COUPLING THE SIMCLIM SYSTEM WITH CROP SIMULATION MODELS FOR DETERMING ADAPTATION STRATEGIES UNDER A CHANGING CLIMATE: AN APPLICATION FOR MAIZE PRODUCTION IN THE SOUTHEASTERN USA

by

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(Under the Direction of Gerrit Hoogenboom)

ABSTRACT

Many studies have addressed the potential impact of climate change on maize production in many regions of USA, however, not for the Southeastern USA. The approaches of prior studies also had limitations and need improvement. The overall goal of this study was to determine the climate change impact on maize production in the Southeastern USA and provide adaptation strategies. The results showed that in order to adapt to the changing climate, maize in Florida should be planted earlier to avoid the higher temperature in the future. Maize in northern region of the Southeastern USA should be planted during April, May, and June. Irrigation also could offset the negative effects of water deficit and high temperature.

INDEX WORDS: Climate Change, General Circulation Model, SimCLIM, CSM-CERES-Maize, EPIC

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CHAPTER 1

INTRODUCTION

Climate is one of the most important factors that control the future supply of food and there is already overwhelming evidence that shows that climate change is reducing crop yield (Gosling et al. 2011, Lobell et al. 2011). Maize (*Zea mays L.*) is one of the three most important cereals and contributes the most to the calories that were either directly or indirectly consumed by humans (Cassman 1999). A significant effect of climate on maize has been found by both historical data and impact studies (Tsvetsinskaya et al. 2003, Kucharik & Ramankutty 2005, Lobell & Field 2007, Eckersten et al. 2010, Lobell et al. 2011, Rowhani et al. 2011).

Many studies have been conducted to understand the biophysical and biological processes of how maize responds to warmer growing seasons, reduced water supply, and increased carbon dioxide (Bunce 2004, Rotter et al. 2011, Li et al. 2014). A negative response to rising temperature has been found for maize yield (Kurek et al. 2007, Lobell & Field 2007). Precipitation is an important driver that affects the inter-annual variability of maize yield. However, the effect of temperature on yield is larger than for precipitation in most situations (Burke et al. 2009, Lobell et al. 2011, Asseng et al. 2013). CO_2 enrichment is generally believed to be able to offset the negative effects on maize grain yield from high temperature extremes (Challinor & Wheeler 2008). However, arguments still exist since some studies insisted that maize does not directly benefit from rising CO_2 (Long et al. 2006, Gosling et al. 2011).

Many limitations in the studies that have been conducted with respect to the potential impact of climate change on maize growth, development, and yield still exist for those literatures.

First of all, many of the studies still focused on conducting a sensitivity analysis research of climate change impact on maize growing. Only a few provided understandable information that is useful for decision-makers or farmers. Secondly, although progress was made on characterizing and analyzing uncertainties in generating future climate (Christensen et al. 2007), it is not likely to mitigate them in short time (Knutti 2010). Given the uncertainties associated with of the climate scenarios, a good approach is to use several possible scenarios as input for the crop simulation models to provide range of possibilities for impact analysis (Iglesias 2006). Thirdly, wide divergence in simulated grain yield by various crop simulation models has been found since these models represent the crop development and growth differently (Palosuo et al. 2011, Rotter et al. 2011, Rötter et al. 2012, Carter 2013). Recent studies have shown that a greater proportion of the uncertainty in climate change impact projections was due to variations among crop models than due to the variations among downscaled general circulation models (Palosuo et al. 2011, Malcolm et al. 2012, Asseng et al. 2013, Rosenzweig et al. 2013). Fortunately, an ensemble of multiple crop models can offer a more robust basis for projecting future crop yields and associated uncertainties rather than relying on individual model simulations (Semenov & Stratonovitch 2010, Rötter et al. 2012, Asseng et al. 2013, Carter 2013). However, most of climate impact studies until very recently are still are based on a single crop model for the analyses.

The National Corn Growers Association (NCGA, http://www.ncga.com) reported that 32.1% of the world's maize is produced by United States and 2% of the US maize is from the southeastern USA. Maize production is important and climate change impact on crop varies with region. This study dedicated the impact of changing climate in 2050 and 2070 for maize production in southeastern USA. Multiple climate scenarios and two crop models were applied.

The overall goal of this study was to determine potential adaptation strategies for crop production in the southeastern USA under a changing climate in 2050 and 2070. The specific objectives were: 1) to compare the performance of two maize crop simulations models, Cropping System Model (CSM)-CERES-Maize and Erosion-Productivity Impact Calculator (EPIC) for maize, 2) to evaluate the accuracy of an Integrated Assessment Model (IAM)-SimCLIM in projecting future climate for specific locations in the southeastern USA, 3) to determine the maize grain yield in 2050 and 2070 based on two crop models under a wide coverage of climate scenarios, and 4) to develop the adaptation strategies for future maize planting.

First of all, in this study we try to address some of the limitations of previously conducted climate change impact studies. In Chapter 2, since few studies have been conducted for comparison of maize crop models (Carter 2013), two popularly used maize simulations models, i.e., CSM-CERES-Maize and EPIC, were calibrated and evaluated first for seven recently released cultivars. Those hybrids were Dyna-Gro V5373VT3, Pioneer 33M57(Hx1/LL/RR2), SS 731CL, Croplan Genetics 851 VT3 PRO, Croplan Genetics 8756 VT3, DeKalb DKC69-71(RR2/YGCB), and Pioneer 31D58. Model calibration was based on the observed crop performance data obtained during 2003 to 2010 from locations Blairsville, Calhoun, Griffin, Midville, Plains, and Tifton in Georgia. Following model evaluation, the two crop models were compared in simulating both rainfed and irrigated grain yield from 1958 to 2012 with the seven calibrated hybrids for six locations.

In Chapter 3, the accuracy of SimCLIM in projecting site-specific climate for the southeastern USA was evaluated. The purpose of this chapter was to develop a good statistical approach for evaluating SimCLIM. Tifton, Georgia was selected as a case study because of the availability of historical weather data for maximum and minimum temperature, precipitation, and especially solar radiation. The evaluation was based on a range of statistical tests, including box-plot, time-series plot, standard deviation, Kolmogorov-Smirnov test (KS-test), and Cumulative Distribution Function (CDF) analyses for minimum and maximum temperature, precipitation, and solar radiation for both the mean and variability of climate.

The comprehensive evaluation for Tifton Georgia from chapter 3 could not represent the southeastern USA. In Chapter 4, 34 locations therefore were selected encompassing the states of Alabama, Florida, and Georgia, for the period from 1993-1998, depending on the availability of data, and ending in 2012. Statistical analysis including box-plot, time-series plot, standard deviation, KS-test, and probability histogram were applied. Site-specific climate variables minimum and maximum temperature, precipitation, and solar radiation for multiple locations over southeastern USA (in Alabama, Florida, and Georgia) were evaluated.

In Chapter 5, the impact of climate change on both rainfed and irrigated maize yield was determined using the two crop simulation models and multiple climate scenarios. Southeastern USA was divided into different climate divisions. It was assumed that the climate for each climate division was similar. A climate division should have similar crop distribution. One location was used to represent one climate division. 22 locations were selected to represent the climate zones in Alabama, Florida, and Georgia. Climate scenarios for those 22 locations in the three states that were generated by SimCLIM were based on 15 GCMs and three gas emission scenarios, A1B, A2 and B1. Under each of the climate scenarios, both rainfed and irrigated grain yield for seven maize hybrids were simulated using the two crop simulation models CSM-CERES-Maize and EPIC. Maize grain yields for planting dates from February to June with a 15-day gap were simulated.

Chapter 6 summarizes the results of this study and proposes possible adaptation strategies for farmers and policy/decision-makers. Furthermore, recommendations are also proposed for future research for climate change impact and adaptation strategy.

CHAPTER 2

A COMPARISON OF THE PERFORMANCE OF THE CSM-CERES-MAIZE AND EPIC MODELS FOR THE SOUTHEASTERN USA USING VARIETY TRIAL DATA[1]

[1] Bao, Y., Hoogenboom, G., McClendon, R.W., and Vellidis, G. to be submitted to Agricultural and Forest Meteorology

2.1 INTRODUCTION

"Crop simulation models integrate the current state-of-the art scientific knowledge from many different disciplines, including crop physiology, plant breeding, agronomy, agrometeorology, soil physics, soil chemistry, soil fertility, plant pathology, entomology, economics and many others" (Hoogenboom 2000). Since agricultural production is determined by weather and climate (Adams et al. 1998), the crop (simulation) models have been used to analyze the potential impact of changing climate in agricultural production (Lobell & Asner 2003, White & Hoogenboom 2010, Semenov & Shewry 2011). Coupling crop models and climate models has been widely used in past and current climate impact analysis (Curry et al. 1995, Easterling et al. 1996, Easterling et al. 1997, Carbone et al. 2003, Parry et al. 2004, Parry et al. 2007, White et al. 2011). Alexandrov and Hoogenboom (2000) used the CERES v.3.5 simulation model for maize (*Zea mays* L.) and winter wheat (*Triticum aestivum* L.) and the CROPGRO v.3.5 model for soybean (*Glycine max* L.) and peanut (*Arachis hypogaea* L.) based on climate projections of Global Circulation Models (GCM) for more than 500 locations in the southeastern region of the USA. Their results concluded that the GCM scenarios projected a decrease in crop yield for the 2020s under the current level of CO_2 and the increased CO_2 tended to increase crop yields. Adaptation options were suggested for changing sowing data, hybrids and cultivar selection, and fertilization to mitigate the potential negative impact of potential warming.

It is well known that the calibration and evaluation of a crop model is always critical when a crop model is applied for new locations and varieties. This procedure can not only promise that crop model can provide accurate information, e.g., simulations of grain yield, but also can show the possible uncertainties that crop models could introduce in impact studies.

Many studies have developed procedures to calibrate crop models based on limited observations, not only for model improvement but also for numerous applications for a range of crops such as maize, soybean, alfalfa (*Medicago sativa*), grain sorghum (*Sorghum bicolor* (L.) Moench), wheat, barley (*Hordeum vulgare* L.), peanut, rice (*Oryza sativa*), cotton (*Gossypium hirsutum L.*), etc. (Cabelguenne et al. 1990, Perez-Quezada et al. 2003, Soler et al. 2007, Ko et al. 2009, Gaiser et al. 2010, Balkovič et al. 2013).

In addition to the calibration and evaluation of single model, studies also have shown that different modeling approaches may lead to significant differences in results from crop growth simulation models (Wolf 2002). The comparison of different crop models' performance in predicting crop phenology (e.g., Porter et al. (1993) and French and Hodges (1985)) and grain yield (e.g., Cerrato and Blackmer (1990)) have been studied and also concluded that some models showed better predictions than the others, which means less uncertainties will be introduced when the models are applied. Recent discussion of uncertainties that crop models could introduce to for climate change impact studies urges the comparison of the performance of different crop models (Semenov & Stratonovitch 2010, Ceglar et al. 2011, Rötter et al. 2012). The recently released cultivars have not been parameterized in the models and therefore need to be calibrated, while the crop models also have improved over time. Therefore, the comparison of different crop models' performance and the use of multiple crop models to minimize the uncertainties from crop models have been acted on internationally, such as The Agricultural Model Intercomparison and Improvement Project (Rosenzweig et al. 2013). While, the comparison of crop models usually contains the calibration and evaluation of each model, and also the sensitivity test under temperature, water, and fertilizer stresses. An accurate sensitivity test also promises the better investigation of the climate change effect on crop growth.

Comprehensive data sets are needed for the comparison of crop models' performance, especially for the more complex dynamic crop growth simulation models (Hoogenboom et al. 2012a). For instance, Anothai et al. (2008) collected detailed phenological and growth analysis data for the calibration of CSM-CROPGRO-Peanut. However, limited observations are normally only available because detailed field experiments are time-consuming and require extensive financial resources. For most impact studies, the calibration and evaluation procedures of the crop simulation models have been ignored. In general, the recommended cultivar coefficients from model designers or previous studies were used for the impact studies, which certainly introduced more uncertainties to the impact studies.

Only a few studies so far have concentrated on multiple model comparisons, such as wheat (Asseng et al. 2013) and barley (Rötter et al. 2012). There is, therefore, also a need to analyze the uncertainties of maize crop models for impact studies, especially with recently released maize hybrids. This study selected two commonly used maize crop simulation models in both the USA and across the globe. One is CSM-CERES-Maize, which is one module of Decision Support System for Agrotechnology Transfer (DSSAT), the other one is Erosion-Productivity Impact Calculator (EPIC) cropping systems model. DSSAT is a software package that incorporates independent models of more than 25 different crops with programs that facilitate the evaluation and application of the crop models for different purposes (Jones et al. 2003, Hoogenboom et al. 2012b). It can simulate growth, development, and yield of a crop growing on a uniform area of land by considering weather, genetics, soil water, soil carbon and nitrogen, and management in single or multiple seasons and in crop rotations at any location where minimum inputs are provided (Hunt & Boote 1998, Jones et al. 2003). The minimum inputs contain soil profile, daily weather data (minimum and maximum temperature, precipitation, and solar radiation), crop management (plant population, row spacing, application of irrigation and fertilizer etc.), and a set of cultivar coefficients. Individual crop growth modules were designed for simulating different crops, which promises an accurate description for the development stages of specific cultivar. CSM-CERES-Maize is the module to simulate growth, development and yield of maize with a daily time step. Growth stages that are simulated by the CSM-CERES-Maize include germination, emergence, end of juvenile, floral induction, 75% silking, beginning grain fill, maturity, and harvest (Jones & Kiniry 1986, Ritchie et al. 1998, Jones et al. 2003). The physiological day accumulator is a function of temperature and day length, while it reaches the threshold given in the cultivar file, the new growth stages is triggered. The potential growth depends on photosynthetically active radiation and its interception, where the actual biomass production is constrained by stresses such as temperature, nitrogen, and water. It also considers the sensitivity of crop to CO_2 concentration.

EPIC was designed to estimate soil productivity as affected by erosion throughout the U.S. (Williams et al. 1989). The components of the EPIC model include weather, hydrology, erosion-sedimentation, nutrient cycling, crop growth, tillage, soil temperature, economics, and plant environment control (Jones et al. 1984b, a, Sharpley et al. 1984, Williams et al. 1984, Williams et al. 1989). Similar to CSM-CERES-Maize, soil profile information, daily weather data, crop management, and a set of cultivar coefficients are the minimum data inputs for EPIC. However, multiple crops are simulated by a single module. The yield is estimated using the harvest index and above-ground biomass. The above-ground biomass in turn is a function of photosynthetically active radiation and leaf area. Leaf area is calculated as a function of heat unit accumulation, crop development states and crop stresses. Unfortunately, this model does not provide the outputs for crop development stages.

The goal of this study was to determine the feasibility to evaluate CSM-CERES-Maize and EPIC with limited maize (*Zea mays L.*) variety trial data. The first objective was to determine the cultivar coefficients for the two crop models with observed grain yield; the second objective was to determine whether the performance of two crop models are comparable in predicting maize grain yield.

2.2 EXPERIMENTAL DATA COLLECTION

In Georgia, variety trials for both rainfed and irrigated maize are conducted at the regional agricultural experimental stations located in Blairsville (34.84°N, 83.93°W), Calhoun (34.34°N, 85.12°W), Griffin (33.26°N, 84.28°W), Midville (32.88°N, 82.22°W), Plains (32.05°N, 84.37°W), and Tifton (31.49°N, 83.53°W) (Table 1). These variety trials are conducted by the University of Georgia (UGA) College of Agricultural & Environmental Science (CAES) Statewide Variety Testing (SWVT) program. In this study data collected from 2003 until 2010 were used (Coy et al. 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010). Soil profile and soil surface data and generic soil information for these seven locations were obtained from the soil analyses conducted by Perkins et al. (1978, 1979, 1982, 1983, 1985, 1986) and Natural Resources Conservation Service (NRCS) of United States Department of Agriculture (USDA). The soil types were Bradson clay loam for Blairsville; Waynesboro loam, Ethowah loam, Rome gravelly clay loam, and Savannah loam for Calhoun; Pacolet sandy loam and Cecil sandy loam for Griffin; Tifton loamy sand and Dothan loamy sand for Midville; Faceville sandy loam and Greensville sandy loam for Plains; and Tifton loamy sand, Fuquay loamy sand, and Dothan loamy sand for Tifton. A soil utility program of DSSAT, SBuild, was used to create the soil inputs based on these local soil profile data.

The daily solar radiation, maximum and minimum air temperature, and precipitation for each location were obtained from the Georgia Automated Environmental Monitoring Network (GAEMN, www.georgiaweather.net), which was first deployed in 1991 (Hoogenboom 1996), with 60 operational stations in 2004 (Garcia y Garcia & Hoogenboom 2005) and over 80 in 2013. The typical maize growing season is April to October for Blairsville, April to September for Calhoun, Griffin, and Midville, and March to September for Plains and Tifton. Blairsville has the highest latitude and elevation and, therefore a relatively longer growing season than the other locations, while Tifton has the lowest latitude and elevation and is located in the Coastal Plains. Precipitation varied among locations and among years due to the variable summer thunderstorms that normally occur in Georgia. Some of the years had a dry season, which was less than 400 mm, i.e., Calhoun in 2007, Griffin in 2006 and 2007, and Midville in 2006 (Table 2.1).

Crop management, planting dates, irrigation amount, fertilizer amount, and planting population corresponded to the local management of the variety trials. Plant population at seeding was around 6 to 8 plants/m^2, row spacing was 76 cm, and the planting depth was 5 cm. The reported dates and amount of irrigation for each individual trial were also obtained and the irrigation method was sprinkler irrigation. Previous crops grown in these fields included maize, cotton, soybean, peanut, and fallow, while in some instances there was a fallow season.

The hybrids, Dyna-Gro V5373VT3, Pioneer 33M57(Hx1/LL/RR2), SS 731CL, Croplan Genetics 851 VT3 PRO, Croplan Genetics 8756 VT3, DeKalb DKC69-71(RR2/YGCB), and Pioneer 31D58, were the selected seven that were planted at all locations, which covered the period of 2003 to 2010 (Table 2.2). The observations included grain yield with 15.5% moisture and final harvest dates, which were used for model calibration and evaluation Observed grain yield was corrected to 0% water content first prior to running the crop models.

2.3 CALIBRATION AND EVALUATION

2.3.1 CSM-CERES-MAIZE

Model calibration and evaluation were based on comparing the model simulations with observations. Multiple years (2003 to 2010) have been considered for calibration and evaluation, some of them were used for calibration and the rest was for evaluation (Table 2.2). Hybrid coefficients were adjusted to make the simulated variables fit well with observations. The hybrid coefficients of the CSM-CERES-Maize model include thermal time from seedling emergence to the end of the juvenile phase (P1), extent to which development is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (P2), thermal time from silking to physiological maturity (P5), maximum possible number of kernels per plant (G2), kernel filling rate during the linear grain filling state and under optimum conditions (G3), and the interval in thermal time (degree days) between successive leaf tip appearances (PHINT) (Table 2.3). The soil fertility factor (SLPF) was also adjusted as it is an input parameter that affects the overall growth rate of simulated total biomass by modifying daily canopy photosynthesis and is attributed to soil fertility differences and soil-based pests, such as nematodes (Mavromatis et al. 2001, Guerra et al. 2008) .

The calibration procedure was similar to the one developed for the CSM-CROPGRO-Soybean models (Bao et al. 2014). This included the Genotype Coefficient Calculator (GENCALC) to calibrate the parameters with corresponding observations and manually adjusted the remainder of the hybrids. GENCALC was designed to calibrate hybrid coefficients especially for DSSAT model calibration. It starts with the initial coefficients that are extracted from the genotype file of DSSAT and it selects the best value for each coefficient by evaluating the root mean square error (RMSE) between the simulated and observed variables (Hunt et al. 1993). The search of appropriate value for each of the genetic coefficients was in a limited range by setting the change for each step, i.e., STEP, and the number of times GENCALC should change the values of a particular coefficient, i.e., LOOP.

First, SLPF was manually adjusted for each location based on the initial set of hybrid coefficients. The values of SLPF range from 0.7 to 0.94 (Jones et al. 1989, Mavromatis et al. 2001). The adjustment started with an initial value, 0.8, until simulated grain yield was similar to the observations. All seven hybrids for all years (2003 to 2010) were used for each of the six locations. The next step was to calibrate hybrid coefficients. Because grain yield was only available from the variety trial data, the hybrid coefficients G2 and G3 could be automatically calibrated by using GENCALC. At the same time the hybrid coefficients P1, P2, P5, and PHINT were manually changed with a certain percentage while GENCALC optimized for G2 and G3. A sensitivity test showed that the loop for manually modifying parameters was 10 for P1, 0.3 for P2, 10 for P5, and 1 for PHINT. The search for P1 ranged from 110 to 458, for P2 ranged from 0 to 3, for P5 ranged from 390 to 1000, and for PHINT ranged from 30 to 75. The initial values were 200, 0.3, 800, and 38.9 for P1, P2, P5, and PHINT respectively. Ideally, the simulated days from planting to maturity (maturity days) should have a good fit with observed maturity days when adjusting P1, P2, P5, and PHINT. However, because no observed maturity days were obtained, the observed days from planting to harvest (harvest days) were used, which is usually longer than the number of days to maturity. The GENCALC searches G2 and G3 by comparing simulated grain yield with observations. For G2 the range was 248 to 990 and for G3 the range was 4.4 to 16.5. The initial value for G2 was 770 and 8.5 for G3. The final step was to use the calibrated hybrid coefficients for evaluation using an independent data set from the variety trial data.

2.3.2 EPIC

EPIC also requires a number of crop-specific coefficients (Table 2.3), which is similar to the CSM-CERES-Maize model. The parameters that were calibrated in this study also have been selected for calibration in previous studies, such as Williams et al. (1989), Cabelguenne et al. (1990) and Guerra et al. (2004), and Ko et al. (2009). The potential heat units (PHU) for maize is defined as the total number of heat units from planting to physiological maturity. Biomass-energy ratio (WA), maximum harvest index (HI), fraction of growing season when leaf area declines (DLAI), maximum potential leaf area index (DMLA) and drought sensitivity parameter (WSYF) were also adjusted. Batch processing was applied to search parameters within a certain range for those six parameters. A sensitivity test was first conducted to determine the optimum range for the optimization. The range for PHU was from 1600 to 2000 with a step of 10; the range for WA was from 40 to 55 with a step of 1; the rage for HI was from 0.1 to 0.6 with a step of 0.05; the range for DMLA was from 2 to 6 with a step of 1; the range for DLAI was from 0.5 to 0.95 with a step of 0.05; and the range for WSYF was from 0.01 to 0.4 with a step of 0.01.. The final step was also using independent variety trial data to evaluate the calibrated hybrid coefficients by comparing simulated grain yield with observations.

