effects in others. A need exists to study the magnitude and extent of climate change impacts on corn yields in Alabama in order for policy makers to start developing adaptation solutions and strategies.

This study assessed the impact of climate change on corn yields in Alabama. Specifically, the research activities included (1) the calibration of the CERES-maize (corn) model in Alabama counties, and (2) assessing the impacts of future climate change on corn yields in Alabama. Six representative counties in Alabama were considered in the study; Limestone and DeKalb in Northern Alabama; Dallas and Autauga in central Alabama; and Henry and Baldwin in Southern Alabama. Of these sites, Limestone, De Kalb, Henry, and Baldwin are high corn producers. A mid-maturing Pioneer 3167 maize (corn) hybrid was used in the current and future yield simulations since it is the most commonly grown in Alabama (ACES, 2015). Results from the study will be the basis for the development of mitigation and adaptation strategies in order to deal with the impacts of climate changes.

Literature Review

Corn growth simulations in past studies have revealed the response of crop growth and development to changing climate variables. Simulations by Tubiello et al. (2002) revealed that increasing temperatures changed the length of the potential corn life cycle. Latitude affected the direction of change whereby, increase in temperatures at high latitudes (northern U.S.) resulted in beneficial longer growing seasons provided farmers used longer-cycle cultivars, while, increase in temperatures at lower latitudes (southern U.S.) resulted in detrimental shorter crop life cycles despite longer growing seasons. These shortened life cycles deny the crops ample time to make use of available resources for maximum growth, development, and yield (Menzel et

al., 2006; Harrison et al., 2011). In another publication, Southworth et al. (2000) reported that high temperatures experienced especially during silking (tasseling) resulted in significant yield decreases. This stage was found to be very sensitive to both direct (physiological) and indirect (increased evapotranspiration) temperature effects.

Changing rainfall intensity and distribution also affects crop growth, development, and yields. Mera et al. (2006) showed that unlike temperatures which have a non-linear effect on yields, rainfall has a linear effect on yields. For instance, Alexandrov and Hoogenboom (2000) found that increased precipitation led to an increase in simulated corn yields in spite of the projected temperature increase with the vice versa holding true. This finding suggests that increased precipitation counterbalances the negative effects of increasing temperatures on yields. However, Rosenzweig et al. (2002) demonstrated the negative influence on corn production of excess rainfall amounts. Similar to crop response to temperature changes, the stage of crop growth and development during which water stress is experienced, determines the impact on the yields. Bianca et al. (2013) concluded that sensitivity to moisture stress can be dramatic and, the phenological phases of grain formation and filling tend to be most affected by moisture stress during the growing season.

Soil water holding capacity is one of the factors which determine the overall crop response to climate change. Akpalu et al. (2008) point out that, soils of high water holding capacity will facilitate crop survival in a future where water availability will be an issue because of their ability to reduce drought incidences. Kang et al. (2009) also found that crops cultivated on soils with high water capacity had a higher resilience to climate change.

The successful use of the CERES-Maize (corn) model in climate change impact studies depends on its proper calibration. One method of calibration that was adopted in this study is the stepwise estimation of a select few soil parameters to ensure that the model yield simulations mimic the observed yield responses to rainfall (Irmak et al., 2001; Mavromatis et al., 2001).

Methodology

CERES-Maize Crop Model
CERES-maize (corn) model in DSSAT v4.6 was used to simulate crop growth. It simulates growth with a daily time step from sowing to maturity and yield by simulating the processes of soil water, nutrient, and plant growth, along with the developmental processes to the formation of the final crop yields and yield components (Thorp et al., 2014). Plant development simulations are based on the growing degree day concept (Thorp et al., 2014). Carbon assimilation and biomass accumulation are simulated as a function of measured solar irradiance whereby the fraction of photosynthetically active radiation intercepted by crop canopy is calculated from the leaf area index (Tsuji et al., 1998). The daily biomass production in the model, is constrained by sub-optimal temperatures, soil water deficits, and nitrogen deficiencies (Tsuji et al., 1998; Southworth et al., 2000).

MarkSim DSSAT weather generator
MarkSim DSSAT weather generator was used to generate future climatologies. It is a web-based tool that uses simple interpolation, climate typing and weather generation with a user interface in Google Earth and provides the user with daily weather data for future climatologies (Jones and Thornton, 2013).

Data

The minimum input data required to run the model for the climate change impact studies includes: daily weather data (solar radiation, rainfall, maximum and minimum temperatures) obtained from the U.S. Department of Agriculture-Agricultural Research Service (USDA-ARS) and National Aeronautics and Space Administration-Prediction of Worldwide Energy Resource (NASA-POWER); soils data (surface soil information - color, permeability, drainage, soil profile information: soil texture, water holding capacity, nitrogen, organic matter content) obtained from the USDA-Natural Resources Conservation Service (USDA-NRCS); published works of Mishra et al. (2013), and from soils prepared by McNider et al. (2011); Crop management data (crop, cultivar, genetic coefficients [Table 1], planting date, row and planting spacing, dates [1month planting window used] and amounts of irrigation, dates and amounts of fertilizer applications per type and other applications [chemicals] and operations [tillage]) obtained from USDA-NASS and Alabama Agricultural Experiment Station.

Table 1. Generated Maize (Corn) Genetic Coefficients (Cultivar - Pioneer 3167)

Cultivar	P1	P2	P5	G2	G3	PHINT
Pioneer 3167 c	166	1.411	916.3	866.4	7.452	41.5

Statistics on county level yields were also obtained from USDA–NASS for the period 1981-2010 (30 years). In spite of the inter-annual yield fluctuations in each of the counties, a positive yield trend was observed for the period (Figure 1). During this period, maize yields increased by 172 kg/ha, 87 kg/ha, 101 kg/ha, 110 kg/ha, 104 kg/ha, and 97 kg/ha per year in Limestone, DeKalb, Dallas, Autauga, Henry, and Baldwin, respectively. The positive yield trends can be attributed to technological advancements such as new sturdy cultivars, more nutrient inputs, optimal sowing dates, precision agriculture etc. (Huang et al., 2015). Changes in precipitation and temperatures can be ruled out as the reason for the positive yield trend as these variables did not show any statistically significant changes within the region over the study period (Herbert and Caudill, 2012). However, the fluctuations around the trend line are due to year to year climate variability.

The annual average maize (corn) yields were adjusted to the year 2006 for technology trends. The adjustment was done to remove the effect of long term technology and management improvements on maize (corn) yields so that the relationship between climate and maize (corn) yield variability could be studied. The yields were adjusted using the linear trend shown below;

Equation 1: $Y'_{ij} = Y_{ij} + $ Slope of linear regression $(A - (i))$

Where:

i = year
j = county
Y'_{ij} = is the adjusted maize (corn) yield in the county (j) in year (i)
Y_{ij} = is the maize (corn) yield for a county (j) in year (i)
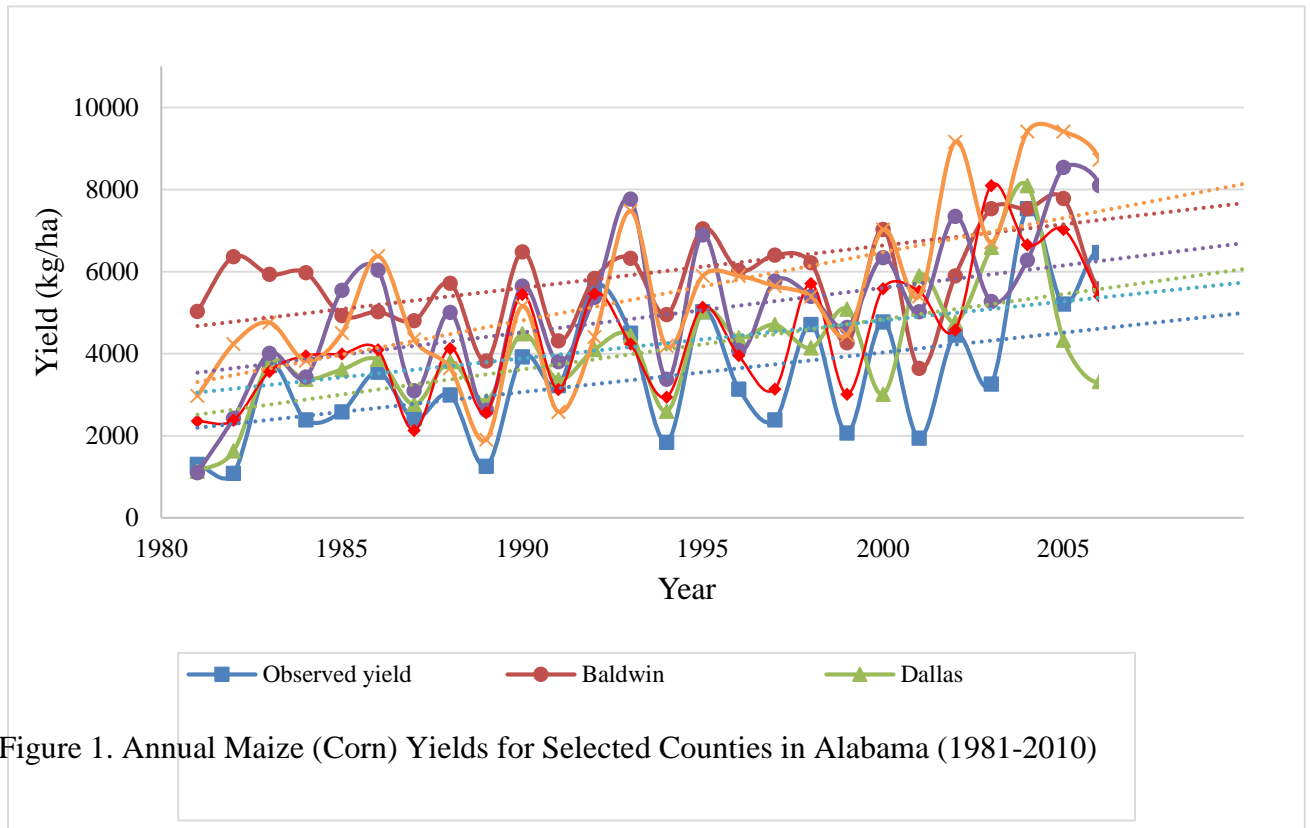A = is the year to which the yields were adjusted (i.e., 2006)