2.3.3 STATISTICAL CRITERIA

The comparison between simulated and observed data for both calibration and evaluation was based on the following criteria: slope of the regression of simulated against observed, the coefficient of determination (R^2), index of agreement (d), and root mean square error (RMSE) (Casella & Berger 2002, Yang et al. 2014a), which were defined as following:

$$R^2 = 1 - \frac{\sum_i (O_i - P_i)^2}{\sum_i (O_i - \bar{O})^2}$$

$$d = 1 - [\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(|P_i'| - |O_i'|)^2}]$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}$$

where n is the number of observations, P_i is the predicted value for the ith measurement, O_i is the observed value for the ith measurement, $\bar{O}$ is the mean of all observations, $P_i' = P_i - \bar{O}$, and $O_i' = O_i - \bar{O}$. For the linear regression of simulated against observed yield, slope, R^2, and d ranged from 0 to 1 and a best fit requires that they are 1. On the other hand, a smaller RMSE also means a better fit. These statistical criteria have been used in many studies for model calibration and evaluation, e.g., Anothai et al. (2008), Mavromatis et al. (2001), Yang et al. (2014b), Soler et al. (2007) etc.

2.3.4 COMPARISON OF CSM-CERES-MAIZE AND EPIC

Following calibration and evaluation, both models were then applied for yield prediction under both irrigated and rainfed production in Blairsville, Calhoun, Griffin, Midville, Plains, and Tifton from 1958 to 2012. One of the objectives of this analysis was to determine the differences in yield prediction between the two models for different environments, but using the same crop management as input. Crop management was the same as those from the variety trial data. The soil types varied with year for the variety trials, but for this analysis the most common soil type was used for each location. This included a Bradson clay loam for Blairsville, an Etowah loam for Calhoun, a Cecil sandy loam for Griffin, a Tifton loamy sand for Midville, a Greensville sandy loam for Plains, and a Tifton loamy sand for Tifton. An analysis of variance (one way ANOVA) along with box-plots was then conducted to determine whether the simulations of CSM-CERES-Maize and EPIC were significantly different. The null hypothesis here was that the simulations of two crop models do not have significant difference. The level of $\alpha = 0.05$ (95% confidence level) was used. If value for p is smaller than α it means that there is a significant difference between the simulations of the two crop models.

2.4. RESULTS

2.4.1 EVALUATION OF CSM-CERES-MAIZE

The calibrated value for the soil fertility factor (SLPF) was 0.8 for Blairsville, 0.76 and 0.70, 0.87, and 0.9 for Calhoun, 0.78 and 0.7 for Griffin, 0.82 and 0.85 for Midville, 0.84 and 0.73 for Plains, and 0.89, 0.9, and 0.89 for Tifton (Table 2.4). The locations that have multiple values for SLPF are because the soil types varied by year. Since SLPF was estimated for each of the six locations and all the hybrids in all years were used for the calibration, the linear regression of each location was based on all hybrids. The statistical criteria that were used to determine the best value for SLPF were slope, R^2, and RMSE. The difference between simulated observed yield was 14% for Tifton, 11% for Plains, and less than 3% for the other four locations. The slope of the linear regression was low for Blairsville (0.391) and it ranged from 0.582 for Midville to 0.997 for Tifton. Blairsville also had a low value for R^2, 0.056, and the value for R^2 for the other locations ranged from 0.432 for Midville to 0.803 for Tifton The value for the d for Blairsville had a 0.475 for d, the other locations ranged from 0.811 to 0.932. Midville had the smallest RMSE, 920 kg/ha, Blairsville, Calhoun, Griffin, and Plains were from 1201 to 1867 kg/ha, and the largest RMSE was 2029 kg/ha for Tifton.

The CSM-CERES-Maize model was calibrated for phenology and growth coefficients for seven hybrids (Table 2.5). The value for the cultivar coefficient P1 ranged from 220 to 330; P2 ranged from 0.9 to 1.8; P5 ranged from 820 to 940; PHINT ranged from 48.9 to 63.9; G2 ranged from 646.8 to 954.8; G3 ranged from 10.94 to 12.64. In some cases the hybrid coefficients had the same value for different hybrids. For example, the value for P1 for Dyna-Gro V5373VT3 and Croplan Genetics 851 VT3 PRO were the same and Dyna-Gro V5373VT3, Pioneer 33M57 (Hx1/LL/RR2), Croplan Genetics 851 VT3 PRO, and DeKalb DKC69-71(RR2/YGCB) had the same value for G2.

A comparison between simulated grain yield based on these calibrated hybrids coefficients and observed data was conducted (Table 2.6). In general, the performance of model varied by hybrids. For the hybrids Dyna-Gro V5373VT3, Pioneer 33M57 (Hx1/LL/RR2), and SS 731CL grain yield was over-estimated in grain yield, which is the expected result since the limitations for simulations are less than reality. However, for some of the hybrids grain yield was under-estimated. Fortunately, the differences between simulated and observed grain yield were no more than 3% of the observations, which means a good fit. The slopes of linear regression for the seven hybrids ranged from 0.71 (SS731CL) to 1.222 (Croplan Genetics 851 VT3 PRO). Hybrid Dyna-Gro V5373VT3 had the best value, 0.997, which is close to 1. The values for R^2 of seven cultivars were from 0.67 (DeKalb DKC69-71(RR2/YGCB)) to 0.885 (Dyna-Gro V5373VT3). The values of d-stat are from 0.9 (DeKalb DKC69-71(RR2/YGCB)) to 0.969 (Dyna-Gro V5373VT3) for seven hybrids. The RMSE ranged from 1033 (Dyna-Gro V5373VT3) to 2051 kg/ha (SS 731CL).

The evaluation of CSM-CERES-Maize was conducted by comparing simulated and observed grain yield for a different set of trial data (Table 2.6). Yield for the hybrids Pioneer 33M57(Hx1/LL/RR2), SS 731CL, and Croplan Genetics 8756 VT3 was over-estimated and the others were under-estimated. The difference between simulated and observed yield were less than 8% of the observed yield. The values for slope of the linear regression ranged from 0.64 (Dyna-Gro V5373VT3) to 1.18 (Pioneer 33M57(Hx1/LL/RR2)). The lowest value was 0.64 for the hybrid Dyna-Gro V5373VT3, which had the highest value for the slope for the calibration. The highest value for the slope for evaluation was 0.911 for Pioneer 31D58, which is close to 1. The value for R^2 was 0.48 for DeKalb DKC69-71(RR2/YGCB), which is low, but the value for R^2 for the other hybrids ranged from 0.703 (SS 731CL) to 0.946 (Dyna-Gro V5373VT3). The values for d-stat ranged from 0.782 (Dekalb DKC69-71(RR2/YGCB)) to 0.966 (Pioneer 33M57(Hx1/LL/RR2)), which were similar to the values found for calibration. The RMSE ranged from 973 to 1980 kg/ha. The values for RMSE for Pioneer 33M57(Hx1/LL/RR2) (973 kg/ha), SS 731CL (1895 kg/ha), and Croplan Genetics 8756 VT3 (1642 kg/ha) were less that the value for RMSE found during calibration. However, the other hybrids had a larger RMSE than for calibration. In summary, the simulated grain yield of evaluation data set showed a good agreement with observed yield and comparable to the calibration data set.

2.4.2 EVALUATION OF EPIC

The EPIC was calibrated for the grain yield and yield components coefficients for seven hybrids (Table 2.5). The values of WA were 50 for all hybrids; 0.5 for HI except for 0.45 for Croplan Genetics 851 VT3 PRO; 0.95 for DLAI for all hybrids; 6 for DMLA except for 5 for Croplan Genetics 851 VT3 PRO; and 0.01 for WSYF which means all hybrids are very sensitive to water stress. The value of PHU was 1800 for Dyna-Gro V5373VT3, SS 731CL, and Croplan Genetics 851 VT3 PRO, 1650 for Pioneer 33M57 (Hx1/LL/RR2), 1730 for DeKalb DKC69-71(RR2/YGCB), and 1770 for Pioneer 31D58.

The accuracy of EPIC model in predicting grain yield varies with hybrids (Table 2.6), which was similar with CSM-CERES-Maize. Average simulated grain yield was over-estimated by EPIC for all the hybrids. SS 731CL showed the worst simulations that had a 23% of over-estimation and the other hybrids were over-estimated by 2% to 15%. The slopes of linear regression ranged from 0.514 (Pioneer 33M57(Hx1/LL/RR2)) to 0.88 (Croplan Genetics 851 VT3 PRO). The values of R^2 ranged from 0.54 (DeKalb DKC69-71(RR2/YGCB)) to 0.814 (Dyn-Gro V5373VT3). All values of d were above 0.84 but SS 731CL showed a value, 0.754. The best d was 0.947 for Dyn-Gro V5373VT3, which is close to 1. Except for SS 731CL with a RMSE, 3772 kg/ha, the RMSE ranged from 1268 kg/ha (Croplan Genetics 851 VT3 PRO) to 2308 kg/ha (Pioneer 31D58) for the other six hybrids.

The evaluation of hybrids coefficients showed that EPIC over-estimated the average grain yield of all hybrids by about 10-23% of observations. The slopes of linear regression for DeKalb DKC69-71(RR2/YGCB) and Pioneer 31D58 are even as low as 0.222 and 0.266. The other hybrids had slope of 0.555 (Dyn-Gro V5373VT3) to 1.26 (SS 731CL). The slope of Pioneer 33M57(Hx1/LL/RR2) was 0.98, which is the best one. DeKalb DKC69-71(RR2/YGCB) also showed lower values in both R^2 and d-stat, which were 0.19 and 0.575. The values of R^2 were from 0.49 (Pioneer 31D58) to 0.86 (Croplan Genetics 8756 VT3). The values of d were from 0.633 (Pioneer 31D58) to 0.875 (Dyn-Gro V5373VT3). The RMSE ranged from 1875 (Pioneer 33M57(Hx1/LL/RR2)) to 4228 kg/ha (SS 731CL).

2.4.3 COMPARISON OF CSM-CERES-MAIZE AND EPIC FOR LONG-TERM SIMULATIONS

The combination of calibration and evaluation data presents a clear map for describing the performance of both crop models for all years and locations in simulating grain yield (Figure 2.1). Because linear regression could possibly mislead a performance analysis, this study also showed simulations against observations with a reference to the 1:1 line. At a first glance, many simulations based on EPIC were higher than observations especially for the hybrids Pioneer 33M57(Hx1/LL.RR2), Croplan Genetics 8756 VT3, and SS731CL. In contrast to EPIC, the simulations based on CSM-CERES-Maize were concentrated more around the 1:1 line, such as for the hybrids Dyna-Gro V5373VT3, Pioneer 33M57(Hx1/LL/RR2), and Pioneer 31D58, which means an accurate simulated grain yield. For the hybrid Dyna-Gro V5373VT3, EPIC tended to slightly over-estimate the low grain yield, while, CSM-CERES-Maize showed more accurate simulations when grain yield was in a low range. For the hybrid Pioneer 33M57(Hx1/LL.RR2) and SS731CL, EPIC over-estimated grain yield and the CSM-CERES-Maize model showed that scatters widely distributed for SS 731CL which was not a good fit and a good fit for the hybrid Pioneer 33M57(Hx1/LL.RR2). For hybrid Pioneer 31D58, both crop models provided similar yield with SS 731CL, which was over-estimated by EPIC and CSM-CERES-Maize did not provide accurate simulations. Both crop models provided accurate simulations for Croplan Genetics 851 VT3 and Croplan Genetics 8756 VT3. Both models were very similar simulations for hybrid DeKalb DKC69-71(RR2/YGCB), however, the EPIC tended to over-estimated the simulations for years of evaluation but CSM-CERES-Maize showed the opposite way for years of evaluation. In summary, the CSM-CERES-Maize showed a slightly better simulation of grain yield that EPIC especially for the hybrids SS731CL and Pioneer 31D58, while the two models were comparable in predicting grain yield for the other hybrids.

Following calibration and evaluation of both models, a long-term simulation analysis was conducted suing 55 years of historical weather data, but the same crop management for each location as is being used for the variety trial data. For rainfed conditions the simulated grain yield for 55 years is shown for both CSM-CERES-Maize and EPIC in Figure 2.2. CSM-CERES-Maize simulated grain yield that ranged from 1000 to 14000 kg/ha, with a median of around 5500 kg/ha to 6500 kg/ha, for the hybrid Dyna-Gro V5373VT3 at the six locations. A large range (difference between maximum value and minimum value) was shown among years, due to differences in precipitation for each year. Simulations for the hybrid Dyna-Gro V5373VT3 with EPIC showed similar to CSM-CERES-Maize for Blairsville, but the maximum and minimum values were about 1000 kg/ha less. For Calhoun, the median, maximum, and minimum values of simulations based on EPIC were about 3000 kg/ha higher than for CSM-CERES-Maize. The yield predictions for EPIC at Griffin were similar to Blairsville. Although a similar median was found for both models at Midville, EPIC showed a smaller range. At Plains, the simulations based on EPIC had a maximum value of about 8200 kg/ha, which was much lower than for CSM-CERES-Maize. However, the yield predictions for both models had a similar median, and EPIC showed that about 50% of the simulations concentrated between 6000 and 7000 kg/ha. At Tifton, the median simulations based on EPIC were about 2000 kg/ha lower than for CSM-CERES-Maize, while the minimum values were about 2000 kg/ha higher. However, about 50% of simulations for EPIC ranged between 5000 and 6000 kg/ha, which was similar to Plains. The simulated yields that CSM-CERES-Maize and EPIC provided for the other six hybrids showed similar values in maximum, minimum, and median with Dyna-Gro V5373VT3, which showed that EPIC provided comparable simulations to CSM-CERES-Maize.

For irrigated conditions the simulated yield for both models was much higher compared to the rainfed conditions and the range was much smaller, mainly because there was no water deficit and the variability of local rainfall was not an issue (Figure 2.3). The irrigated grain yield that based on CSM-CERES-Maize ranged from about 8000 to 15000 kg/ha and the median was about 11000 kg/ha for Dyna-Gro V5373VT3. The simulations based on EPIC had very similar range with CSM-CERES-Maize, however, with different median, 12000 kg/ha. EPIC had higher simulations at Blairsville than the other locations. Based on both CSM-CERES-Maize and EPIC, the irrigated simulations of Croplan Genetics 8756VT3, DeKalb DKC69-71(RR2/YGCB), and

Croplan Genetics 851VT3 PRO showed similar distributions with Dyn-Gro V5373VT3. In contrast to those hybrids, these two crop models showed large differences in simulating Pioneer 33M57(Hx1/LL/RR2), SS 731CL, and Pioneer 31D58 which was consistent with results of calibration and evaluation (as shown in Figure 2.1). In general, the simulations of Pioneer 33M57(Hx1/LL/RR2), SS 731CL, and Pioneer 31D58 were very similar, which were from 6500 to 14500 kg/ha for CSM-CERES-Maize and 9000 to 16500 kg/ha for EPIC. However, simulations based on EPIC at Blairsville were 11000 to 18000 kg/ha for SS 731CL. The medians were about 11000 to 12000 kg/ha for CSM-CERES-Maize and 13000 to 14000 kg/ha for EPIC. The same with the other hybrids, higher simulations were shown at Blairsville by EPIC for those three hybrids.

In addition to the box-plots, the Anova test showed that two crop models provided significantly different rainfed Dyna-Gro V5373VT3 at Griffin, Plains, and Tifton; rainfed Pioneer 33M57(Hx1/LL/RR2) was significantly different at Griffin and Plains; rainfed SS 731CL was significantly different at Blairsville; rainfed Croplan Genetics 851 VT3 PRO was significantly different at Blairsville and Plains; rainfed Croplan Genetics 8756 VT3 was significantly different at Blairsville and Calhoun; rainfed DeKalb DKC69-71(RR2/YGCB) was significantly different at Calhoun and Griffin; rainfed Pioneer 31D58 was significantly different at Calhoun. For irrigated maize, Dyna-Gro V5373VT3 was significantly different at Blairsville, Calhoun, and Midville; Pioneer 33M57(Hx1/LL/RR2) and SS 731CL were significantly different at all locations; Croplan Genetics 8756 VT3 was significantly different at Blairsville.

2.5 DISCUSSION

This study conducted the calibration and evaluation for two commonly used maize crop models, CSM-CERES-Maize and EPIC, only based on observed grain yield of multiple years and locations in Georgia. The same as previous studies concluded that CSM-CERES-Maize can simulate grain yield accurately for various environments (Jagtap et al. 1993, Ritchie & Alagarswamy 2003, Soler et al. 2007). In this study, the difference between simulated and observed yield was not more than 3% for calibration and not more than 8% for evaluation based on CSM-CERES-Maize. The statistical criteria, including slope, R^2, and RMSE, also showed a good fit except the values for R^2 were 0.48 for DeKalb DKC69-71(RR2/YGCB). Simulated grain yield was over-estimated by EPIC for all the hybrids and the differences between simulated and observed yield ranged from 2% to 23% for calibration and from 10 to 20% for evaluation, which were larger than for CSM-CERES-Maize. The same as the results from the study of Balkovič et al. (2013) that higher yields were underestimated and lower yield were overestimated.

Differences exist between the two crop models in simulating maize yield which was caused by the differences in model structure and parameter values (Asseng et al. 2013). However, their performances were still consistent and comparable for all hybrids. In general, both models provided the most accurate simulations for Dyna-Gro V5373VT3, Croplan Genetics 851 VT3, Pioneer 33M57(Hx1/LL.RR2), and Croplan Genetics 8756 VT3, and less accurate for DeKalb DKC69-71(RR2/YGCB). However, CSM-CERES-Maize showed more accurate simulations in grain yield of SS731CL and Pioneer 31D58.

All crop models suffer from considerable structural and parameter uncertainty and from lack of independent datasets to evaluate them thoroughly (Knutti 2010, Rötter et al. 2012), how confidence we are in predicting crop grain yield by crop models is always an important issue to be discussed before the models' application (Asseng et al. 2013, Carter 2013). However, this study was conducted with long term variety trial data with multiple years and multiple locations and also with two crop models, which mitigates the above uncertainties. Although we had limited observations, the calibrated results that were provided by our approaches were reasonable.

2.6 CONCLUSION

The results from this study showed that long-term variety trial data that only include yield observations and harvest dates can be used for the calibration and evaluation of crop simulation models, such as CSM-CERES-Maize and EPIC. However, long-term simulations based on the two crop simulation models were significantly different at some locations, which should be caused by the parameters of the two models. The application of those two crop simulation models should be aware of the difference.

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Table 2.1: Maximum and minimum temperature and precipitation during the crop growing season from 2003 to 2010 for the six locations of this study. The crop growing season ranged from April to October for Blairsville, April to Sep Calhoun, Griffin, Midville, and March to Sep for Plains and Tifton.

Location	Year	Maximum Temperature (°C)			Minimum Temperature (°C)			Precipitation (mm)
		Max	Min	Average	Max	Min	Average	
Blairsville	2003	31.8	9.6	24.8	19.9	-0.9	12.2	1037
	2005	34.7	8.4	25.5	21.1	-3.8	12.5	837
	2006	34.2	7.7	25.7	21.4	-4.3	11.9	736
	2007	35.9	3.7	26.5	19.8	-5.6	12	576
	2008	28.6	7.8	24.6	21.8	-3.9	11.9	438
	2009	28.6	4.1	24.1	20	-4.9	12.6	1036
	2010	33.5	14.3	26.4	21.9	-1.3	13	812
Calhoun	2003	34.1	8.5	27.9	21.5	-0.9	15.3	964
	2004	35.3	14.7	28.2	22.5	-1.1	15.4	823
	2005	36.1	10.7	28.6	22.6	-1.7	15.2	723
	2006	38.6	18.1	29.8	22.8	-0.4	15.3	469
	2007	39.9	6.7	30.1	22.4	-6	14.6	293
	2008	37.1	10	28.7	22.7	-2.1	14.7	503
	2009	36.1	8	27.8	21.6	-4.3	15.1	675
	2010	37.4	17	30.2	23	0.5	15.7	523
Griffin	2003	32.8	7.3	27.5	22.5	4.1	16.9	954
	2004	34.8	14.4	28.2	22.4	1.3	17.2	877
	2005	35.5	13.8	27.9	24.3	1.5	17.1	867
	2006	36.7	17.7	29.4	24.1	4.3	17.4	383
	2007	38.6	7.7	29.1	25.8	-2.8	17.2	379
	2008	35.9	10.2	28.5	22.9	1.4	17.1	470
	2009	35.5	7.9	27.9	24.4	-0.4	17.6	516
	2010	37.2	17.1	30.3	25.2	4.8	18.8	546
Midville	2003	34.5	9	28.9	23.8	2.1	18.5	941
	2004	37.1	17	30.1	23.9	2.2	18.5	806
	2005	36.9	15.5	29.9	25.3	4.3	18.3	614
	2006	38.4	17.8	30.8	24.4	3.6	18.3	359
	2007	39.5	11	30.7	25.4	-1.5	17.8	475
	2008	38.1	14	30.4	24.2	1.9	18.3	494
	2009	37	9.9	30	26.2	1.9	18.7	824
	2010	38.5	20.3	31.9	25.8	6	19.3	539
Plains	2003	34.6	8.9	28.1	23.1	-0.7	16.9	846
	2004	36.2	14.9	28.8	23.6	0	16.6	866
	2005	36.2	6.4	27.9	24.9	-2.8	16.4	1084
	2006	38.8	14.2	29.7	24	-0.1	16.7	687
	2007	39.2	11	29.7	24.6	-1.1	16.3	535
	2008	37.4	10.5	28.4	23	-2	16	704
	2009	36	8.9	27.7	24.6	-3.7	16.5	858
	2010	38.8	10.5	29.8	25.5	-1.4	17.4	568
Tifton	2003	34.4	10.9	28.2	23.6	0.5	18.2	987
	2004	35.1	14.6	28.8	25.5	2	18.1	939
	2005	35	7.5	27.8	25.2	-2.3	17.6	781
	2006	36.5	13.3	29.4	25	1.1	17.7	421
	2007	37.3	11.8	29.3	25.4	0.1	17.5	537
	2008	35.4	11.3	28.4	24.2	-0.1	17.5	663
	2009	35.8	9	28.3	25	-1.9	18.1	1054
	2010	37.5	11.3	29.4	25.4	-0.8	18.3	648

Table 2.2: Average grain yield for seven selected maize hybrids for six locations in Georgia.