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Figure 1. Annual Maize (Corn) Yields for Selected Counties in Alabama (1981-2010)

Calibration of the CERES-Maize (Corn) Model

The assumption was that soils will be the same in future climate scenarios. Therefore, soil parameters were calibrated based on the step by step estimation method applied by Mavromatis et al. (2001). Experiment files were created in XBUILD tool of DSSAT v4.6 to simulate the 30 years of baseline corn growth and yields with the observed historical weather and crop management of each year specified. The unadjusted soils were used in the initial baseline simulations with the adjusted yields. After each run, the model's d-statistic and Root Mean Square Error (RMSE) for a given site were checked to assess model performance and efficiency. Special attention was given to how well the model(s) simulated the good yielding years and the water limited (low yielding) years in the baseline. To achieve the best fit, the Photosynthesis Factor also known as Soil Fertility Factor (SLPF) and the delta (difference between the Drained Upper Limit (DUL) and the Drained Lower Limit (LL)) were manually optimized through systematic shifts with the aid of the 1:1 scatter plots of the simulated versus the observed yields. By optimizing the delta (DUL-LL), the site soils were calibrated to mimic the lower or higher water holding capacity to improve the fit for the water limited years in the baseline. By optimizing the SLPF, the site soils were calibrated to mimic the good (high) yielding years. Soil parameter estimation was done until values which allowed the models to best mimic the observed annual average yields were obtained. Successive shifts of the DUL which yielded DUL values larger than the SAT values (saturation point/volumetric soil water content), led to consequent positive shifts of SAT values by 0.1 cm³/cm³ in each of the soil layers based on the correlation of the simulated and observed values in the 1:1 scatter plots. The Soil Root Growth Factor (SRGF) for soil layers with their centers in the top 30cm of soil were set to 1, with the SRGF for the other layers beneath estimated using Gijsman et al. (2007) relationship; 1 times

exp (-0.02 LayerCentre), with LayerCenter being the depth from the top of the soil surface to the center of the layer of interest. The optimized SLPF and delta soil parameters and model statistics can be seen in Table 2.

Table 2. Optimized soil parameters with CERES-Maize Model Statistics

County	Soil Series	Soil Parameters		Model Statistics	
		SLPF (0-1)	"Delta" (cm³/cm³)	RMSE%	d – statistic
Autauga	Lucedale sandy loam	0.93	0.10	30.00	0.74
Baldwin	Dothan sandy loam	1.00	0.12	16.00	0.74
De Kalb	Dickson silt loam	0.78	0.13	25.70	0.68
Henry	Orangeburg sandy loam	0.80	0.14	30.70	0.74
Limestone	Decatur silt loam	0.87	0.25	24.70	0.65
Dallas	Canton Bend sandy Loam	0.74	0.17	36.00	0.62