Variety	Average grain yield (kg/ha)		Calibration Years	Evaluation Years
	Irrigated	Rainfed		
Dyna-Gro V5373VT3	10400	8669	2008, 2010	2009
Pioneer 33M57(Hx1/LL/RR2)	10258	9183	2007, 2009	2008
SS 731CL	9582	8268	2007, 2009	2008
Croplan Genetics 851 VT3 PRO	10470	8351	2008, 2010	2009
Croplan Genetics 8756 VT3	10877	7908	2009, 2010	2008
DeKalb DKC69-71(RR2/YGCB)	10538	8807	2004, 2006, 2007, 2008, 2010	2003, 2005, 2009
Pioneer 31D58	11619	7966	2006, 2008, 2010	2007, 2009

Table 2.3: Cultivar coefficients for CSM-CERES-Maize model

CSM-CERES-Maize Cultivar Coefficients		**Min**	**Max**	**Initial value**	**Unit**
P1	Thermal time from seedling emergence to the end of the juvenile phase	110	458	200	Degree days
P2	Extent to which development is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate	0	3	0.3	Day hr^{-1}
P5	Thermal time from silking to physiological maturity	390	1000	800	Degree days
G2	Maximum possible number of kernels per plant	248	990	770	Kernel/plant
G3	Kernel filling rate during the linear grain filling state and under optimum conditions	4.4	16.5	8.5	Mg day^{-1}
PHINT	The interval in thermal time (degree days) between successive leaf tip appearances	30	75	38.9	Degree days
EPIC Cultivar Coefficients					
WA	Biomass-Energy ratio	40	55	40	
BE	Crop parameter - converts energy to biomass				kg·ha·MJ-1·m-2
HI	Potential harvest index - ratio of crop yield to above ground biomass	0.1	0.6	0.5	
To	Optimal temperature for a crop				°C
Tb	Base temperature for a crop (plant start growing)				°C
DMLA	Maximum LAI potential for a crop	2	6	6	
DLAI	Fraction of growing season when leaf area starts declining	0.5	0.95	0.8	
HUIo	Heat unit index value when leaf area index starts declining				
ah1, ah2	Crop parameters that determine the shape of the leaf-area-index development curve				
af1, af2	Crop parameters for frost sensitivity				
Ad	Crop parameters that governs leaf area index decline rate				
ALT	Aluminum tolerance index number				
CAF	Critical aeration factor for a crop				
HMX	Maximum crop height				m
RDMX	Maximum root depth for a crop				m
WSFY	Water stress factor for adjusting harvest index				
bn1, bn2, bn3	Crop parameters for plant N concentration equation				
bp1, bp2, bp3	Crop parameters for plant P concentration equation				
PHU	Potential Heat Units	1600	2000	1800	°C

Table 2.4: Estimation of the soil fertility factor (SLPF) for six locations and observed (Obs.) and simulated (Sim.) grain yield for CSM-CERES-Maize. Statistics include slope of regression; coefficient of determination (R^2); index of agreement (d-stat); and root mean square error (RMSE) between simulated and observed yield.

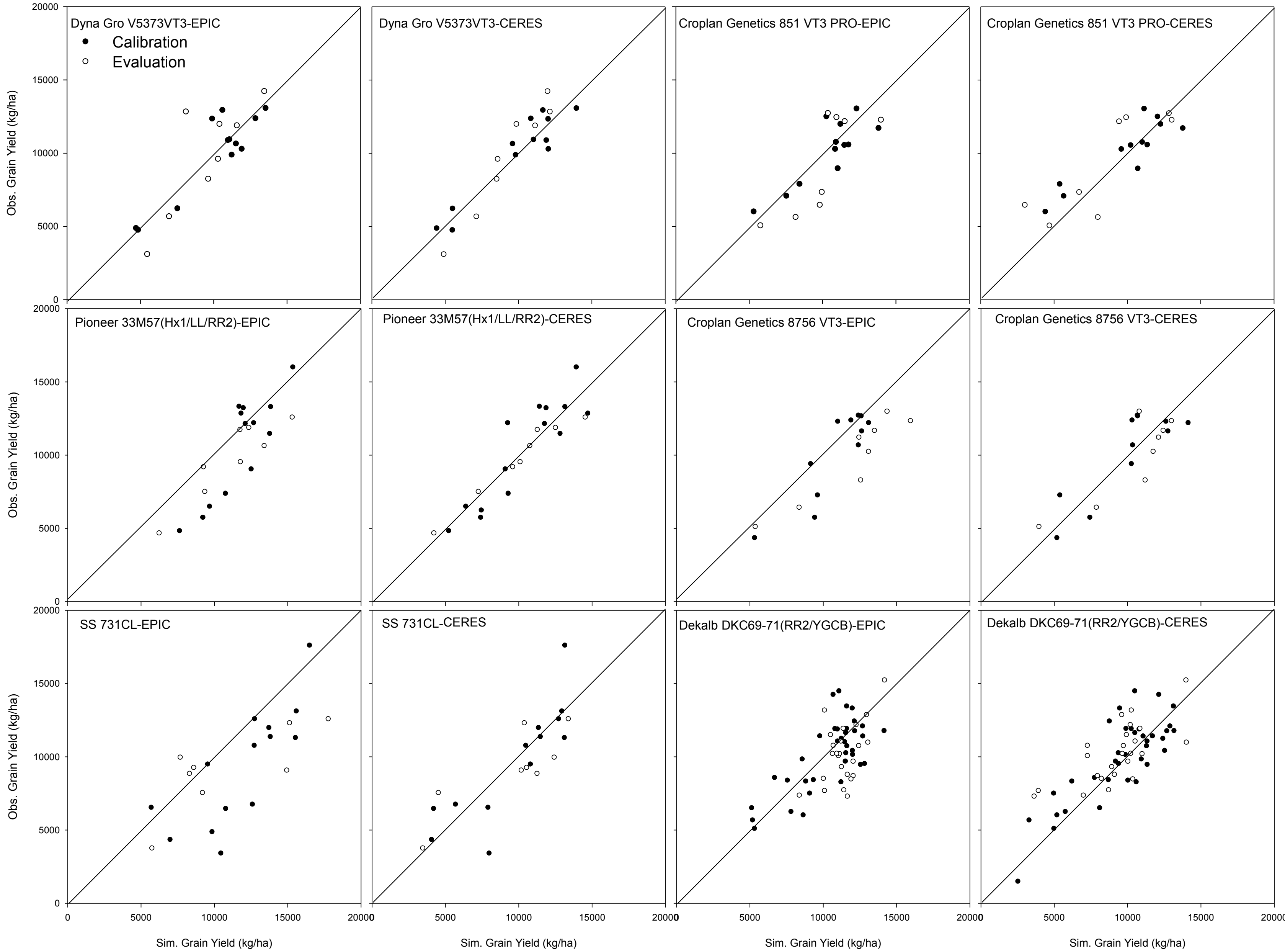
Location	SLPF	Obs. (kg/ha)	Sim. (kg/ha)	Slope	R^2	d-stat	RMSE (kg/ha)
Blairsville	0.8	13276	12870	0.391	0.056	0.475	1867
Calhoun	0.76,0.7, 0.87, 0.9	8020	8260	0.713	0.732	0.914	1632
Griffin	0.78, 0.70	9014	9023	0.741	0.784	0.932	1201
Midville	0.82, 0.85	11868	11898	0.582	0.432	0.811	920
Plains	0.84, 0.73	9639	10697	0.618	0.65	0.816	1718
Tifton	0.89,0.9, 0.89	10178	8801	0.997	0.803	0.898	2029

Table 2.5: Optimized cultivar coefficients for CSM-CERES-Maize and EPIC for the selected seven maize hybrids.

Parameter	Dyna-Gro V5373VT3	Pioneer 33M57 (Hx1/LL/RR2)	SS 731CL	Croplan Genetics 851 VT3 PRO	Croplan Genetics 8756 VT3	DeKalb DKC69-71(RR2/YGCB)	Pioneer 31D58
CSM-CERES-Maize							
P1	310	260	220	310	290	330	270
P2	1.8	1.5	1.2	0.9	1.8	0.9	0.9
P5	900	940	820	820	940	840	900
G2	646.8	646.8	954.8	646.8	677.6	646.8	708.4
G3	12.43	10.94	12.64	12.64	12	12.64	11.79
PHINT	63.9	58.9	53.90	48.9	63.9	48.9	58.9
EPIC							
WA	50	50	50	50	50	50	50
HI	0.45	0.50	0.55	0.45	0.5	0.45	0.5
DLAI	0.95	0.95	0.95	0.95	0.95	0.95	0.95
WSYF	0.01	0.01	0.01	0.01	0.01	0.01	0.01
DMLA	6.0	6.0	6.0	5.0	6.0	6.0	6.0
PHU	1800	1650	1800	1800	1800	1730	1770

Table 2.6: The average observed (Obs.) and simulated (Sim.) grain yield for the CSM-CERES-Maize and EPIC calibration and evaluation of the seven hybrids. Statistics include slope of regression; coefficient of determination (R^2); index of agreement (d-stat); and root mean square error (RMSE) of simulated and observed yield.

Calibration	**Obs.**	**Sim. (kg/ha)**		**Slope**		**R^2**		**d-stat**		**RMSE (kg/ha)**	
Variety	**(kg/ha)**	***CERES***	***EPIC***	***CERES***	***EPIC***	***CERES***	***EPIC***	***CERES***	***EPIC***	***CERES***	***EPIC***
Dyna-Gro V5373VT3	9891	9912	10102	0.997	0.866	0.885	0.814	0.969	0.947	1033	1268
Pioneer 33M57(Hx1/LL/RR2)	10263	10310	11815	0.747	0.514	0.812	0.755	0.94	0.83	1512	2279
SS 731CL	9630	9725	11937	0.710	0.6	0.715	0.587	0.909	0.754	2051	3772
Croplan Genetics 851 VT3 PRO	10068	9846	10459	1.222	0.88	0.803	0.713	0.921	0.909	1378	1268
Croplan Genetics 8756 VT3	10083	10022	10907	0.822	0.684	0.734	0.785	0.922	0.898	1515	1602
DeKalb DKC69-71(RR2/YGCB)	9897	9643	10454	0.832	0.7	0.67	0.54	0.9	0.85	1683	1713
Pioneer 31D58	10311	10014	11467	0.863	0.71	0.744	0.603	0.925	0.84	1644	2308
Evaluation											
Dyna-Gro V5373VT3	9649	9326	9530	0.64	0.555	0.946	0.681	0.941	0.875	1436	2094
Pioneer 33M57(Hx1/LL/RR2)	9678	9725	11223	1.18	0.98	0.897	0.838	0.966	0.872	973	1875
SS 731CL	9128	9559	10961	1.083	1.26	0.703	0.854	0.892	0.66	1895	4228
Croplan Genetics 851 VT3 PRO	9219	8498	10108	0.884	0.557	0.711	0.63	0.902	0.84	1980	2161
Croplan Genetics 8756 VT3	9745	10434	11995	0.902	1.1	0.732	0.86	0.91	0.84	1642	2569
DeKalb DKC69-71(RR2/YGCB)	10155	9302	11411	0.84	0.222	0.48	0.19	0.782	0.575	1935	2225
Pioneer 31D58	10450	9770	12119	0.911	0.266	0.772	0.49	0.926	0.633	1883	3198


Dyna Gro V5373VT3-EPIC
Calibration
Evaluation
Dyna Gro V5373VT3-CERES
Croplan Genetics 851 VT3 PRO-EPIC
Croplan Genetics 851 VT3 PRO-CERES
Pioneer 33M57(Hx1/LL/RR2)-EPIC
Pioneer 33M57(Hx1/LL/RR2)-CERES
Croplan Genetics 8756 VT3-EPIC
Croplan Genetics 8756 VT3-CERES
SS 731CL-EPIC
SS 731CL-CERES
Dekalb DKC69-71(RR2/YGCB)-EPIC
Dekalb DKC69-71(RR2/YGCB)-CERES
Obs. Grain Yield (kg/ha)
Sim. Grain Yield (kg/ha)
0
5000
10000
15000
20000

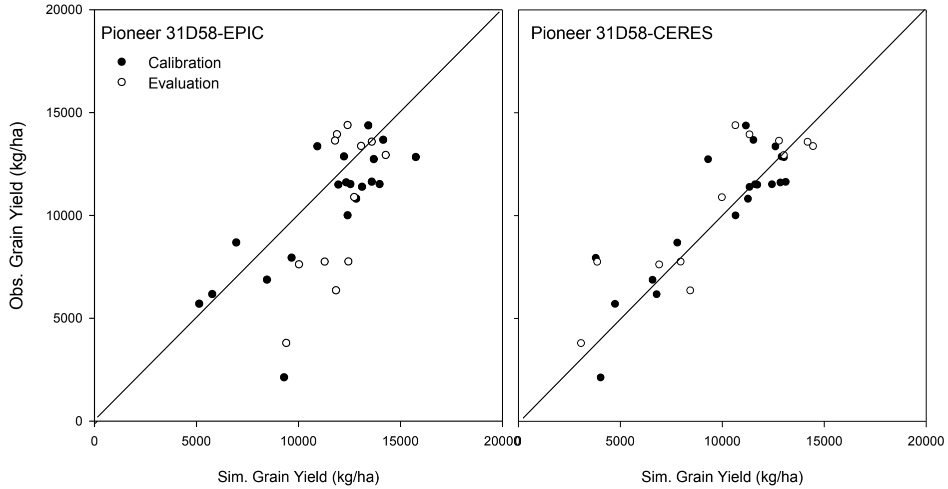


Figure 2.1: A comparison between simulated and observed grain yield based on the CSM-CERES-Maize and EPIC models for calibration and evaluation of the seven hybrids and the 1:1 line.

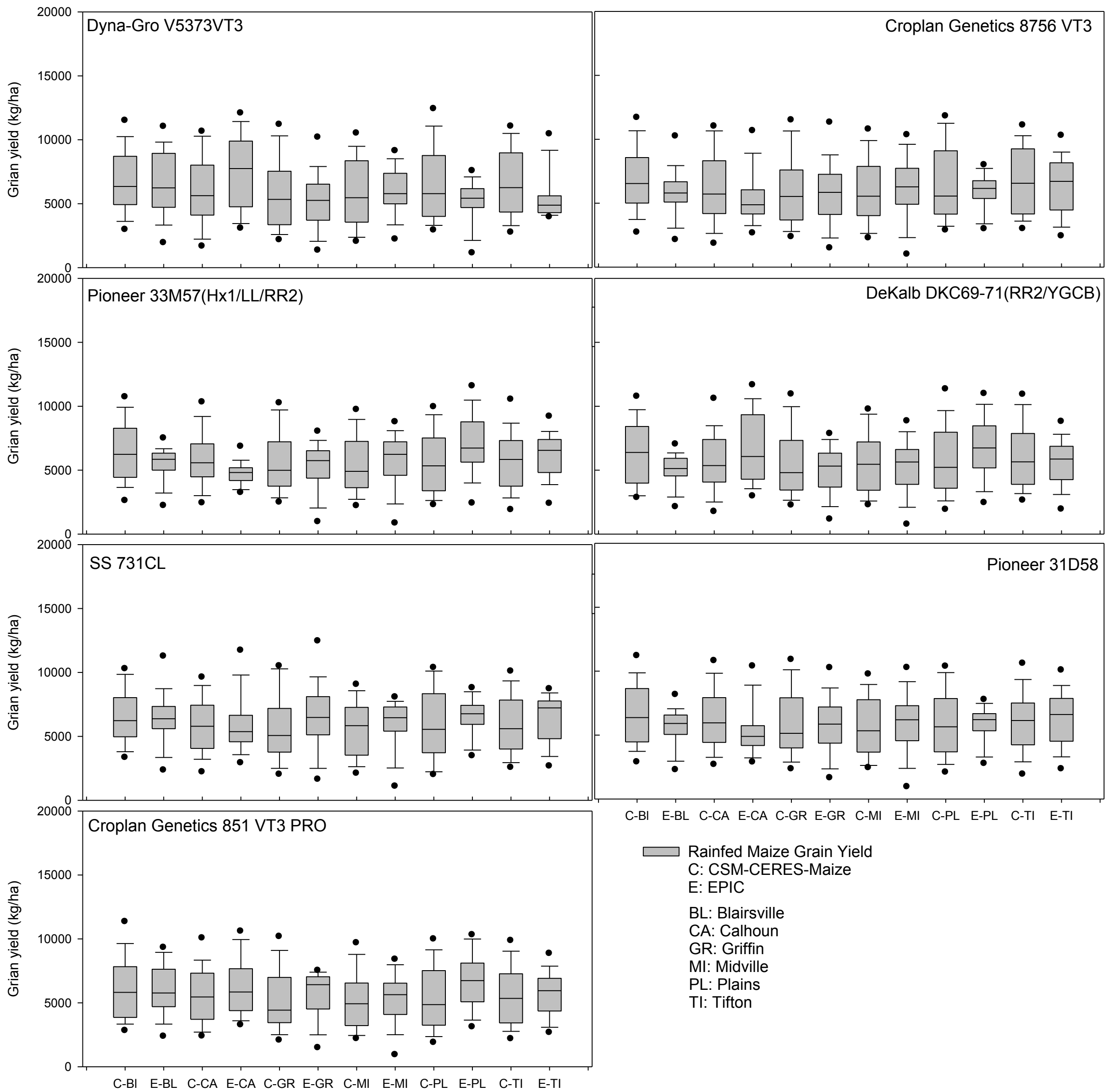


Figure 2.2: Box-plot for rainfed grain yield based on the CSM-CERES-Maize and EPIC for seven hybrids using historical weather data from 1958 to 2012 for Blairsville, Calhoun, Griffin, Midville, Plains, and Tifton, Georgia.

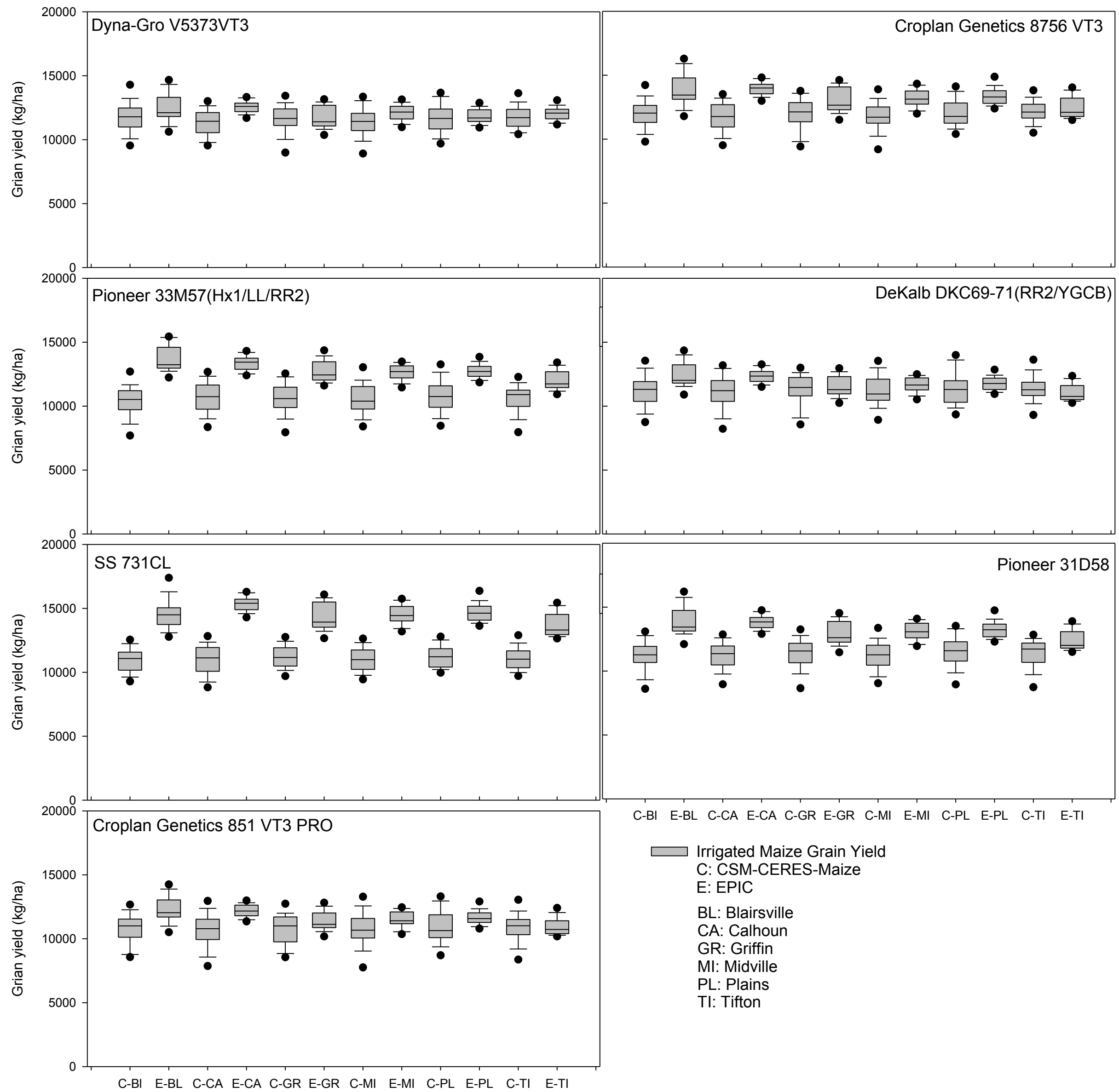


Figure 2.3: Box-plot for irrigated grain yields based on CSM-CERES-Maize and EPIC for seven hybrids using historical weather data from 1958 to 2012 for Blairsville, Calhoun, Griffin, Midville, Plains, and Tifton, Georgia.

CHAPTER 3

EVALUATION OF SIMCLIM FOR PROJECTING SITE-SPECIFIC CLIMATE IN THE SOUTHEASTERN USA: AN EXAMPLE FOR TIFTON, GEORGIA[1]

[1] Bao, Y., Hoogenboom, G., Seymour, L., McClendon, R.W., and Vellidis, G. to be submitted to Climate Research

3.1 INTRODUCTION

During the past decade significant progress has been made in the generation of climate scenarios that have a higher spatial and temporal resolution (Bronstert et al. 2007, Christensen et al. 2007, Fowler et al. 2007, Mearns 2010, Rummukainen 2010), especially due to the need for regional climate impact studies (Tubiello & Fischer 2007, Hatfield et al. 2008, Tingem & Rivington 2008). Although the General Circulation Models (GCMs) have been improved for generating both global and regional climate projections (Meehl et al. 2007, Moss et al. 2010), empirical, dynamical, and statistical methods have been developed to downscale the global climate projections to regional scale because of the high demand in computer resources for running GCMs and the relatively low spatial resolution of the GCMs (Mearns et al. 2003b, Benestad 2004, Wilby et al. 2004, Christensen et al. 2007, Jakob Themeßl et al. 2011). All downscaling methods assume that GCMs can provide correct climate projections (Giorgi & Coppola 2010) since the driving data are obtained from the GCMs.

The dynamical downscaling is generally referred to as Regional Climate Models (RCMs). They generate regional climate projections based on the same physical-dynamical description of the fundamental climate processes that is at the core of GCMs (Hewitson & Crane 1996, Castro 2005, Di Luca et al. 2011), which is the nested model of GCMs. One advantage of RCMs is that the nested model is consistent with the large-scale atmospheric circulation, and thus it has the potential for capturing mesoscale nonlinear effects and for providing coherent information among multiple climate variables (Christensen et al. 2007, Bader et al. 2008). Another advantage is that the RCMs can also be used for seasonal prediction and climate process studies (Wang et al. 2004, Bader et al. 2008). However, the ability of RCMs to simulate the regional climate is strongly dependent on the realism of the large-scale circulation provided by the lateral boundary conditions from GCMs, and thus the parameterization schemes that RCMs use to represent sub-grid scale processes may be operating outside the range for which they were designed (Solomon et al. 2007, Leduc & Laprise 2008, Foley 2010). Furthermore, higher resolution RCMs need more detailed topography and physical parameterizations, which add significantly to the computational cost (Christensen et al. 2007). In addition to the technical limitations, the projections from RCMs are in grids which are also not fine enough for the impact studies since many impact applications requires the equivalent of point climate data (Wilby et al. 2004).

Statistical downscaling (SD) is based on a statistical model to estimate the local and regional climate characteristics, while the large-scale output of GCM simulation is the input for this model (Wilby et al. 2004, Solomon et al. 2007, Giorgi et al. 2009). However, one major weakness with SD is whether the predictor-predictand relationships can be assumed stationary (time invariance) so that they can be used for future climate projection (Murphy 1998, Mearns et al. 1999, Winkler et al. 2012). Fortunately, recent experiments with RCMs has shown that the stationary assumption for predictor-predictand relationships is valid for future climate forcing, provided that the choice of predictors is judicious (Wilby et al. 2002, Wilby et al. 2004).

SimCLIM is a climate model that uses a simple statistical method called pattern scaling to downscale climate projections and it has been used for a number of GCMs. It downscales the climate predictions of a GCM by normalizing Atmosphere-Ocean General Circulation Model (AOGCM) response patterns according to the global mean temperature (Santer 1990, Mitchell 2003). Kenny et al. (1995) showed that SimCLIM can generate climate projections at global, regional, and site- specific scales. The large-scale outputs of 15 GCMs (Table 3.1) were downscaled under six gas emission scenarios. Climate factors, maximum temperature, minimum temperature, mean temperature, precipitation, solar radiation, and wind can be generated for regional/site-specific scale. SimCLIM has been commonly used for climate change impact studies by coupling its projections with impact models because of its capability for generating climate projections for a specific location (Albertin et al. 2011, Jha 2012, Warrick et al. 2012). A comprehensive climate model is the only way to project climate in future (Murphy et al. 2004, Solomon et al. 2007). Therefore, the uncertainties of climate models largely affect the accuracy of mitigation and adaptation strategies that are proposed based on impact studies (Randall et al. 2007, Rivington et al. 2008, Foley 2010). Thus, it is important to evaluate how well the climate models can provide climate projections for specific locations. However, only a few studies so far have evaluated the ability of SimCLIM to generate site-specific climate projections, including for the USA.

For evaluation of the climate models numerous studies have compared the predictions with present climate or paleoclimate because future climate data are not available (Coquard et al. 2004, Wilby et al. 2004, Gleckler et al. 2008, Pierce et al. 2009, Braconnot et al. 2012, Dowsett et al. 2012). Statistics have replaced original "eyeball" assessments and now play an important role in quantitatively evaluating climate models by checking whether the projections fit observations for both climate mean and climate variability (Murphy 1988, Katz 1992, Murphy 1998, Berk et al. 2001, Murphy et al. 2004, McKitrick & Tole 2012). Unfortunately, there is still no one perfect statistic that can evaluate all aspects of climate projections. Therefore, many evaluation studies have used multiple statistics. Different statistics test different characteristics of climate data and the ones that are commonly used include mean error (bias), mean square error (MSE), root mean square error ($RMSE$), correlation coefficient (r), probability density function (PDF), and the Kolmogorov-Smirnov test (KS-test) for both the temporal and spatial analysis for daily (e.g., Nikulin et al. (2010)), monthly (e.g., Radić and Clarke (2011)), and seasonal climate data (e.g., Pierce et al. (2009), Schaller et al. (2011)).

Bias, MSE, and $RMSE$ are usually defined as summary statistics. Bias between projections and observations is the most direct way to identify whether the projections are different from observations. For instance Nikulin et al. (2010) compared the bias between the estimation of maximum temperature from different climate models with the observations over Europe. Rivington et al. (2008) compared the projected and observed maximum and minimum temperature using time series graphs for specific locations. This showed the differences between projections and observations as well as climate trends. MSE is the second moment of bias, which is a way to quantify the difference between projections and observations in terms of variance and bias (Murphy 1988, Murphy et al. 2004). $RMSE$ is the square root of mean square error that is more often used for evaluating the difference between projections and observations for both climate mean and variability (Walsh et al. 2008, Ishizaki et al. 2012). However, evaluation based on bias is mostly dependent on eyeball, which put the conclusion in risks if only use this kind of statistics. Another limitation is that the summary statistics, such as $MSE/RMSE$, attempt to encapsulate enormous of information may obscure more than they enlighten (Berk et al. 2001). Compared to the summary statistics, the statistical inference PDF and KS-test are more instructive.

So far SimCLIM has not been evaluated for North America including the southeastern United States. There is, therefore, a need to evaluate the accuracy of SimCLIM in generating future climate scenarios before the application of any impact study. The overall goal of this study was to determine whether SimCLIM is able to provide accurate site-specific climate projections for the southeastern United States using Tifton, Georgia as a case study. The evaluation was based on multiple statistical tests to avoid the limitations of individual statistics and to evaluate the different aspects of both the climate predictions and observations.

3.2 DATA AND METHOD

3.2.1 DATA

Tifton, Georgia (31.494 ºN, 83.526 ºW) was selected for this study because this location has the longest period of observed daily weather data based on automated weather recording devices. In addition, Tifton can be considered centrally located with respect to row crop agriculture in Georgia and other states in the southeastern USA, which was one of the overall goals of the impact study. The observed weather data included minimum and maximum air temperature (ºC), precipitation (mm), and solar radiation (MJ/m^2) from 1992 to 2012. The data were obtained from the Georgia Automated Environmental Monitoring Network (AEMN, www.georgiaweather.net). The Georgia AEMN is a network of automated weather stations that was first deployed in 1991 (Hoogenboom 1996) and encompassed 80 stations in 2010 (Garcia y Garcia & Hoogenboom 2005). Although the period of historical data from 1992 to 2012 is relatively short, it is the most complete and accurate set of observed weather data that includes solar radiation and, therefore, introduces fewer uncertainties into the evaluation (Gleckler et al. 2008, Pincus et al. 2008, Radić & Clarke 2011).

The corresponding climate projections for Tifton for the same period were generated with SimCLIM, however, with monthly values. The version of SimCLIM used for this study provides downscaled climate change projections based on 15 GCMs (Table 3.1) from the Coupled Model Intercomparison Project Phase 3 (CMIP3). The performance of these 15 GCMs has been evaluated from many aspects (Piper et al. 1996, Wolf 2002, Allan & Soden 2007, Rotter et al. 2011, White et al. 2011). They also have been widely used for projecting future climate scenarios

(French & Hodges 1985, Solomon et al. 2007, White et al. 2011), providing driving date for regional climate scenarios and impact assessment (Porter et al. 1993, CCSP 2008, Hoogenboom et al. 2012). The gas emission scenarios from the Special Report on Emissions Scenarios (SRES) are applied by SimCLIM for the climate projections after 1990 (Nakicenovic & Swart 2000). Because the analysis was conducted for the period from 1992 to 2012, the effects of gas emissions were considered. SimCLIM provides six choices of gas emission scenarios, including A1B, A1FI, A1T, A2, B1, and B2. These gas emission scenarios are the illustrative marker scenarios of SRES, which cover the entire range of gas emissions from the SRES scenarios.

3.2.3 STATISTICAL EVALUATION

A statistical analysis was conducted to compare the projected minimum temperature, maximum temperature, precipitation, and solar radiation with observed data. The selection of the statistics was based on three principals: the statistical tests are not based on too many assumptions; the tests are able to evaluate the different characteristics of the data; and the tests have been widely accepted in climate research. First of all, the bias between projections and observations were calculated and depicted using box-plot. The box-plot includes the values for median, mean, lower (25%, Q_1) and upper (75%, Q_3) quartiles, and outliers for a particular variables; the box-plot does not make any assumption with respect to the data population. The outliers were defined as the values that are out of the following range: $[Q_1 - 1.5\,IQR, Q_3 + 1.5\,IQR]$ (1), where $IQR = Q_3 - Q_1$ (2).

In addition to the box-plot, the difference between climate means for projections and observations were also compared using the following equation:

$$\Delta = \overline{Proj.} - \overline{Obs.} \qquad (3)$$

for minimum temperature, maximum temperature, and solar radiation, and

$$\Delta = \overline{(Proj.} - \overline{Obs.})\times 100/\overline{Obs.} \qquad (4)$$

which was percentage for precipitation. Where $Obs.$ is observation and $Proj.$ is projection. The calculations were based on the entire data set from 1992 to 2012 for each of the 15 GCMs.

The monthly standard deviation was used to determine whether the projections can capture the variability of observations for each month. Furthermore, the ratio of standard deviation (SD) set was calculated to determine whether the projections can capture the annual variability of the observations:

$$F = Proj.SD/Obs.SD \qquad (5)$$

F is 1 which means a perfect match for the temporal variability of observations and projections. Otherwise, projections cannot capture the temporal variability when F is 0.

The time series plot is the most direct method for analyzing time series data, as it shows the climate trends for both the projections and observations. Finally, the statistical inference, Kolmogorov-Smirnov test (KS-test, $\alpha = 0.05$) and the Cumulative Distribution Function (CDF), were applied to test whether the projections and observations represented the same population without making any assumptions about the distribution of the data. The null hypothesis of the KS-test is that both projections and observations are from the some population. For CDF, two close lines for projections and observations mean a good fit; otherwise, the projections and observations do not fit well. Additional details about the selected statistics can be found in Semenov and Shewry (2011) and Rötter et al. (2012).

3.3 RESULTS

3.3.1 ANALYSIS FOR MULTIPLE GCMS

3.3.1.1 BIAS FOR MONTHLY PROJECTIONS

The bias between projected monthly maximum temperature and observations from 1992 to 2010 were based on 15 GCMs and six gas emission scenarios as described previously (Figure 3.1a – 3.1f). For the maximum temperature projections for gas emission scenario A1B (Figure 3.1a), the bias between the projections of the 15 GCMs and observations ranged from -4 ºC to 6 ºC, with the negative values representing an underestimation and the positive values representing an overestimation. All GCMs showed that mean of the biases was about 0.5 ºC, which showed that the average maximum temperature was overestimated. The median of the biases was about 0.6 ºC, which meant that more than 50% of the monthly maximum temperatures were overestimated. All 15 GCMs had at least one outlier that one monthly maximum temperature was overestimated almost 6 ºC. The bias for the maximum temperature projections for the other scenarios including A1FI (Figure 3.1b), A1T (Figure 3.1c), A2 (Figure 3.1d), B1 (Figure 3.1e), and B2 (Figure 3.1f) were virtually identical with the A1B scenario and showed no difference among the scenarios. Similar results were found for the other variables, including minimum temperature, precipitation, and solar radiation. The results are, therefore, not shown and in the remaining analysis only the results for the A1B scenario are discussed.

For the minimum temperature projections the bias ranged from -6 ºC to 4 ºC (Figure 3.1g). The mean value was overestimated by 0.8 ºC, and median, 0.7 ºC, showed that more than 50% of the monthly minimum temperatures were underestimated. The outliers also showed that the overestimation of minimum temperature reached about 4 ºC and underestimation reached about 5.5 ºC. Precipitation showed large biases, ranging from -150 mm to 150 mm without taking into consideration any of the outliers (Figure 3.1h). The mean bias showed that the average value for precipitation was overestimated, and the median showed that more than 50% of the monthly precipitation projections were overestimated. However, many of the outliers showed that monthly precipitation projections were largely underestimated up to 300 mm. The biases between projected solar radiation and the observations ranged from -5 MJ/m^2 to 6 MJ/m^2 (Figure 3.1i). The values of mean and median showed an overestimation for most months. Finally, all the statistics, median, mean, lower (25%) and upper (75%) quartiles of four variables in the box-plot were almost identical for all 15 GCMs, which meant that there was no significant difference among the downscaled projections for Tifton based on the 15 GCMs.

3.3.1.2 ANNUAL MEAN AND VARIABILITY

The projections based on all 15 GCMs had very close values in annual standard deviations and climate means (Table 3.2) under gas emission scenario A1B. Comparing with observations, minimum temperature was underestimated by 0.8 °C to 0.9 °C; maximum temperature was overestimated by 0.6 °C to 0.7 °C; the precipitation was overestimated by 10%; solar radiation was overestimated by 0.7 MJ/m^2. The ratios of the annual standard deviation for minimum temperature, maximum temperature, and solar radiation were 1.0 which showed that SimCLIM was able to capture the temporal variability for the period 1992 to 2012. However, the ratio of standard deviation for precipitation was only 0.3 which meant that SimCLIM had no skill in predicting precipitation.

3.3.2 ANALYSIS BASED ON GCM CSIRO-30

Since no difference was found among 15 GCMs and among the six scenarios (Figure 3.1) based on above analysis, only one GCM, i.e. CSIRO-30, and one scenario, i.e., A1B, was selected to be statistically analyzed. The GCM CSIRO-30 has a relatively finer resolution (1.9º ×

1.9º) compared to the other GCMs, which could introduce less uncertainty for downscaling (Table 3.1).

Time series plots were first used to identify whether the annual variability of projected climate data match observations in climate factors, monthly maximum and minimum temperature, precipitation, and solar radiation during 1992 to 2012 (Figure 3.2). In general, the projections were able to capture the annual variability of maximum and minimum air temperature and solar radiation. The minimum temperature showed a better match with observations than maximum temperature. However, both the projected maximum and minimum temperature showed a disparity for the minimum values during the winter and maximum temperature values during the summer. The same problem was also found for solar radiation. The projected precipitation ranged from 60 mm to 140 mm. However, observed precipitation ranged from 0 mm to 380 mm. The projected precipitation obviously missed the variability of observed precipitation.

The biases between the projected and observed monthly maximum temperature, minimum temperature, precipitation, and solar radiation of GCM CSIRO-30 and observations for 1992 to 2012 were calculated and shown by box-plot (Figure 3.3). The biases between projected and observed maximum and minimum temperature varied with month (Figure 3.3a and 3.3b). For maximum temperature the biases ranged from -4 ºC to 4 ºC, but February reached 6 ºC. The means of biases were generally around 0.5 ºC to 2 ºC for the 12 months, which showed that the maximum temperature for each month was overestimated. The medians were about 0.5 ºC to 1 ºC, which showed that most of the maximum temperature was overestimated. In general, the bias for maximum temperature for the months of May, July, August, and October was smaller than for the other months, while for March and December they were larger than the other months. For minimum temperature, the bias ranged from -5 ºC to 4 ºC (Figure 3.3b). Mean and median values were very close, which ranged from -0.1 ºC to -1 ºC. This meant that the minimum temperature for most years and also the average minimum temperature were underestimated. June, July, August, and September had much smaller difference from the observations than the other months, which meant better projections for these four months.

The projected precipitation showed much larger biases when compared to the observations, ranging from -200 mm (underestimated) to 150 mm (overestimated), with outliers as high as -300 mm (Figure 3.3c). The bias for precipitation varied with month, with most of them not larger than 100 mm. March and June showed the largest range for the biases, while the biases for May had the smallest range. The ranges for the biases of solar radiation varied with month (Figure 3d). They ranged from -3 MJ/m^2 to 3 MJ/m^2 for January to April, -4 MJ/m^2 to 8 MJ/m^2 for May, and -2 MJ/m^2 to 6 MJ/m^2 for the other months. The mean values of January were very close to zero. The mean values of February to May ranged from -1 MJ/m^2 to -0.5 MJ/m^2 and showed that the average solar radiation was underestimated. The means of rest months were from 0.2 MJ/m^2 to 3 MJ/m^2, which were overestimated.

The standard deviation was used to identify whether SimCLIM can reproduce the temporal variability of the present climate (Figure 3.4). Ideally, the projections are believed to represent the variability of the current climate if the standard deviation of the projections is close to the standard deviation of the observations. However, the standard deviations of all four projected monthly variables from 1992 to 2012 was almost zero, especially for precipitation and solar radiation, which meant that the projections cannot capture the variability of the current climate.

Based on the analysis with the KS-test, which is one type of statistical inference, it can be concluded that only projected maximum temperature and observed maximum temperature were from the same data population, while the projected minimum temperature, precipitation, and solar radiation were different from the observed minimum temperature, precipitation and solar radiation population. The CDF (Figure 3.5) showed that the projected maximum and minimum temperature and solar radiation had the same distribution as the observed maximum and minimum temperature and solar radiation, while the projected precipitation only covered a narrow range of values, which was unrealistic compared to the distribution of the observed precipitation values.

3.4 DISCUSSION

The generation of climate change scenarios for Tifton, Georgia, USA was statistically compared with the observed data in this study. The downscaled climate scenarios from 1992 to 2012 based on 15 GCMs from SimCLIM were virtually identical, while there was no difference among the six gas emission scenarios either. The SimCLIM model provided reasonable projections for climate mean and trend for maximum temperature, minimum temperature, and solar radiation based on the analysis of the GCM CSIRO-30, while the climate variability was not well reproduced. Also, the downscaled scenarios had little skill for precipitation either for climate mean or climate variability. Their results were similar to Mearns et al. (2003a) who stated that it is a challenge to generate climate scenarios for the southeastern United States. In addition, other studies also have shown that that GCMs have limited ability to provide climate variability (Christensen et al. 2007, Flato et al. 2013).

SimCLIM uses pattern-scaling, which is a simple method for providing regional climate scenarios (Santer 1990). Although the simplified downscaling method saves time and resources, uncertainties from GCMs, gas emission scenarios, downscaling method, and observations are introduced when downscaling (Randall et al. 2007, Bader et al. 2008, Mearns 2010, Rowell 2011).. The accuracy of pattern-scaling was evaluated by Mitchell (2003) for downscaling of temperature and precipitation. He concluded that this method is generally accurate, however, still with some limitations. First of all, pattern scaling assumes that there is a linear relationship between local climate change and the amount of global warming. However, a non-linear relationship was found during the evaluation, which introduced some statistically significant errors into downscaled projections. Secondly, the precipitation projections were worse compared to temperature since the patter scaling can only capture the pattern of precipitation for long periods. Our study also showed that the pattern scaling of SimCLIM cannot accurately provide downscaled precipitation for the short period of evaluation from 1992 to 2012. Thirdly, it is well known that climate trends and patterns are easier to be detected with longer period of observations, and 30 years of observations are the suggested period for evaluating climate models. Thus, the shorter period of only 21 years used in this study is also one main reason for the tiny differences among downscaled projections based on multiple GCMs.

In summary, although there are still limitations for site-specific climate scenarios, this study showed that SimCLIM still can provide accurate projections for maximum temperature, minimum temperature, and solar radiation, especially with some confidence for climate mean and variability. SimCLIM can only provide monthly climate projections; however, the tool to perturb historical daily weather data can also generate the daily weather data for future climate scenarios.

3.5 CONCLUSION

Based on the statistical analyses it can be concluded that SimCLIM is able to capture the mean and variability for maximum temperature, minimum temperature, and solar radiation. However, SimCLIM did not regenerate precipitation accurately.

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Table 3.1: The General Circulation Models that were evaluated in this study.