Future Climate Change Scenarios – MarkSim
Future climate change scenarios were downloaded from the MarkSim DSSAT weather generator (Jones and Thornton, 2013; http://gisweb.ciat.cgiar.org/MarkSimGCM/). IPSL-CM5A-MR, a French General Circulation Model (GCM), with a spatial resolution of 1.2587 × 2.5 (latitude by longitude) (Dufresne et al., 2013) was selected. Data were downloaded in DSSAT friendly format for the following future scenarios: 2045 RCP 4.5 IPSL- CM5A-MR; 2045 RCP 8.5 IPSL-CM5A-MR; 2075 RCP 4.5 IPSL-CM5A-MR, and 2075 RCP 8.5 IPSL-CM5A-MR. The two years "2045" (representative year for the period 2030-2060) and "2075" (representative year for the period 2060-2090) were chosen in order to study the impacts of short-term and long-term climate change on crop yields. The Representative Concentration Pathways (RCPs) quantitatively describe and provide time and space dependent trajectories of anthropogenic greenhouse gases and pollutants together with their collective radiative forcing, and are used as input to climate models (IPCC, 2014). This study used the medium and high emission scenarios, i.e., RCP 4.5 and RCP 8.5, respectively. In order to study the impacts of climate change on corn yields, the methodology used by Jones and Thornton (2003) was adopted. The resultant seasonal analysis experiments for each county were as follows: crop growth and development simulations for the baseline (current climate: 1981-2010) and for the future climate scenarios from IPSL-CM5A-MR for the periods: 2045 RCP 4.5, 2045 RCP 8.5, 2075 RCP 4.5, and 2075 RCP 8.5.

<div align="center">

Results and Discussion

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Adjusted Yields
County corn yield adjustments to the year 2006 resulted in trend line gradients close to zero (Figure 2). The adjustments resulted in adjusted yields which were a reflection of yields under current climate with no contributions from technological advancements. The adjusted yields were used for model calibrations.

Model calibration

The greater than 0.5 d-statistic (Table 2) indicate good CERES-Maize (corn) model performance in simulating historical yields in each of the study sites. The final optimized SLPF values ranged from 0.74 to 1.00 (Table 2) which lie within the range of values supported in literature (Irmak et al., 2001; Mavromatis et al., 2001) where, values less than 1.00 indicate some soil fertility limitations not yet improved by farm management, as well as site-specific biotic limitations. Changes in "delta" from 0.120cm³/cm³ to 0.245cm³/cm³ between drained upper limit (DUL) and drained lower limit (LL) for each soil layer occurred at all sites except Autauga. The final saturation point/volumetric soil water content (SAT) values were between 0.30cm³/cm³ and 0.52cm³/cm³. These increases in delta (DUL-LL) and SAT were combined with slight reductions in SLPF with the exception of Baldwin County. In all the sites, soil root growth factor (SRGF) was varied throughout the layers as described by Gijsman et al. (2007).

Figure 2. Annual Maize (Corn) Yields Adjusted to the Year 2006 for Technology Trends
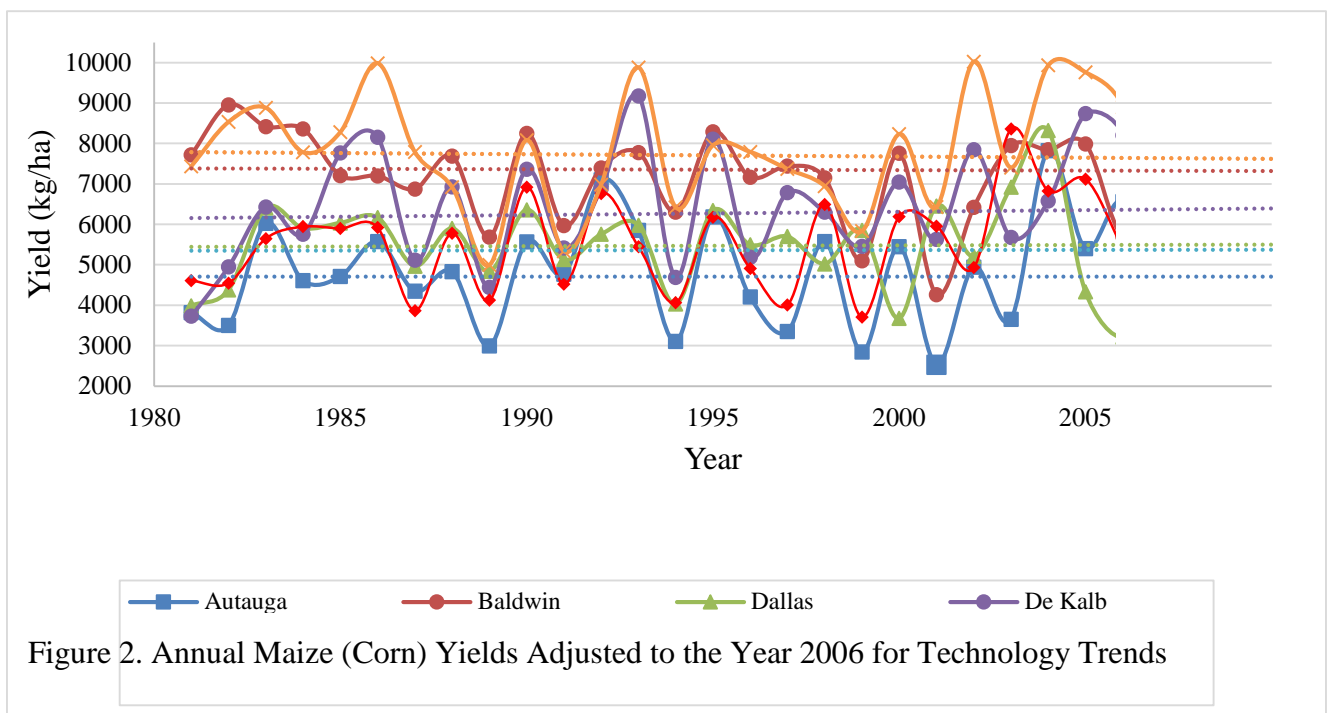
The RMSE% values indicate the uncertainties associated with each of the models. These uncertainties arise as a result of assumptions during model set up such as, one soil type in study area, one maize (corn) cultivar used, similar management practices, similar planting dates, etc. Other factors and/or events not considered in the models, e.g., extreme short-duration weather events (sudden heavy rainfalls, strong winds, hail, short-term water deficits/excesses at critical crop growth stages, etc.), also contribute to the imprecise annual yield simulations (Liu et al., 2011). In the calibrations the R square value was ignored during the assessment of model performance because the study used time series data (30-year historic yields) which are auto correlated values.

Consequences of Climate Change on Maize (Corn) Yields
Changes in yield were evaluated by comparing the future maize (corn) yields to the historic baseline yields (1981-2010), on the same cultivar, and then by stating the change as a percentage difference (Figures 3 and 4).
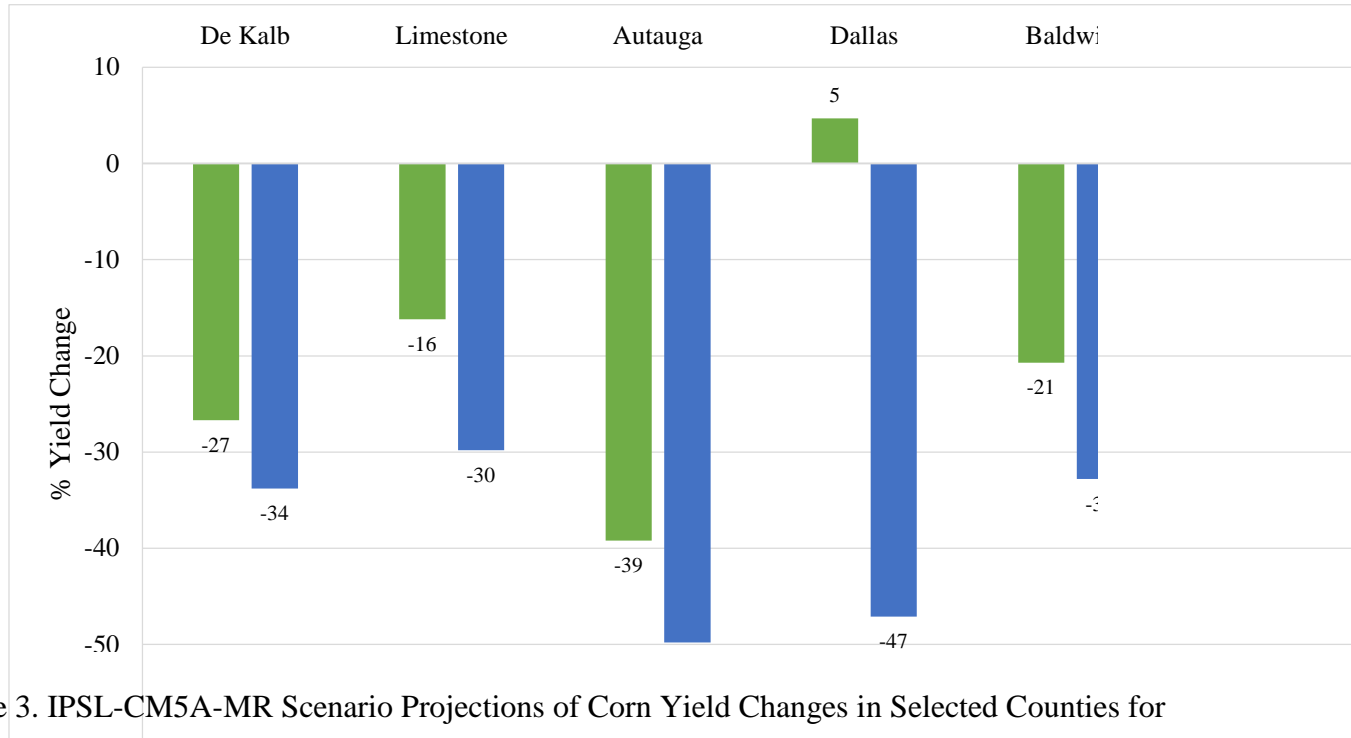