Acronym	Source	Country	Resolution
BCCR-BCM2	Bjerknes Centre for Climate Research, University of Bergen, Norway	Norway	1.9º × 1.9º
CCCMA-31	Canadian Centre for Climate Modeling & Analysis	Canada	2.8º × 2.8º
CNRM-CM3	Me´te´o-France/Centre National de Recherches Me´te´orologiques	France	1.9º × 1.9º
CSIRO-30	CSIRO Atmospheric Research	Australia	1.9º × 1.9º
ECHO-G	Meteorological Institute of the University of Bonn, Meteorological Research Institute of KMA	Germany, Korea	3.9º × 3.9º
GFDLCM20	NOAA/Geophysical Fluid Dynamics Laboratory	USA	2.0º × 2.5º
GFDLCM21	NOAA/Geophysical Fluid Dynamics Laboratory	USA	2.0º × 2.5º
GISS-ER	NASA/Goddard Institute for Space Studies	USA	4º × 5º
INMCM-30	Institute for Numerical Mathematics	Russia	4º × 5º
IPSL-CM4	Institute Pierre Simon Laplace	France	2.5º × 3.75º
MIROCMED	Center for Climate System Research, National Institute for Environmental Studies, and Frontier Research Center for Global Change	Japan	2.8º × 2.8º
MPIECH-5	Max Planck Institute for Meteorology	Germany	1.9º × 1.9º
MRI-232A	Meteorological Research Institute	Japan	2.8º × 2.8º
NCARPCM1	National Center for Atmospheric Research	USA	2.8º × 2.8º
UKHADCM3	Hadley Centre for Climate Prediction and Research/Met Office	UK	2.75º × 3.75º

Table 3.2: The difference between mean, $\Delta = \overline{Proj.} - \overline{Obs.}$ for Minimum temperature (Tmin), Maximum temperature (Tmax), and Solar radiation (Rad), and the difference for precipitation (Precip), $\Delta = \overline{(Proj.} - \overline{Obs.})/\overline{Obs.}$, and the ratio of standard deviation (SD), $F = \frac{Proj.SD}{Obs.SD}$, at Tifton, Georgia. GCM is the General Circulation Model. Projections were based on gas emission scenario A1B.

GCM	Δ				F			
	Tmax	Tmin	Precip	Rad	Tmax	Tmin	Precip	Rad
BCCRBCM2	0.6	-0.8	0.1	0.7	1.0	1.0	0.3	1.0
CCCMA-31	0.6	-0.8	0.1	0.7	1.0	1.0	0.3	1.0
CNRM-CM3	0.6	-0.8	0.1	0.7	1.0	1.0	0.3	1.0
CSIRO-30	0.6	-0.8	0.1	0.7	1.0	1.0	0.3	1.0
ECHO-G	0.6	-0.8	0.1	0.7	1.0	1.0	0.3	1.0
GFDLCM20	0.6	-0.8	0.1	0.7	1.0	1.0	0.3	1.0
GFDLCM21	0.7	-0.8	0.1	0.7	1.0	1.0	0.3	1.0
GISS-ER	0.6	-0.8	0.1	0.7	1.0	1.0	0.3	1.0
INMCM-30	0.6	-0.8	0.1	0.7	1.0	1.0	0.3	1.0
IPSL-CM4	0.6	-0.8	0.1	0.7	1.0	1.0	0.3	1.0
MIROCMED	0.7	-0.8	0.1	0.7	1.0	1.0	0.3	1.0
MPIECH-5	0.6	-0.8	0.1	0.7	1.0	1.0	0.3	1.0
MRI-232A	0.6	-0.8	0.1	0.7	1.0	1.0	0.3	1.0
NCARPCM1	0.6	-0.9	0.1	0.7	1.0	1.0	0.3	1.0
UKHADCM3	0.6	-0.8	0.1	0.7	1.0	1.0	0.3	1.0

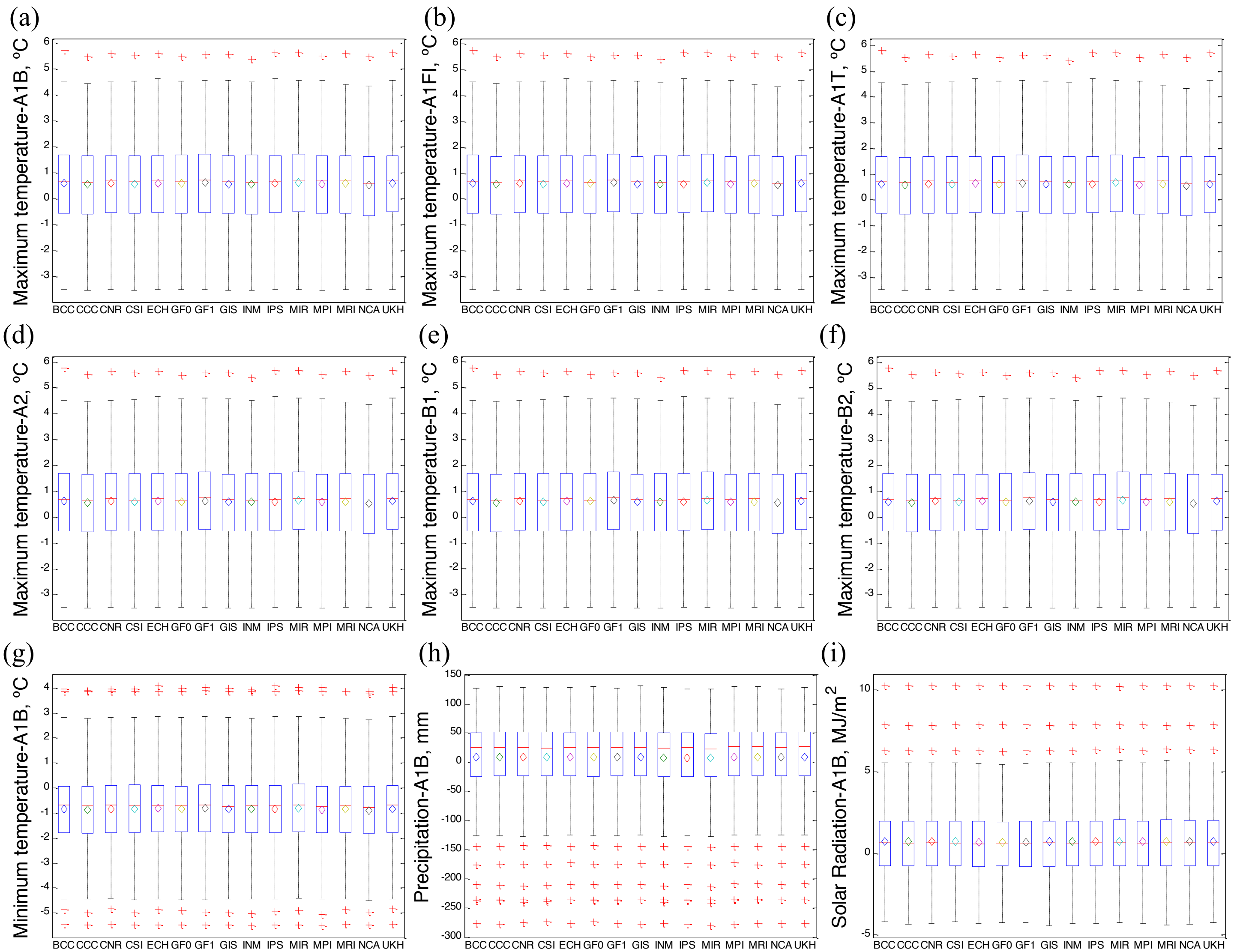
(a)
Maximum temperature-A1B, °C
(b)
Maximum temperature-A1FI, °C
(c)
Maximum temperature-A1T, °C
(d)
Maximum temperature-A2, °C
(e)
Maximum temperature-B1, °C
(f)
Maximum temperature-B2, °C
(g)
Minimum temperature-A1B, °C
(h)
Precipitation-A1B, mm
(i)
Solar Radiation-A1B, MJ/m²
BCC CCC CNR CSI ECH GF0 GF1 GIS INM IPS MIR MPI MRI NCA UKH

Figure 3.1: Box-plot for the bias of projected monthly maximum temperature under gas emission scenario A1B (a), A1FI (b), A1T (c), A2 (d), B1 (e), B2 (f), projected monthly minimum temperature under A1B (g), projected monthly precipitation under A1B (h), and projected monthly solar radiation under A1B (i) based on 15 GCMs from 1992 to 2012 for the corresponding observations.

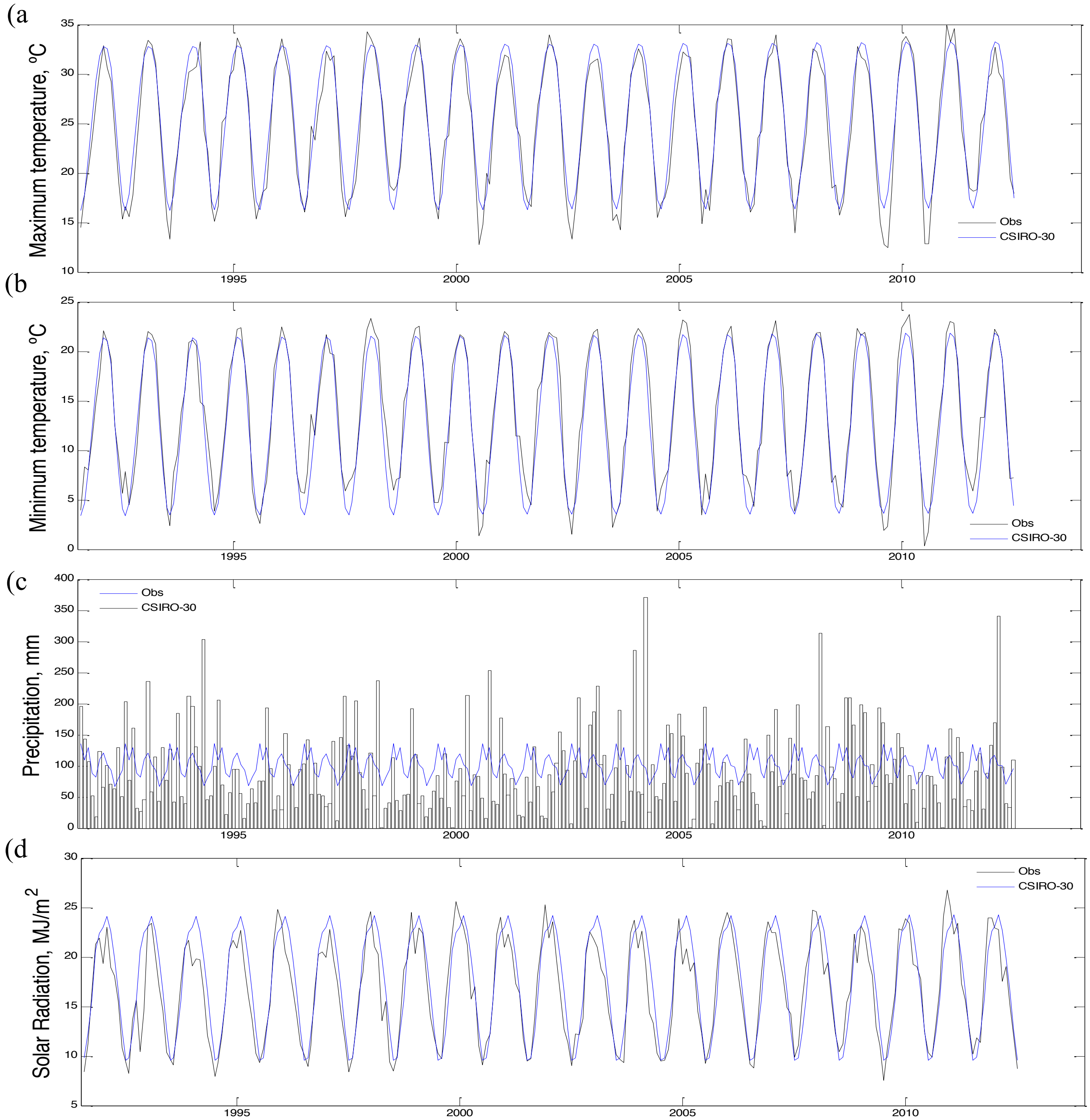

Figure 3.2: Time series plots for both projections and observations from 1992 to 2012 including monthly maximum temperature (a), monthly minimum temperature (b), monthly precipitation (c), and monthly solar radiation (d) based on the GCM CSIRO-30.

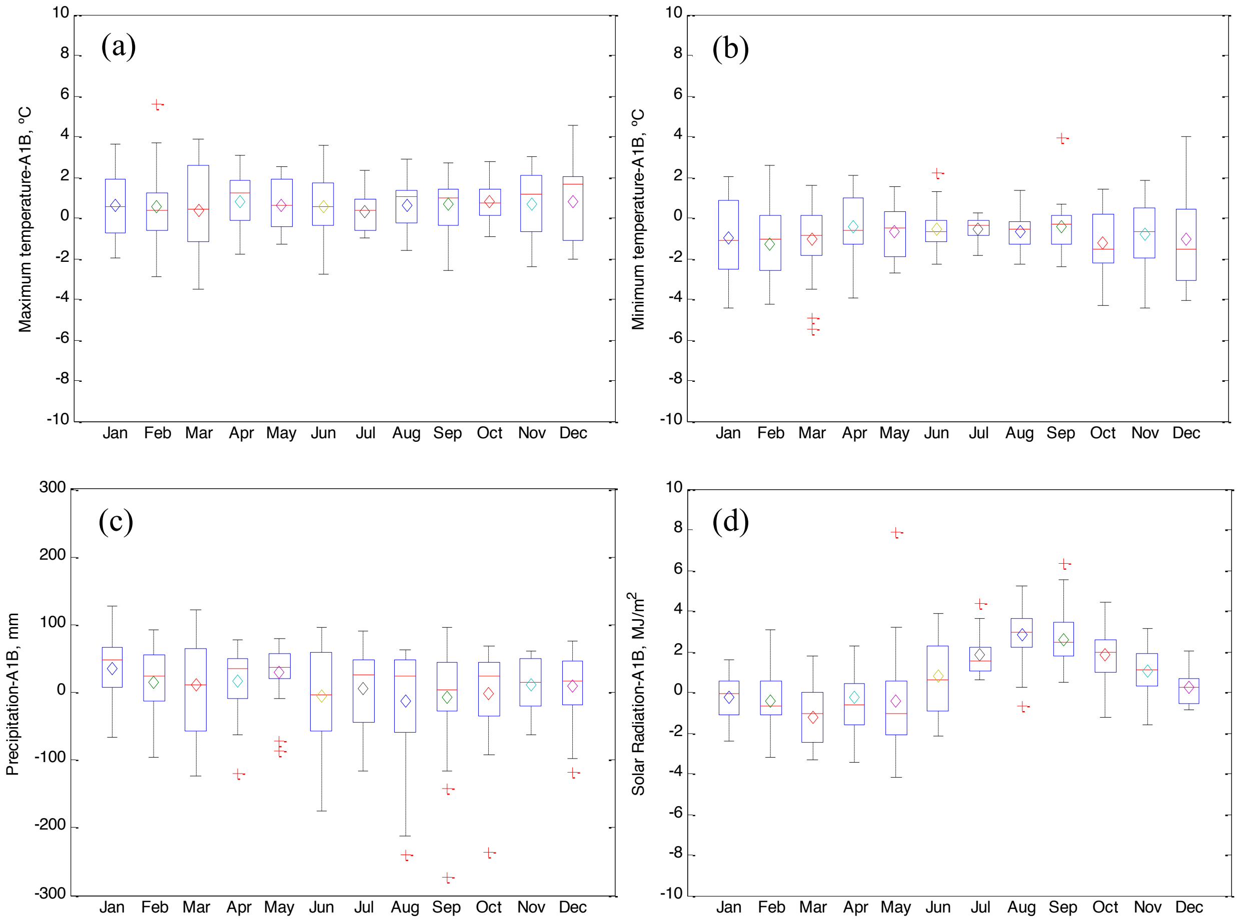

Figure 3.3: Box-plot for bias between projections and observations during 1992 to 2012 including monthly maximum temperature (a), monthly minimum temperature (b), monthly precipitation (c), and monthly solar radiation (d) based on the GCM CSIRO-30.

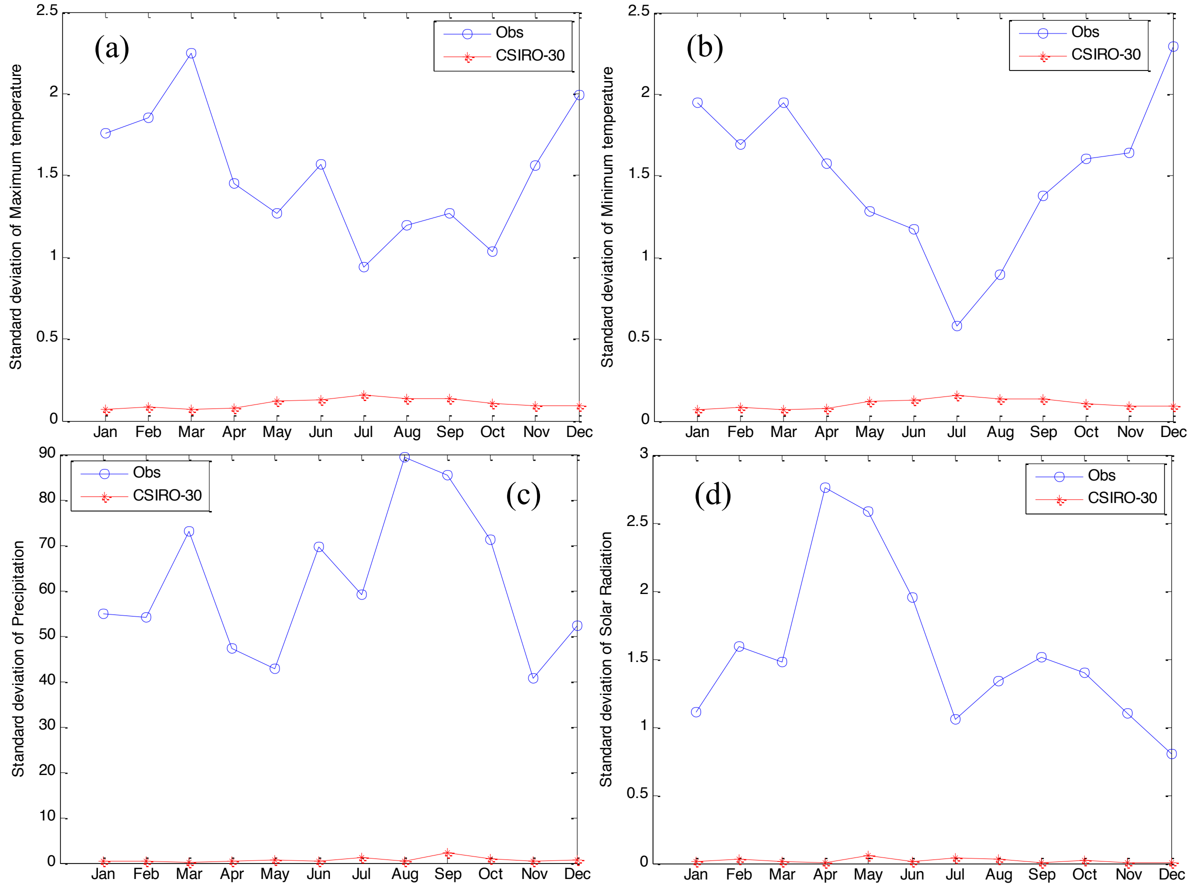

Figure 3.4: Standard Deviations of projections and observations from 1992 to 2012 for monthly maximum temperature (a), monthly minimum temperature (b), monthly precipitation (c), and monthly solar radiation (d) based on the GCM CSIRO-30.

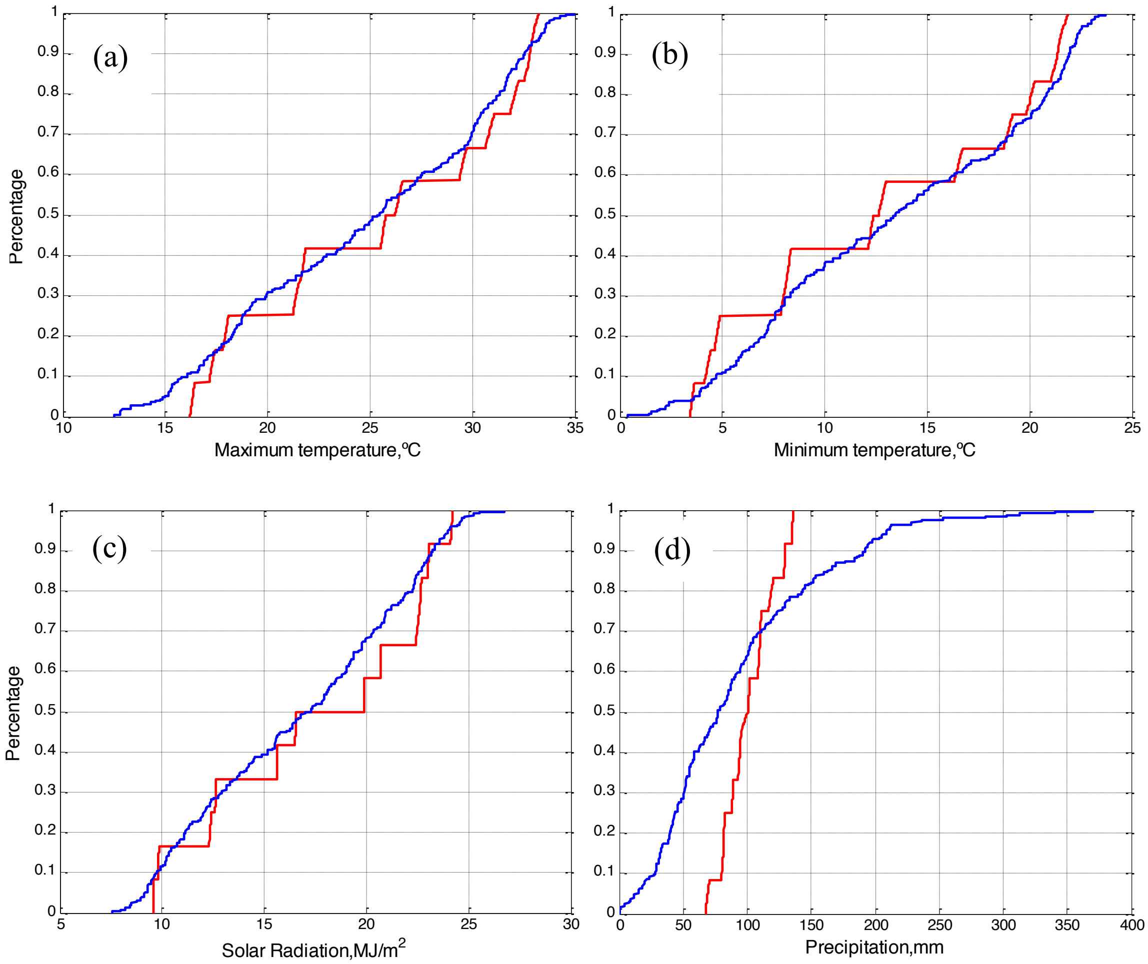

Figure 3.5: CDFs of projections and observations from 1992 to 2012 for monthly maximum temperature (a), monthly minimum temperature (b), monthly precipitation (c), and monthly solar radiation (d) based on the GCM CSIRO-30.