Figure 3. IPSL-CM5A-MR Scenario Projections of Corn Yield Changes in Selected Counties for 2045

In 2045, representative year for 2030-2060, yield decreases prevail in all counties under both the medium (RCP 4.5) and the high (RCP 8.5) emission scenarios projected by the IPSL-CM5A-MR with the exception of a 5% yield increase in Dallas county in the medium emission scenario. The projected yield decreases in the high emission scenarios (RCP 8.5), which ranged from -30% to -50%, were more extreme than in the medium emission scenarios (RCP 4.5), which were between +5% to -39%. These results show Limestone and Dallas as the most resilient counties, and Autauga as least resilient county to climate change.

In 2075, representative year for 2060-2090, the yield decreases are more severe (over 50%) compared to the yield decreases in 2045 with the decreases being greater in the high emission scenarios (RCP 8.5) than in the medium emission scenarios (RCP 4.5). The yield decreased from 12% to 49% under RCP 4.5, and from 72% to 88% under RCP 8.5. Dallas County was the least vulnerable and Autauga County the most vulnerable under the medium emission scenario. Also, Limestone County was the least vulnerable and Dallas County was the most vulnerable under the high emission scenario.
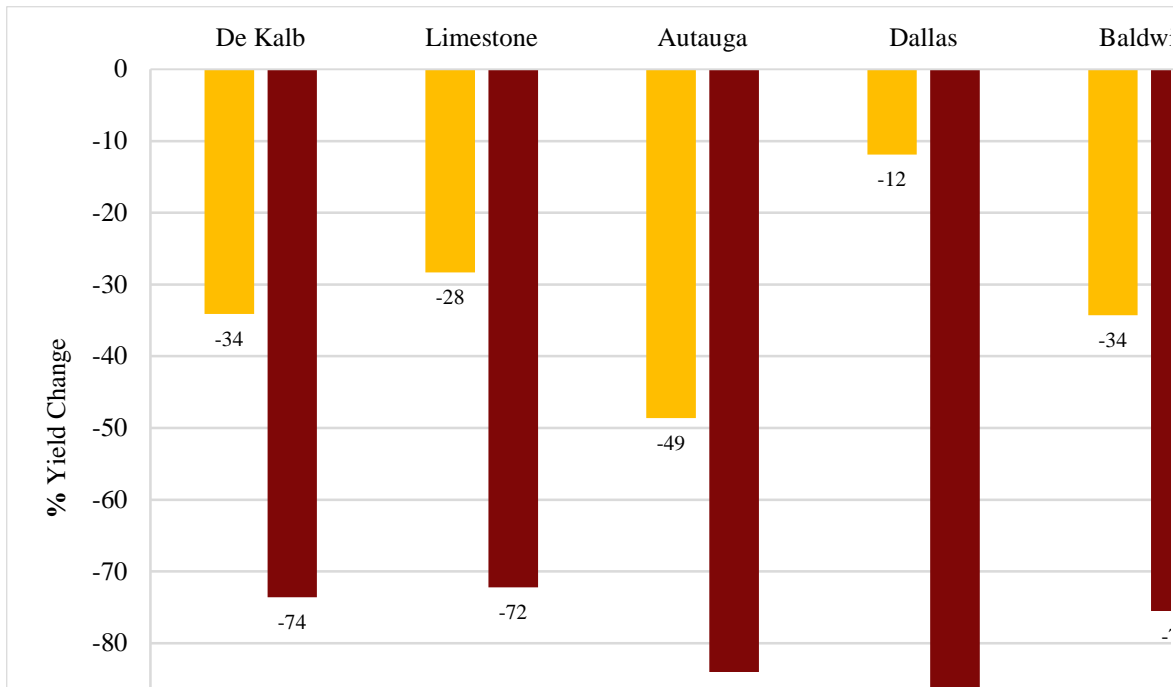
Figure 4. IPSL-CM5A-MR Scenario Projections of Corn Yield Changes in Selected Alabama Counties for 2075

The climate projected for each of the counties was a major contributor to the crop projections made, with precipitation increase contributing to yield increases in Dallas County in the 2045 medium emission scenario. However, another possible factor could be the water holding capacities ("delta") of the representative soils for the counties (Table 2). After the calibration of the CERES-models, Decatur silt loam of Limestone County had the highest water holding capacity of 0.25cm³/cm³ followed by Dallas with a value of 0.17cm³/cm³. Lucedale sandy loam of Autauga had the lowest water holding capacity of 0.10cm³/cm³. The high water holding capacity was shown to promote survival of crops by reducing drought instances in future climate scenarios where there is low water availability (Akpalu et al., 2008; Kang et al., 2009) .

Consequences of Changing Climate on Phenology
Current temperatures in Alabama are already high; therefore, projected temperature increases will affect maize (corn) yields. The region already has a long growing season, and therefore, any increase in temperatures will only serve to hasten crop growth and development. In this study, model phenology simulations (Figures 5 and 6) reveal how projected high temperatures would shorten critical crop stages (e.g., time to anthesis and time to maturation), all of which are essential for optimum plant and grain size (Harrison et al., 2011).
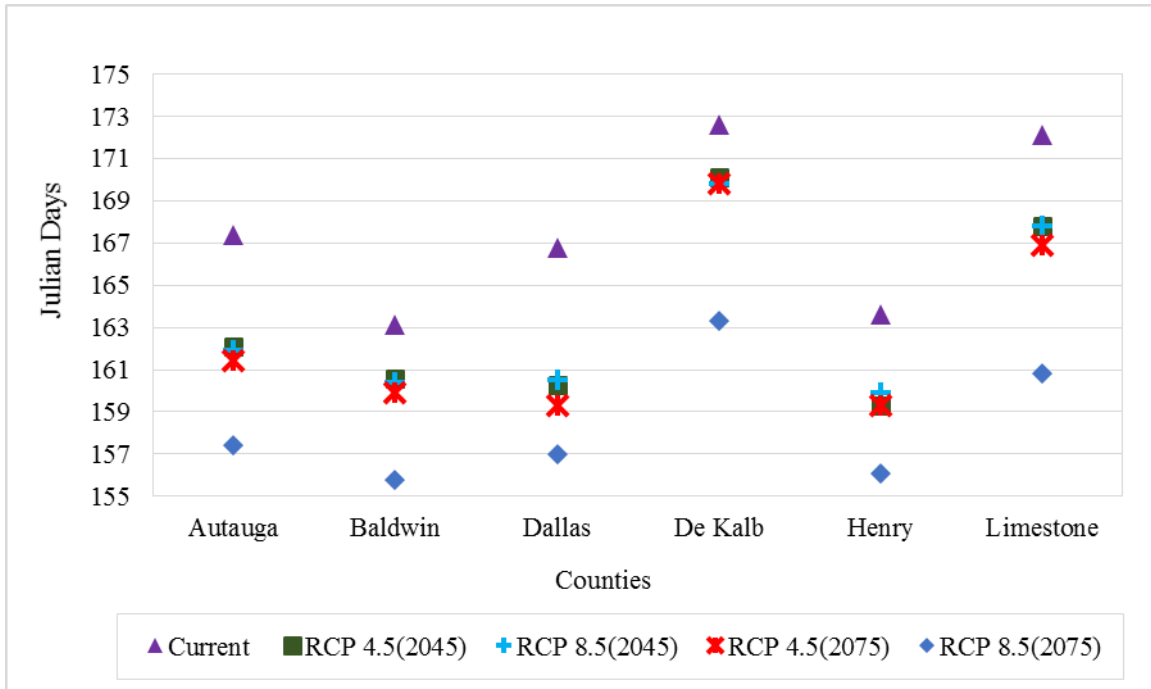
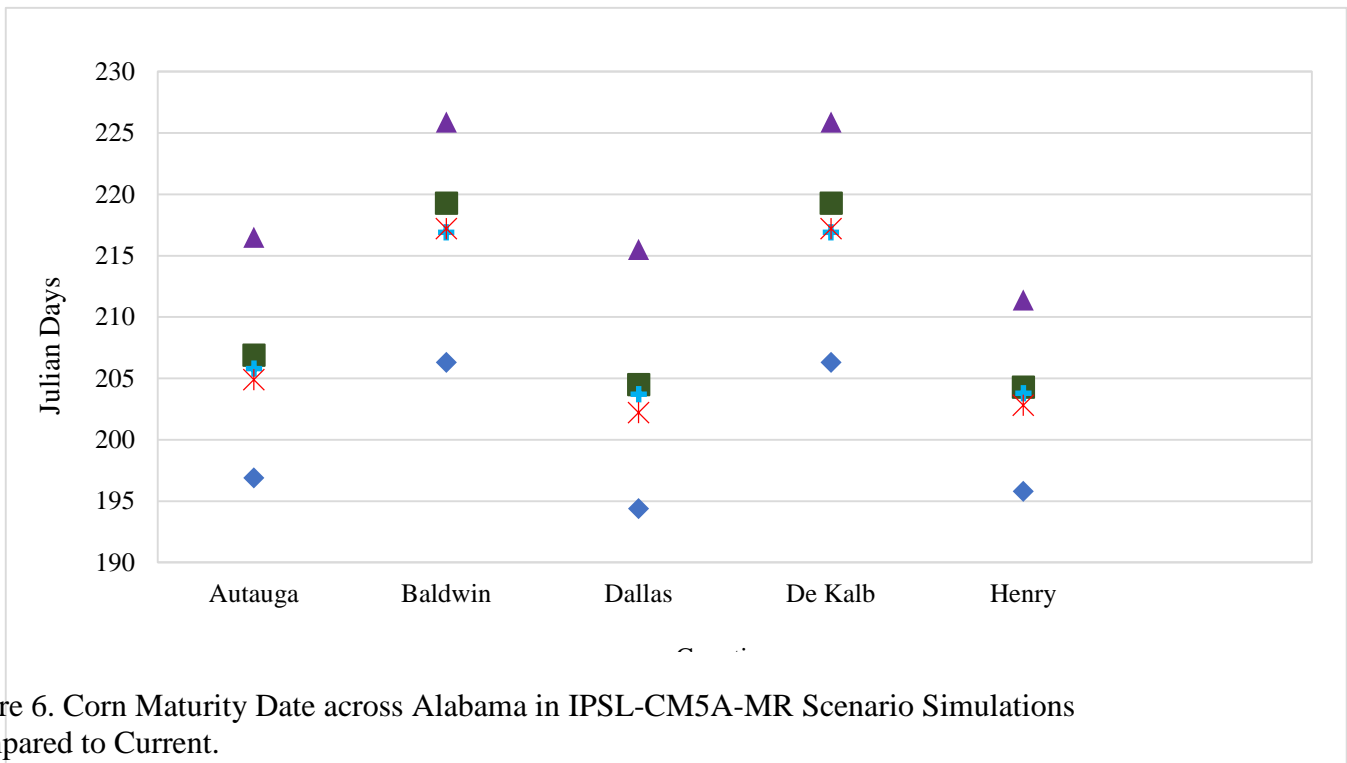Figure 5. Corn Anthesis Date across Alabama in IPSL-CM5A-MR Scenario Simulations Compared to Current.