CHAPTER 4

SIMCLIM'S PERFORMANCE TO PROJECT CLIMATE FOR SPECIFIC LOCATIONS IN THE SOUHTEASTERN USA[1]

[1] Bao, Y., Hoogenboom, G., Seymour, L., McClendon, R.W., Vellidis, G., and Ortiz, B. to be submitted to Climate Research

4.1 INTRODUCTION

Agriculture is a significant part of the culture and economy of the southeastern USA (Gray & Thompson 1933, Carter 2003). With the rapid increase in populations and the shift to biofuels there has been an increase in the demand of crop producing during recent years. Agriculture is weather dependent (White & Hoogenboom 2010), but the southeastern USA is characterized by both a temporal and spatial weather variability due to its landscape and the surrounding Atlantic Ocean and Gulf of Mexico (Misra 2013). Agriculture is especially vulnerable to extreme events. Similar to other regions across the globe, the climate in the southeastern USA is changing, such as increasing temperature, decreasing number of freezing days, increasing heavy downpours in many parts (Mirhosseini et al. 2013, Misra 2013). Therefore, a comprehensive understanding of climate change impact on crop production is crucial for providing strategies to minimize the potential negative effects on southeastern USA agriculture.

The most popular method to study impact of climate on agriculture is coupling climate models and crop models. Organizations such as the Southeast Climate Consortium (SECC, http://www.seclimate.org/) and the Florida Climate Institute (FCI, http://floridaclimateinstitute.org/) have evaluated regional climate projections for the southeastern USA (Lim et al. 2007, Hwang et al. 2011, Hwang et al. 2013, Michael et al. 2013, Selman et al. 2013). Others have studied the impact of climate change on crop production in this region (Bolson et al. 2013, Bucklin et al. 2013, Cammarano et al. 2013, LaRow 2013, Misra et al. 2013, Solís & Letson 2013). These regional climate projections were generated based on statistical, dynamical, and a combination of these two downscaling methods. Asefa and Adams (2013) introduced a statistical bias corrections technique based on Bayesian approach for regional climate projections over central Florida. Misra et al. (2013) analyzed the performance of a dynamic downscaling model, i.e., the Regional Spectral Model, in projecting climate for southeastern USA at a horizontal grid resolution of 10 km. Hwang et al. (2013) combined the statistical and dynamical downscaling method to reproduce local-scale spatiotemporal precipitation and temperature data.

However, all previous studies have been challenged by some difficulties. The climate of the southeastern USA, especially precipitation, is difficult to reproduce (Robinson & Henderson 1992, Henderson & Vega 1996, Mearns et al. 2003). Furthermore, the main uncertainties concerning future climate from a physical system point of view were summarized as following: "the natural internal variability of the climate system, the trajectories of future emissions of greenhouse gases and aerosols, and the response of the global climate system to any given set of future emission/concentrations, and the application of downscaling methods yields higher resolution projections but presents another source of uncertainty" (Cox & Stephenson 2007, Tebaldi & Knutti 2007, Knutti et al. 2008, Mearns 2010). Mearns (2010) also pointed out that the uncertainties of downscaling methods is considered to be more important in the context of adaptation studies because regional adaptation studies require information at a higher resolution. Therefore, the evaluation of regional climate models is usually conducted to quantify the uncertainties that climate models probably would introduce into future climate projections, especially for sectorial applications.

The regional climate model SimCLIM was introduced by Bao et al. (2015) to study the impact of climate change on soybean production in the southeastern USA. This climate model has been widely applied for impact studies around the world. For instance, Warrick et al. (2012) analyzed impact on rainwater harvesting for the southeast Queensland; Kenny et al. (1995, 2000,

2001) studied the impact on environment and agriculture in New Zealand; Albertin et al. (2011) studied the impact on North Carolina interbasin transfer; Jha (2012) analyzed the impact on water supply at Kathmandu Valley. SimCLIM uses a statistical method called pattern-scaling to downscale the gridded projections of Global Climate Models (GCMs) for a region and a specific location. Pattern-scaling was first proposed by Santer et al. (1990) to generate climate scenarios. It was then developed as a convenient solution to provide a low cost alternative to expensive AOGCM and RCM experiments for creating a range of climate scenarios that embrace uncertainties relating to different emissions, concentration and forcing scenarios (Kenny et al. 1995, Mitchell 1999, Hulme et al. 2000, Kenny et al. 2000, Mitchell 2003).

The application of SimCLIM as a downscaling tool also cannot avoid introducing uncertainties from GCMs, gas emission scenarios, the pattern downscaling method, and baseline data. These issues are similar to other downscaling methods for regional climate projections. Bao et al. (2015) evaluated the performance of SimCLIM for downscaling climate data for one location, i.e. Tifton, Georgia. Downscaled climate projections were based on 15 GCMs and six gas emission scenarios. This study found that SimCLIM can provide accurate climate patterns for monthly maximum and minimum temperature and monthly solar radiation, but not for monthly precipitation for Tifton, Georgia.

So far the evaluation of SimCLIM was only based on one location, which certainly cannot represent the spatial variability of climate over the southeastern USA. Therefore, multiple locations should be evaluated because of the spatial climate variability across the southeastern USA. The goal of this study was, therefore, to determine the suitability of SimCLIM in generating site-specific climate projections for the southeastern USA, including the states of Alabama, Florida, and Georgia.

4.2 MATERIALS AND METHODS

4.2.1 HISTORICAL CLIMATE DATA

The states, Alabama (AL), Florida (FL), and Georgia (GA), were considered as representative states for the southeastern USA. In general, observations with a period of 30 years or longer are normally used for evaluation of climate model (Randall et al. 2007, Kostopoulou et al. 2009). However, these evaluations are based on temperature and precipitation only. For climate change applications in agriculture solar radiation is also an important parameters as it drives the biomass production through photosynthesis and also affects potential evapotranspiration. Although there are sites that have long-term daily historical weather data, none of these sites include solar radiation. Therefore, 34 locations with relatively long observation periods and that included solar radiation, in addition to daily maximum and minimum temperature and precipitation, were selected. These 34 locations evenly span three states (Figure 4.1) and all locations had observations for daily minimum air temperature (ºC), maximum air temperature (ºC), precipitation (mm), and solar radiation (MJ/m^2), except for Alabama where solar radiation was not available

The stations for Alabama included Auburn, Belle Mina, Brewton, Cullman, Grand Bay, Headland, Marion Junction, Sand Mountain, Thorsby, and Union Springs and were obtained from the Agricultural Weather Information Service (AWIS, http://www.awis.com/). The weather stations from Alabama have been operational since 1996. The weather stations for Florida included Alachua, Citra, Homestead, Immokalee, Jay, Lake Alfred, Macclenny, Marianna, Quincy, and Umatilla were obtained from the Florida Automated Weather Network (FAWN, http://fawn.ifas.ufl.edu/). FAWN has been operational since 1997 and is managed the University of Florida's Institute of Food and Agricultural Sciences. The weather stations for Georgia included Calhoun, Floyd, Blairsville, Watkinsville, Elberton, Griffin, Plains, Eatonton, Midville, Statesboro, Attapulgus, Tifton, and Savannah (Figure 4.1) and were obtained from the Georgia Automated Environmental Monitoring Network (AEMN, www.georgiaweather.net). The first station of the AEMN was installed in 1991 (Hoogenboom 1996) and the AEMN currently has more than 80 operational stations (Garcia y Garcia & Hoogenboom 2005). The period of record for location varied due to the differences in the date of installation and quality control issues. The stations in Georgia generally had a longer period of record, spanning from 1993/1994 to 2012. The period of record that was used for evaluation of the stations in Alabama spanned from 1996/1998 to 2012. However, those stations missed solar radiation data in many years. The period of record in Florida spanned from about 1997/1998 to 2012. Although the historical data from 1992 to 2012 is relatively short for evaluation, it was the most complete and accurate set of daily observed data for maximum and minimum temperature, precipitation, and solar radiation that was available for the three states (Gleckler et al. 2008, Pincus et al. 2008, Radić & Clarke 2011).

4.2.2 PROJECTED CLIMATE DATA

For the specific locations, SimCLIM can only provide monthly climate data. It was used to generate the monthly climate data for the selected locations during the period 1991 to 2012 for which observed daily weather data were available. The analysis of this study, therefore, was based on monthly climate variables. The generated climate variables include monthly maximum temperature, minimum temperature, precipitation, and solar radiation. Monthly maximum and minimum temperature and solar radiation were the average values. The monthly precipitation was total value of a month. For each of the selected locations, monthly climate data for 15 GCMs were generated (Table 4.1). The gas emission scenario from the Special Report on Emissions

Scenarios (SRES) was applied by SimCLIM for the climate projections after 1990 (Nakicenovic & Swart 2000). As Bao et al. (2015) have concluded that the difference among gas emission scenarios could not be identified for such short period of weather data, the commonly used gas emission scenario A1B was therefore considered in this study for generating climate variables. SimCLIM calculates the future projections using the following equations

$$Future\ Max = Baseline\ Max + Normalized\ values \times GMTC,$$

$$Future\ Min = Baseline\ Min + Normalized\ values \times GMTC,$$

$$Future\ Pre = Baseline\ Pre \times (1 + Normailize\ values \times GMTC),$$

$$Future\ Rad = Baseline\ Rad \times (1 + Normailize\ values \times GMTC),$$

which Max is the maximum temperature, Min is the minimum temperature, Pre is the precipitation, Rad and is the solar radiation, $Baseline\ Values$ $(Max, Min, Pre, and\ Rad)$ are usually 30 years (usually from 1961 to 1990) or even longer observations which were obtained from the dataset of the Global Historical Climatology Network (GHCN)-Daily, $GMTC$ is the Global Mean Temperature Change that is derived from Model for the Assessment of Greenhouse-gas Induced Climate Change (MAGICC) (CLIMSystems 2014).

4.2.3 STATISTICAL COMPARISON

Multiple statistical criteria were applied to compare the projected monthly maximum temperature, minimum temperature, precipitation, and solar radiation with average monthly observations for each location. The statistical tests that were applied did not have too many assumptions for the data sets that were analyzed. These statistical tests were selected in order to be able to evaluate different aspects of the data set, and the statistical tests are accepted methodologies in the field for atmospheric and climatological sciences. This is similar to the approach that was used for the detailed evaluation for Tifton, Georgia conducted by Bao et al

(2015). The most commonly used methods includes descriptive statistics, such as mean, median, and standard deviation, box-plot, and statistical inference, including the Kolmogorov-Smirnov test (KS-test). Those statistical criteria were widely applied for climate models' evaluation, e.g., Mearns et al. (2003), Kiktev et al. (2003), Anagnostopoulos et al. (2010), Kostopoulou et al. (2009), Cammarano et al. (2013), Misra et al. (2013), Voldoire et al. (2013).

First of all, the temporal evaluation was conducted for projected monthly maximum and minimum temperature, monthly precipitation, and monthly solar radiation at each location. The difference between multiple years' of means of monthly projections and observations were calculated as the follows:

$$\Delta = \overline{Proj.} - \overline{Obs.}$$

for monthly maximum and minimum temperature and monthly solar radiation. The difference between projected and observed monthly precipitation was in percentage:

$$\Delta = \overline{(Proj.} - \overline{Obs.})/\overline{Obs.}$$

when Δ is 0 there is good fit between projections and observations. Otherwise, disparity exists between the monthly projections and observations. The larger the value for Δ, the larger the difference between monthly projections and observations.

Secondly, the bias between the projected and observed monthly data were calculated and depicted using a box-plot for each location. Statistics that are included in a box-plot include the median, mean, lower quartile (Q_1, 25%), higher quartile (Q_3, 75%), whiskers (between quartiles and lowest/highest values), and outliers. This approach makes no assumption with respect to the data population. The outliers of bias were defined as the values that are out of the following range:

$$[Q_3 + 1.5\, IQR, Q_1 - 1.5\, IQR]$$

where IQR is interquartile range and defined as

$$IQR = Q_3 - Q_1$$

Thirdly, to show the climate trends both the projections and observations were displayed as time series for each location in this study. Fourthly, the projections and observations were summarized in probability histograms to determine if they have the same distribution. Fifthly, the projections and observations were tested with the statistical inference Kolmogorov-Smirnov test (KS-test) to determine if the both projection and observations have the same population. The KS-test makes no assumptions about the distribution of data and the null hypothesis of this approach is that projections and observations are from the same data population. A p value close to 0 means a rejection to the null hypothesis, and the value close to 1 means acceptable of null hypothesis.

Finally, the standard deviation was calculated to determine whether the projections could capture the temporal variability of observations for each location. The ratio of the temporal standard deviation was defined as:

$$F = \frac{Proj.\ SD}{Obs.SD}$$

where $Obs.$ is observation, $Proj.$ is projection, and SD is the standard deviation. When F is 1, there is a perfect match for the temporal variability of both the observed and projected data. Otherwise, the projections cannot capture the temporal variability when F is 0. In addition to the variability, the climate mean for both the projections and observations was also compared.

In addition to the evaluation for specific locations, the spatial variability of projections for multiple locations was also evaluated by comparing with observations. First of all, the standard deviation for each month for all 34 locations was calculated for both projections and observations. In general, a large standard deviation means a large variability among those locations. When the standard deviation of projections is smaller than the standard deviation of the observations, the projections fail to capture the observed spatial variability. When the standard deviation of projections is larger than the standard deviation of the observations, the projections for multiple locations show a larger difference than observation. In addition to the comparison of variability of the 34 locations, the mean, median, and spread of projections and observations of each month were compared using graphs of data distributions. When the statistics, e.g. mean, median, and spread of data, for both observations and projections are the same, it means a good fit between the projections and observations. If the statistics are different, then the projections fail to capture observations.

4.3 RESULTS

4.3.1 TEMPORAL PROJECTIONS

4.3.1.1 BIASES BASED ON AVERAGE OF 15 GCMS

In general, biases existed between the projections and observations for the four climate variables in monthly values, maximum and minimum temperature, precipitation, and solar radiation, for all locations (Figure 4.2). Negative values for biases mean the projections underestimated observations. Otherwise the projections overestimated the observations. First of all, the average of climate projections based on 15 GCMs was compared with observations at all locations.

In Alabama, the biases between projected monthly maximum temperature and observations ranged between -0.4 °C to 0.4 °C for Cullman, Grand Bay, Marion Junction, Thorsby, and Union Springs. While, the biases were about -0.2 °C to 0 °C for the other locations in Alabama ((Figure 4.2). The monthly minimum temperature biases were relatively smaller and ranged from -1.2 °C to 0 °C for most locations. However, the biases were -1.8 °C for Auburn. The monthly precipitation biases ranged from 17% to 25% for all locations.

In Florida, three locations Alachua, Jay, and Quincy showed relatively larger monthly maximum temperature biases than the other locations, which were about 0.8 °C to 1 °C (Figure 4.2). The biases were less than 0.5 °C for the other locations, but Umatilla had a bias of -0.3 °C. The monthly minimum temperature biases were 0.8 °C for Alachua and ranged from -0.6 °C to 0.5 °C for the other locations. The monthly precipitation biases ranged from 3% to 16% for all locations, except 27% for Lake Alfred. For monthly solar radiation, biases ranged from about 0.5 MJ/m^2 to 2.8 MJ/m^2 for all locations in Florida.

In Georgia, the biases of monthly maximum temperature were less than 0.5 °C for most locations, but 0.8 °C for Statesboro and 0.7 °C for Tifton. The biases of monthly minimum temperature ranged from about -0.8 °C to 0.9 °C for all locations, with 1.5 °C for Eatonton. The biases of monthly precipitation ranged from 5% to 20%. The biases of monthly solar radiation were less than 2.2 MJ/m^2 for all locations.

4.3.1.2 BIASES BASED ON SINGLE GCMS

In order to conduct a detailed performance of the projections of the 15 GCMs, six locations were selected as representatives for the 34 locations in southeastern USA. Those locations were Attapulgus, Blairsville, and Midville for Georgia, Auburn for Alabama, Lake Alfred and Homestead for Florida, ranging from the most southern to most northern locations of the study area (Figure 4.3).

Using Attapulgus (Georgia) as a central location, the biases between the projected monthly maximum temperature and the observations ranged from about -4 °C to 6 °C. The boxplot of those biases in monthly maximum temperature showed a mean value of 0 °C for all the 15 GCMs. All 15 GCMs showed almost identical values for the mean, 25%, 50%, and 75% for the monthly maximum temperature biases. However, the outliers varied with GCM. For monthly minimum temperature, the biases between projections and observations ranged from -5 °C to 8 °C. The mean value of those biases was about 1 °C, which means the average monthly minimum temperature was over-estimated by about 1 °C. The monthly minimum temperature biases of the 15 GCMS also showed almost identical values for the mean, 25%, 50%, and 75%, and even the outliers. The biases of monthly precipitation ranged from -150 mm to 150 mm, while a few years showed biases ranging from -450 mm to - 150 mm, which treated as outliers in the box-plot. The mean of monthly precipitation biases was about 20 mm. The similar values of mean, 25%, 50%, 75%, and even outliers were too close to be identified among the 15 GCMs. All GCMs seemed to over-estimate most years' monthly solar radiation, with the biases ranging from - 3 MJ/m^2 to 12 MJ/m^2. The mean of monthly solar radiation biases was about 2 MJ/m^2.

SimCLIM performed similarly for Blairsville, Midville, Auburn, Homestead, and Lake Alfred compared to Attapulugs. However, the values and ranges for the statistics showed some differences (Figure 4.3). At Blairsville, the monthly maximum temperature biases ranged from about -4 °C to 6 °C and the mean bias was overestimated by about 1 °C. The monthly minimum temperature biases ranged from -6 °C to 6 °C, while the mean bias was almost 0 °C. The monthly precipitation biases ranged from -200 mm to 150 mm, while the mean bias was about 20 mm. The monthly solar radiation bias ranged from -5 MJ/m^2 to 6 MJ/m^2 and mean was about 0. The results for Midville were very similar to Blairsville. However, the mean monthly minimum temperature was underestimated by about 1 °C and the mean monthly solar radiation was overestimated by about 1 MJ/m^2. For Auburn, the biases of monthly maximum temperature ranged from -4 °C to 5 °C, while the mean bias was almost 0 °C. The range for biases of monthly minimum temperature ranged from -7 °C to 4 °C, while the mean bias was about 2 °C. The monthly precipitation biases ranged from -200 mm to 150 mm and the mean bias was overestimated by about 20 mm. At Homestead, the biases of monthly maximum temperature ranged from about -3 °C to 4 °C, while the mean bias was 0. The monthly minimum temperature biases ranged from -4 °C to 6 °C, while the mean bias was 0. The monthly precipitation biases ranged from about -200 mm to 200 mm, while the mean bias was also 0; however, the outliers reached -400 mm. The monthly solar radiation biases ranged from -5 MJ/m^2 to 10 MJ/m^2, but the outliers reached -10 MJ/m^2 and mean bias was 2 MJ/m^2. At Lake Alfred, mean monthly minimum temperature was underestimated by about 1 °C, mean monthly precipitation was overestimated by 20 mm, while the monthly precipitation and monthly solar radiation did not show many outliers.

4.3.1.3 CLIMATE VARIABILITY

The ratio of projected and observed standard deviations of each climate variable was calculated to quantify the difference in temporal climate variability among the 15 GCMs for Attapulgus, Blairsville, and Midville for Georgia, Auburn for Alabama, and Lake Alfred and Homestead for Florida (Table 4.1). For monthly maximum and minimum temperature, the ratios of the standard deviations of projections and observations ranged from about 0.95 to 0.99 at Attapulgus, Blairsville, Midville, and Auburn. The ratios were 0.82 to 0.92 at Homestead and Lake Alfred. This indicated that the projected monthly maximum and minimum temperatures captured the variability of the observations. The ratios of standard deviations of monthly solar radiation ranged from 1 to 1.25 at all six locations, which also showed that the projections were able to capture the variability of the observations. However, the monthly precipitation at all locations showed very low ratios, which indicated that the projected monthly precipitation did not capture the variability of the observations. These ratios ranged from 0.3 to 0.37 for Attapulgus, Blairsville, and Midville, and they ranged from 0.5 to 0.72 for Auburn, Homestead, and Lake Alfred.

4.3.1.4 DATA DISTRIBUTION OF CLIMATE BASED ON GCM CSIRO AND OBSERVATIONS

Since the pervious analysis showed that there was no significant difference among the 15 GCMs in generating monthly maximum and minimum temperature, monthly precipitation, and monthly solar radiation for specific locations, the GCM CSIRO was selected as the representative GCM to conduct a detailed analysis of the performance of SimCLIM. Several studies have shown that the GCM CSIRO can reproduce climate over the continental U.S. (Giorgi & Shields 1999, Mearns et al. 2003) and it also has a relatively high spatial resolution compared to many of the other GCMs. GCMs can address the internal variability better for longer periods (Stocker et al. 2013) and, therefore, the locations with longest observation period were selected as example to address the difference between the distribution of the projections and observations. These locations included Blairsville and Attapulgus from Georgia, which had the longest observations from 1993 to 2012 (Figure 4.4).

For Blairsville, projected monthly maximum temperature ranged from about 9 °C to 32 °C, while the observations ranged from about 5 °C to 32 °C. The temporal variability of the projections and observations from 1993 to 2012 were close, as indicated by the standard deviation that was 7.14 for the projections and 7.17 for the observations. The projected monthly minimum temperature ranged from -6 °C to 19 °C and observations ranged from -3 °C to 18 °C, while the standard deviation was 7.15 for the projections and 7.34 for the observations. The projected monthly solar radiation ranged from 7 MJ/m^2 to 24 MJ/m^2 and observations were from

5 MJ/m^2 to 26 MJ/m^2, and the standard deviation was 5.52 for projections and 5.45 for observations. The projected monthly precipitation showed a very narrow range from 110 mm to 170 mm, while the observations ranged from 11 mm to 310 mm. The standard deviation for the monthly precipitation was 16.72 for the projections and 53.18 for observations, which means that projections could not capture the climate patterns of the observations. For Attapulgus the SimCLIM also showed that projected monthly maximum and minimum temperature and monthly solar radiation were able to capture the observations for both the range and standard deviations. However, the projected monthly precipitation showed much narrower ranges and smaller standard deviations than the observations.

4.3.1.5 TIME SERIES BASED ON GCM CSIRO AND OBSERVATIONS

Blairsville and Attapulgus for Georgia and Lake Alfred for Florida were selected to analyze the climate trend along with time (Figure 4.5), which represented the northern, middle, and southern study area. The comparison of projected monthly maximum and minimum temperature with the corresponding observations for all three locations showed that the projections matched the observations well. However, there was a disparity between the projections and observations especially for extreme temperatures for both the monthly maximum and minimum temperature. The projected monthly solar radiation for Blairsville matched well with the observations. However, there was a large different between projected and observed monthly solar radiation for Attapulgus and Lake Alfred. Also, the projections for monthly precipitation did not regenerate the observations at all three locations.

4.3.1.6 KS-TESTS BASED ON GCM CSIRO AND OBSERVATIONS

The KS-tests were conducted for monthly maximum and minimum temperature, monthly precipitation, and monthly solar radiation for all locations for the three states. For monthly maximum temperature, the KS-tests showed that both the projections and observations were from the same data population for all locations except for Alachua and Umatilla in Florida (Table 4.2). For monthly minimum temperature, the projections for many locations had a different data population than the observations. These locations included Auburn, Brewton, Cullman, Headland, and Thorsby in Alabama, Immokalee and Lake Alfred in Florida, and Eatonton, Tifton, and Savannah in Georgia. The projections for Alabama were less accurate than for the other two states. Based on the KS-test it can be concluded that the monthly precipitation projections did not show any skill. The monthly solar radiation showed that only projections at Blairsville and Elberton in Georgia captured the observations.

4.3.1.7 F-RATIO BASED ON GCM CSIRO AND OBSERVATIONS

The F ratio, which is the ratio of the standard deviations of the projections and observations, for monthly maximum temperature for all locations for Alabama ranged from 1 to 1.06 and the Δ, which is the difference of the means between the projections and observations, ranged from -0.4 °C to 0.4 °C which were not rejected by KS-test. The ratio of the monthly minimum temperature ranged from 1.04 to 1.13 and Δ ranged from -1.7 °C to 0.1 °C. The locations that were rejected by the KS-test showed that the absolute Δ were larger than 1 °C. The F ratio of monthly precipitation were from 2.47 to 3.09 and Δ were from 9.1 °C to 24.9 °C, therefore, all locations were rejected. For the locations in Florida, the F ratio for monthly maximum temperature ranged from 1.01 to 1.1and the Δ for monthly temperature ranged from were and -1 °C to 0.3 °C. The F ratio for monthly minimum temperature ranged from 1.05 to 1.21 and the Δ for monthly minimum temperature ranged from -0.6 °C to 0.7 °C. The F ratio for monthly precipitation ranged from 1.55 to 2.82 and the Δ for monthly precipitation ranged from 0.5 mm to 23.1 mm. The F ratio for solar radiation ranged from 0.74 to 0.93 and the Δ for monthly solar radiation ranged from 0.5 MJ/m^2 to 2.8 MJ/m^2. Monthly precipitation and monthly solar radiation for all locations in Florida were rejected. For locations in Georgia, the F ratio of monthly maximum temperature ranged from 0.99 to 1.13 and the Δ for monthly maximum temperature ranged from -0.7 °C to 0.1 °C. The F ratio for monthly minimum temperature ranged from 1 to 1.12 and the Δ for monthly minimum temperature ranged from -0.8 °C to 1.5 °C. The F ratio for monthly precipitation ranged from 2.22 to 4.97 and the Δ for monthly precipitation ranged from 6 mm to 16.2 mm. The F ratio for monthly solar radiation ranged from 0.85 to 1.02 and the Δ for monthly solar radiation ranged from 0 MJ/m^2 to 2.2 MJ/m^2.

4.3.2 SPATIAL VARIABILITY

The spatial data distributions for both the projections and observations for all locations were compared in order to evaluate SimCLIM's ability to capture the spatial variability among all locations for the monthly climate variables (Figure 4.6). For January, the projected monthly maximum and minimum temperature showed the ability to capture the means, maximum value, and standard deviations (data spread). The standard deviations were 4.02 and 4.09 for the projected and observed monthly maximum temperature and 3.64 and 3.81 for projected and observed monthly minimum temperature. However, SimCLIM did not reproduce the extremes of monthly maximum and minimum temperature. The projected monthly solar radiation in January showed a very similar distribution as the observed monthly solar radiation, with a narrow range, but the extremes were not reproduced by the projections. The standard deviation was 1.1 for the projected solar radiation and 1.67 for the observed solar radiation. The spread and means of the projected monthly precipitation for January showed a large difference from the observed precipitation. The standard deviation was 27.5 for the projected monthly precipitation and 52.16

for observed precipitation. The four projected variable for February, March, April, May, September, October, November, and December had a similar performance as January.

SimCLIM did capture the mean and spread of the observed monthly maximum and minimum temperature in June, however, missed the extremes. The projected monthly solar radiation in June showed larger mean value than observations and did not capture the variability. SimCLIM also showed no skill in projecting monthly precipitation in June, which was the same as January. Projections in July and August were with the similar performance with June.

4.4 DISCUSSION

SimCLIM was evaluated by Bao et al (2015) in generating site-specific climate projections, but only for one location Georgia, US. The limitations of those studies were improved in this study. For coupling SimCLIM with application models such as crop simulation models for the southeastern USA, this study evaluated the performance of SimCLIM with respect to being able to reproduce recent site-specific climate for multiple locations in the southeastern USA. Furthermore, in order to respond to the recent research that found that the application of multiple GCMs introduces fewer uncertainties into impact studies (Tebaldi & Knutti 2007, Knutti 2010, Asseng et al. 2013), downscaled climate projections of 15 GCMs were compared for these multiple locations. The statistical analysis of this study concluded that SimCLIM could generate maximum and minimum temperature and solar radiation with confidence for the southeastern USA. This conclusion is similar with many studies stated that the generation of temperature is with confidence (Lim et al. 2007, IPCC 2013). However, improvements are still needed for generating precipitation in the southeastern USA, similar to the results of Bao et al. (2015) who only evaluated one location The precipitation is difficult to be reproduced in southeastern USA (Robinson & Henderson 1992, Henderson & Vega 1996, Mearns et al. 2003, Misra 2013) that has also been proved in this study. The study of Hwang et al. (2013) that evaluated the projections of precipitation for Tampa Bay in Florida also found out significant bias from observed precipitation when generated the precipitation projections.

In comparison to dynamic downscaling methods, the statistical downscaling method of SimCLIM is simple and therefore could possibly cause more uncertainties. However, the downscaled projections for specific location are definitely an advantage of SimCLIM, especially when they are applied for impact studies, such as crop yield prediction for a particular location. This study also highlighted the uncertainties associated with the generation of climate scenarios with SimCLIM. The evaluation of SimCLIM in this study was based on monthly values because this model does not generate daily projections. This could possibly cause bias for the evaluation of the projections and thus also for the applications. Fortunately, the application can be partially compensated for with the perturbation of long-term daily observations. Another limitation is the lack of long-term observations. Although the observations that were used were the most complete data, climate patterns cannot be completely shown by the short period (10 to 21 year). As summarized by Stocker et al. (2013) that climate projections provide better interanual variability with longer period than shorter period. The evaluation of this study showed that the climate variability cannot be completely reproduced by SimCLIM.

4.5 CONCLUSION

In summary, SimCLIM can be applied for climate change impact studies with confidence in projecting maximum temperature, minimum temperature, and solar radiation. However, the projected precipitation may introduce more uncertainties especially with respecting to the climate variability. Fortunately, the perturbation tool for the local long-term observation can be able to offset some of the uncertainties associated with using monthly data.

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Table 4.1: The ratio of the standard deviations for the projected and observed data ($F = \frac{Proj.SD}{Obs.SD}$) for Attapulgus, Blairsville, and Midville in Georgia, Auburn in Alabama, Homestead and Lake Alfred in Florida. Projections were based on 15 GCMs and gas emission scenario A1B.

	F	BCC	CCC	CNR	CSI	ECH	GF0	GF1	GIS	INM	IPS	MIR	MPI	MRI	NCA	UKH
Attapulgus	Max	0.97	0.97	0.97	0.98	0.97	0.98	0.98	0.97	0.98	0.97	0.98	0.97	0.97	0.98	0.97
	Min	0.95	0.95	0.95	0.95	0.95	0.95	0.96	0.95	0.96	0.95	0.95	0.95	0.95	0.95	0.95
	Pre	0.34	0.35	0.34	0.34	0.37	0.36	0.34	0.36	0.35	0.35	0.34	0.37	0.34	0.35	0.35
	Rad	1.17	1.17	1.17	1.18	1.16	1.17	1.17	1.17	1.17	1.16	1.17	1.17	1.16	1.16	1.17
Blairsville	Max	0.99	0.99	0.99	1.00	0.99	1.00	1.00	0.99	1.00	0.99	0.99	0.99	0.99	1.00	0.99
	Min	0.97	0.97	0.97	0.98	0.97	0.98	0.98	0.97	0.98	0.97	0.97	0.97	0.97	0.98	0.97
	Pre	0.32	0.32	0.33	0.31	0.31	0.32	0.32	0.34	0.32	0.31	0.33	0.32	0.32	0.31	0.33
	Rad	1.01	1.01	1.02	1.01	1.00	1.01	1.02	1.01	1.01	1.00	1.01	1.01	1.01	1.01	1.01
Midville	Max	0.96	0.96	0.96	0.97	0.96	0.97	0.97	0.96	0.97	0.96	0.97	0.96	0.96	0.97	0.96
	Min	0.97	0.97	0.97	0.98	0.97	0.98	0.98	0.97	0.98	0.97	0.98	0.97	0.97	0.98	0.97
	Pre	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
	Rad	1.1	1.1	1.1	1.0	1.0	1.1	1.1	1.1	1.1	1.0	1.1	1.1	1.0	1.0	1.1
Auburn	Max	0.98	0.98	0.98	0.99	0.98	0.99	0.99	0.98	0.99	0.98	0.98	0.98	0.98	0.99	0.98
	Min	0.95	0.96	0.96	0.96	0.95	0.96	0.97	0.95	0.96	0.95	0.96	0.96	0.96	0.96	0.96
	Pre	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	Rad	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/
Homestead	Max	0.91	0.91	0.91	0.91	0.91	0.92	0.91	0.91	0.91	0.91	0.92	0.91	0.92	0.92	0.91
	Min	0.83	0.82	0.83	0.82	0.82	0.83	0.83	0.82	0.83	0.83	0.83	0.82	0.83	0.83	0.82
	Pre	0.65	0.65	0.66	0.65	0.66	0.65	0.64	0.65	0.65	0.66	0.64	0.66	0.65	0.66	0.65
	Rad	1.25	1.23	1.23	1.24	1.22	1.24	1.23	1.24	1.23	1.23	1.23	1.23	1.23	1.23	1.23
Lake Alfred	Max	0.92	0.92	0.92	0.92	0.91	0.92	0.93	0.91	0.92	0.92	0.93	0.91	0.92	0.92	0.91
	Min	0.91	0.92	0.91	0.92	0.91	0.92	0.92	0.91	0.92	0.91	0.92	0.91	0.92	0.92	0.91
	Pre	0.70	0.69	0.69	0.68	0.72	0.70	0.69	0.70	0.69	0.70	0.68	0.70	0.69	0.72	0.71
	Rad	1.1	1.1	1.1	1.1	1.1	1.13	1.14	1.14	1.13	1.12	1.13	1.13	1.13	1.13	1.13

/: there is no observed solar radiation

Table 4.2: The k value of the KS test, the ratio of standard deviations for the projected and observed data ($F = \frac{Obs.SD}{Pro.SD}$) and the difference between mean of the projected and observed data ($\Delta = \overline{Proj.} - \overline{Obs.}$) for the 34 weather stations in Alabama, Florida, and Georgia. The difference for monthly precipitation was in percentage ($\Delta = (\overline{Proj.} - \overline{Obs.})/\overline{Obs.}$). / means no solar radiation

Location	KS test, k value				F				Δ			
	Max	Min	Pre	Rad	Max	Min	Pre	Rad	Max	Min	Pre	Rad
Auburn	0	1	1	/	1.01	1.04	2.24	/	0.2	-1.7	20.3	/
Belle Mina	0	0	1	/	1.03	1.06	2.87	/	0.1	-0.7	22.8	/
Brewton	0	1	1	/	1.06	1.13	3.09	/	0.0	-1.2	19.4	/
Cullman	0	1	1	/	1.03	1.08	2.70	/	0.3	-1.1	9.1	/
Grand Bay	0	0	1	/	1.03	1.10	3.20	/	0.4	0.1	21.3	/
Headland	0	1	1	/	1.02	1.06	2.61	/	0.1	-1.3	20.0	/
Marion Junction	0	0	1	/	1.04	1.08	2.62	/	-0.4	-0.2	16.3	/
Sand Mtn	0	0	1	/	1.04	1.09	2.59	/	-0.1	-0.5	21.7	/
Thorsby	0	1	1	/	1.00	1.06	2.47	/	-0.4	-1.0	24.9	/
Union Springs	0	0	1	/	1.02	1.06	2.70	/	0.3	-0.1	22.9	/
Alachua	1	0	1	1	1.04	1.10	2.20	0.82	-1.0	0.7	8.6	1.6
Citra	0	0	1	1	1.02	1.08	1.84	0.81	-0.2	-0.3	15.8	2.0
Homestead	0	0	1	1	1.10	1.21	1.55	0.81	-0.4	0.4	0.5	1.8
Immokalee	0	1	1	1	1.09	1.19	1.60	0.84	-0.2	0.2	9.1	0.5
Jay	0	0	1	1	1.03	1.06	2.82	0.88	-1.0	0.1	15.0	0.9
Lake Alfred	0	1	1	1	1.09	1.09	1.46	0.88	-0.3	-0.6	23.1	1.7
Macclenny	0	0	1	1	1.05	1.12	2.40	0.74	-0.5	-0.1	4.7	2.8
Marianna	0	0	1	1	1.05	1.07	2.79	0.93	-0.2	-0.4	15.3	1.0
Quincy	0	0	1	1	1.01	1.05	2.53	0.83	-0.8	0.0	15.6	1.8
Umatilla	1	0	1	1	1.06	1.08	2.11	0.89	0.3	0.4	15.7	1.3
Calhoun	0	0	1	1	1.03	1.04	2.31	0.92	-0.2	0.4	13.2	1.2
Floyd (Rome)	0	0	1	1	1.02	1.05	2.98	0.85	0.1	-0.1	12.9	1.8
Blairsville	0	0	1	0	1.00	1.02	3.18	0.99	-0.4	-0.2	15.8	0.0
Watkinsville	0	0	1	1	1.01	1.01	2.95	0.94	-0.3	-0.6	10.5	1.0
Elberton	0	0	1	0	1.01	1.04	3.59	1.02	0.0	-0.6	16.2	0.0
Griffin	0	0	1	1	1.03	1.02	3.33	0.99	-0.5	-0.2	6.9	0.4
Plains	0	0	1	1	0.99	1.01	3.49	0.95	-0.5	0.0	6.7	1.3
Eatonton	0	1	1	1	1.03	1.02	3.21	0.95	-0.5	1.5	8.5	0.9
Midville	0	0	1	1	1.03	1.01	3.18	0.97	-0.4	-0.4	9.3	0.8
Statesboro	0	0	1	1	1.00	1.02	2.73	0.95	-0.7	0.4	15.9	0.8
Attapulgus	0	0	1	1	1.04	1.08	2.22	0.89	-0.3	0.7	10.9	2.2
Tifton	0	1	1	1	1.02	1.02	2.47	0.91	-0.6	-0.8	8.7	0.7
Alma	0	0	1	1	1.04	1.00	3.40	0.98	-0.3	-0.4	12.3	1.8
Savannah	0	1	1	1	1.13	1.12	4.97	0.96	-0.1	0.9	6.0	1.5

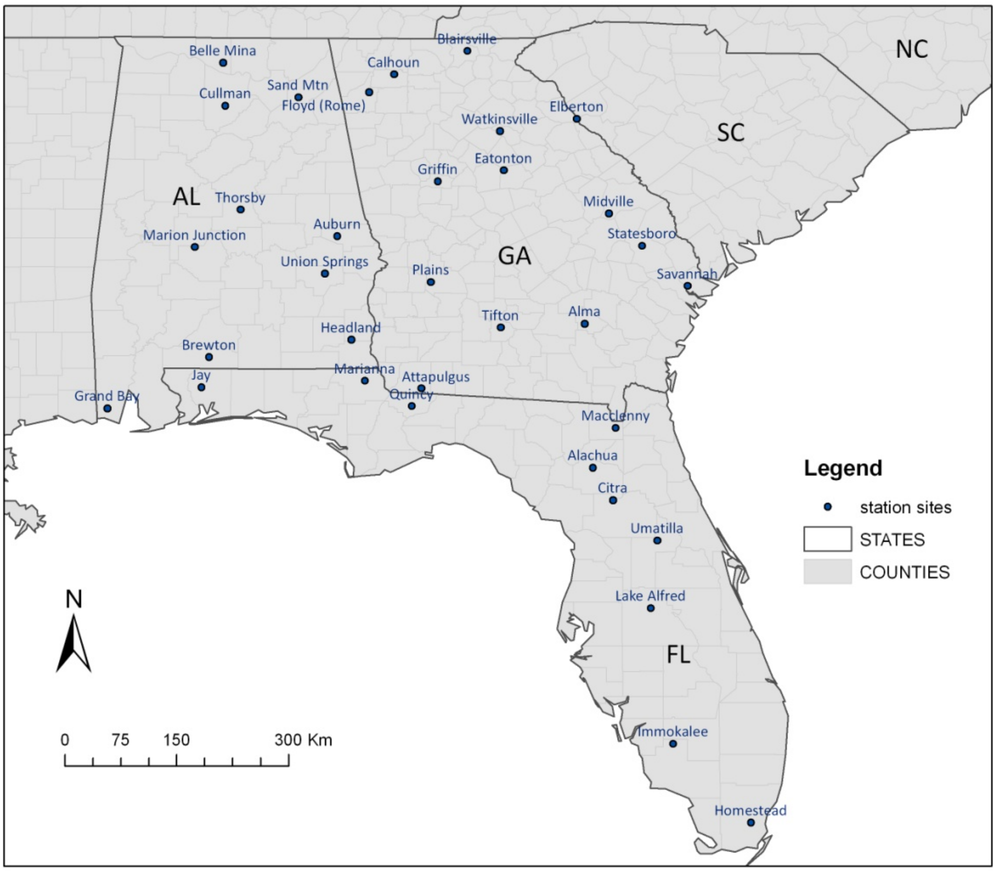
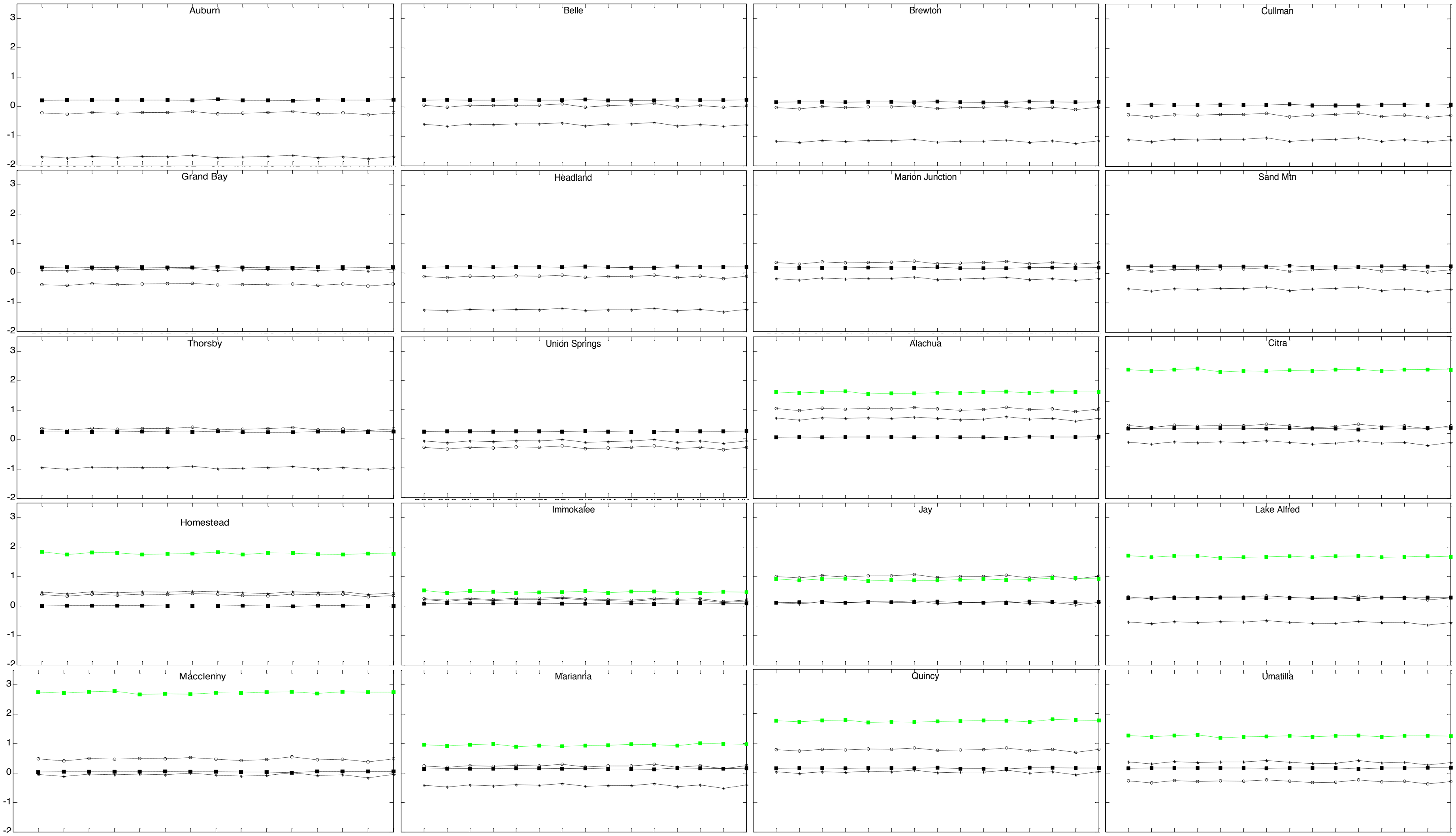


Figure 4.1: Study region and the 34 selected locations.