Figure 6. Corn Maturity Date across Alabama in IPSL-CM5A-MR Scenario Simulations Compared to Current.

The impact of hastened reproductive stages (anthesis, maturity) was evident in both scenarios (RCP 4.5 and RCP 8.5) but grew steadily worse at higher levels of emissions. In all counties, the days to anthesis were shortened in future climate scenarios, with decreases of up to 6 days in 2045, under the medium emission scenario. In 2075, there is approximately double the decrease in days to anthesis experienced in 2045, with the high emission scenario experiencing decreases of between 9 to 13 days. Time to maturity was also shortened with the high emission scenario, in 2075 experiencing decreases of between 16 to 21 days. For both scenarios, increased maximum and minimum temperature impacted yields by hastening maturity, thereby decreasing the length of the life cycle which cut short the period of time the crops would have had to make use of available resources to capture assimilate and grow grain (Menzel et al., 2006; Tubiello et al., 2002; Southworth et al., 2000). Recent studies have however, highlighted the possibility that the CERES-Maize (corn) model predicts too strongly the reduction in yields because of accelerated life cycle. Kumudini et al. (2014) suggests that there is a chance that the CERES-Maize model is wrong in its maize development simulations in response to temperature. They point out that the model could be too sensitive and thus accelerate life cycle too fast with rising temperature especially during the grain-filling phase where the present heat unit approaches are quite wrong.

Conclusion

Impacts of climate change on Alabama state non-irrigated corn production were successfully assessed through the use of a crop simulation model, under medium and high emission scenarios. The study concludes that climate change could potentially result in decreasing corn yields in Alabama. In 2045, representative year for 2030-2060, the projected average decreases in corn yield trends were 19.5% and 37.3%, respectively, under RCP 4.5 (medium emission) and RCP 8.5 (high emission). However, in 2075, representative year for 2060-2090, projected average decreases for corn were 32.5% and 77.8%, respectively, under RCP 4.5 (medium emission) and RCP 8.5 (high emission). Such negative projections are a clear call for the development of adaptation strategies and policies to sustain current corn yields. This may involve the development of longer-cycle hybrids, improved cultivars which are heat and drought tolerant. The most vulnerable groups of farmers, who happen to be small-scale and limited-resource farmers, would benefit from climate change education and assistance with adaptation strategies.

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