Auburn
Belle
Brewton
Cullman
Grand Bay
Headland
Marion Junction
Sand Mtn
Thorsby
Union Springs
Alachua
Citra
Homestead
Immokalee
Jay
Lake Alfred
Macclenny
Marianna
Quincy
Umatilla
3
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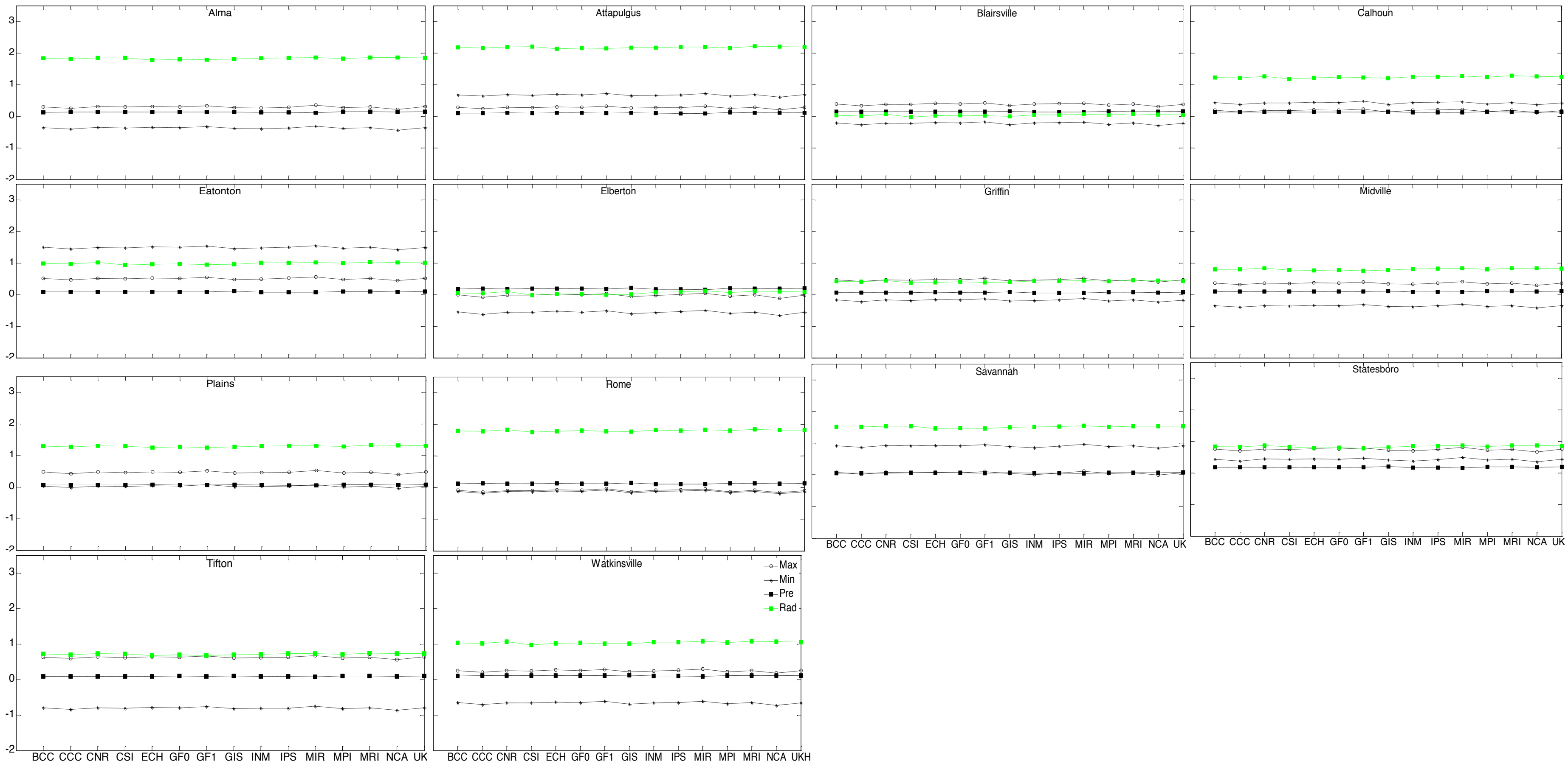
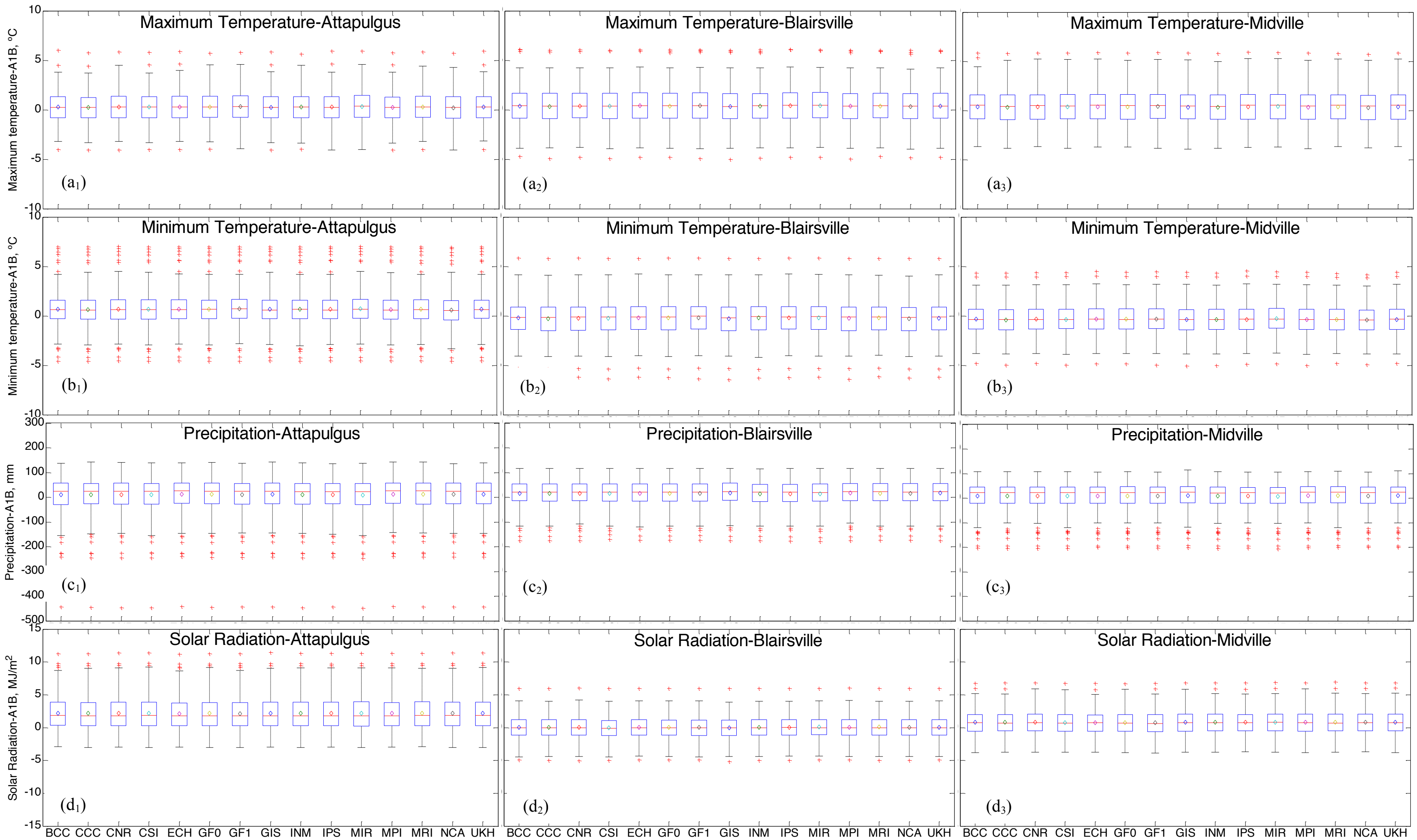


Figure 4.2: The difference between mean values of downscaled projections based on 15 GCMs and observations for 34 locations in Alabama, Florida, and Georgia. The climate variables were monthly maximum and minimum temperature, monthly precipitation, and monthly solar radiation from 1993 to 2012. Observed solar radiation in many years was missing for all locations in Alabama.


Maximum Temperature-Attapulgus
Maximum Temperature-Blairsville
Maximum Temperature-Midville
Maximum temperature-A1B, °C
(a₁)
(a₂)
(a₃)
Minimum Temperature-Attapulgus
Minimum Temperature-Blairsville
Minimum Temperature-Midville
Minimum temperature-A1B, °C
(b₁)
(b₂)
(b₃)
Precipitation-Attapulgus
Precipitation-Blairsville
Precipitation-Midville
Precipitation-A1B, mm
(c₁)
(c₂)
(c₃)
Solar Radiation-Attapulgus
Solar Radiation-Blairsville
Solar Radiation-Midville
Solar Radiation-A1B, MJ/m²
(d₁)
(d₂)
(d₃)
BCC CCC CNR CSI ECH GF0 GF1 GIS INM IPS MIR MPI MRI NCA UKH

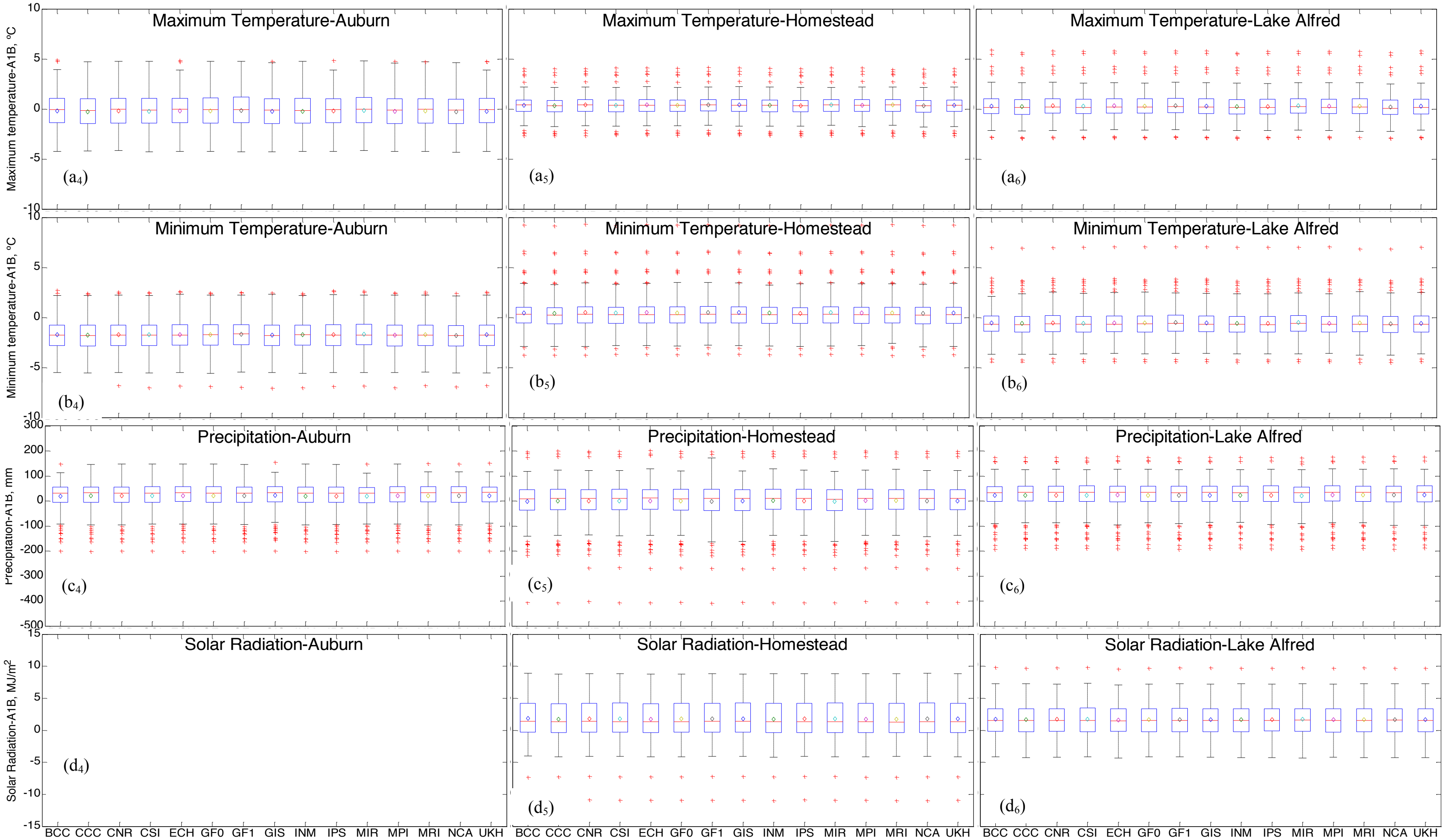


Figure 4.3: Box-plots for the bias of projected monthly maximum and minimum temperature, monthly precipitation, and monthly solar radiation base on 15 GCMs and gas emission scenario A1B from the corresponding observations from 1993 to 2012. Locations were Attapulgus, Georgia (a_1 - d_1); Blairsville, Georgia (a_2 - d_2), Midville, Georgia (a_3 - d_3), Auburn, Alabama (a_4 - d_4), Homestead, Florida (a_5 - d_5), and Lake Alfred, Florida (a_6 - d_6). Statistics, median, mean, lower quartile (25%), higher quartile (75%), whiskers, and outliers are shown in the plots.

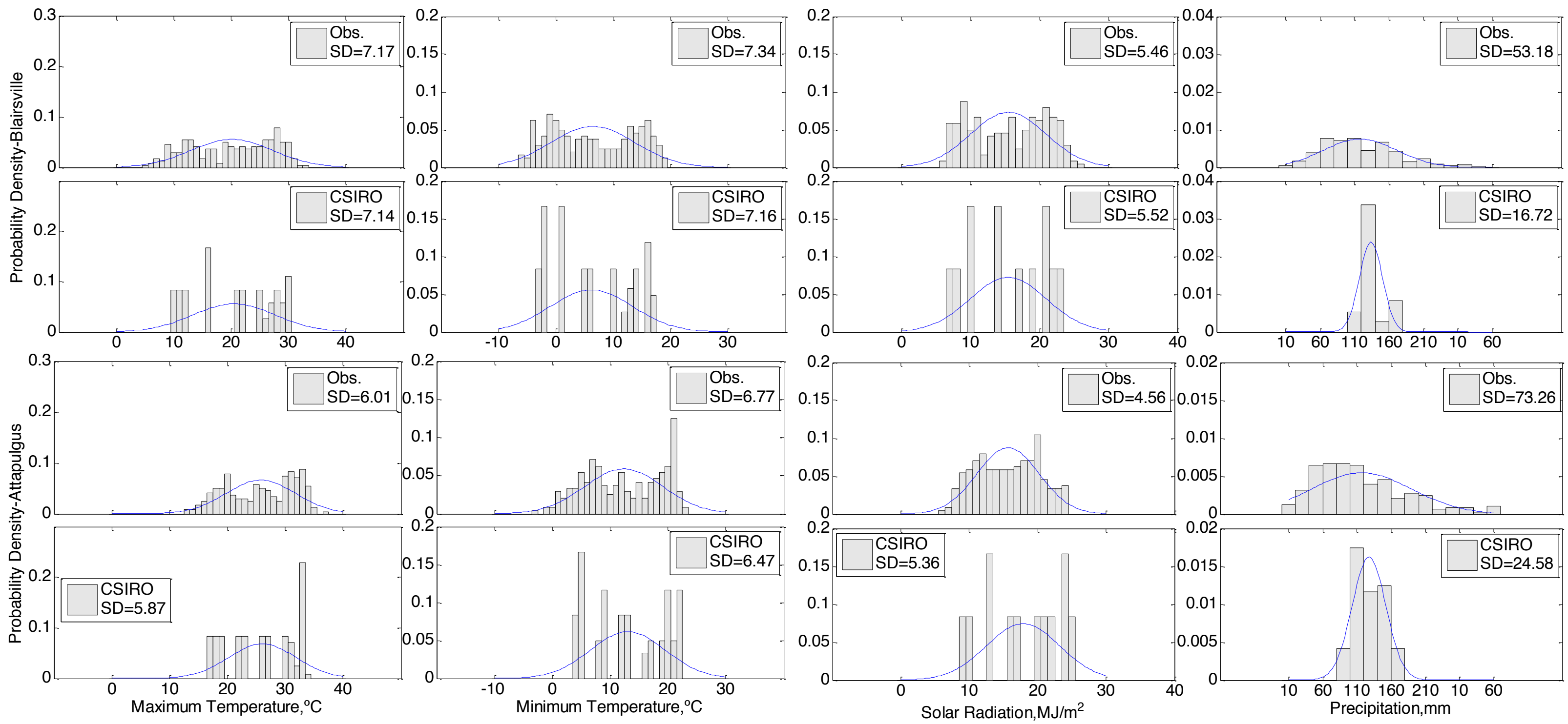


Figure 4.4: Probability histogram for the projections and observations from 1992 to 2012 for monthly maximum and minimum temperature, monthly precipitation, and monthly solar radiation based on the GCM CSIRO-30 and gas emission scenario A1B for Blairsville and Attapulgus, Georgia.

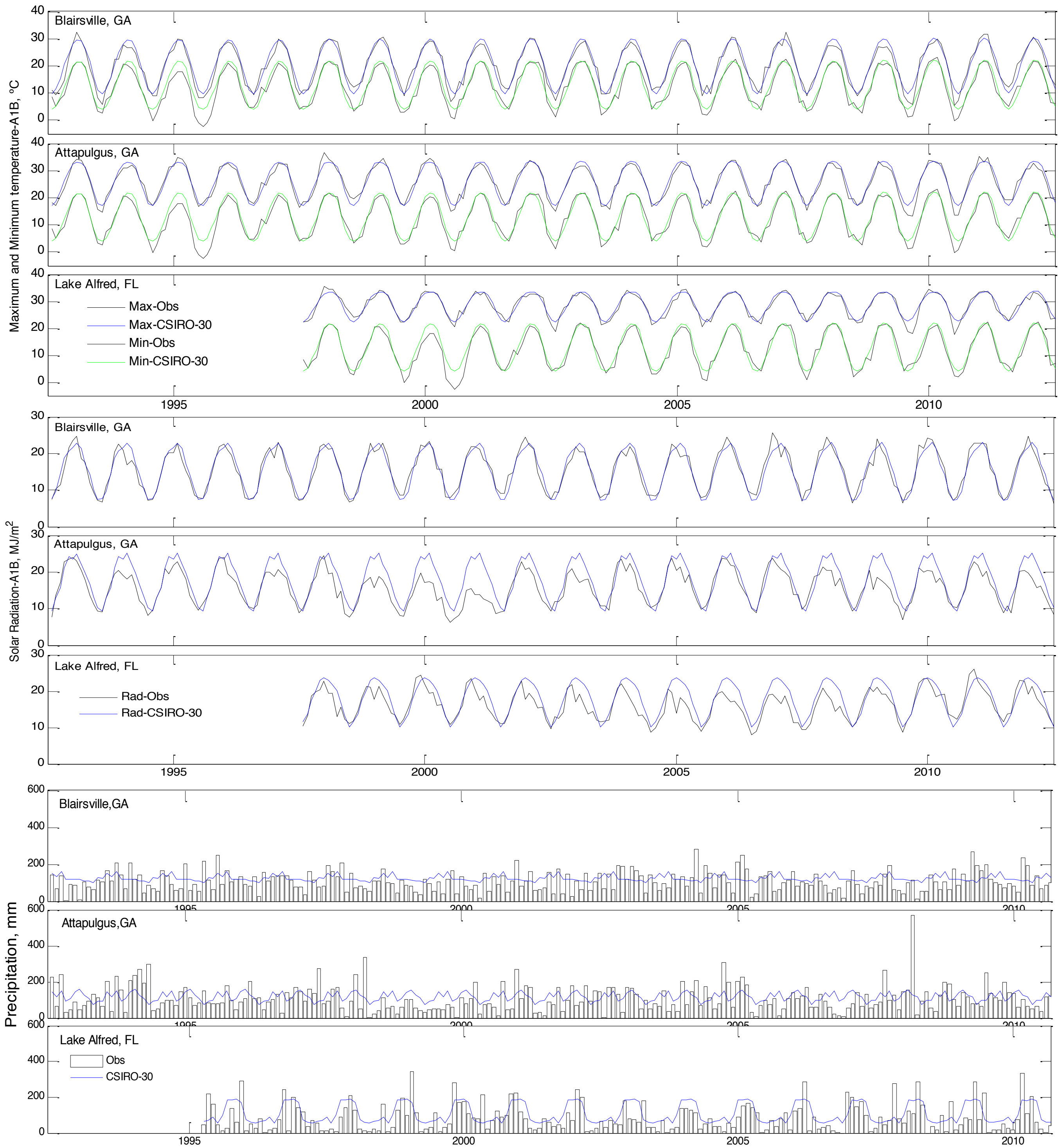
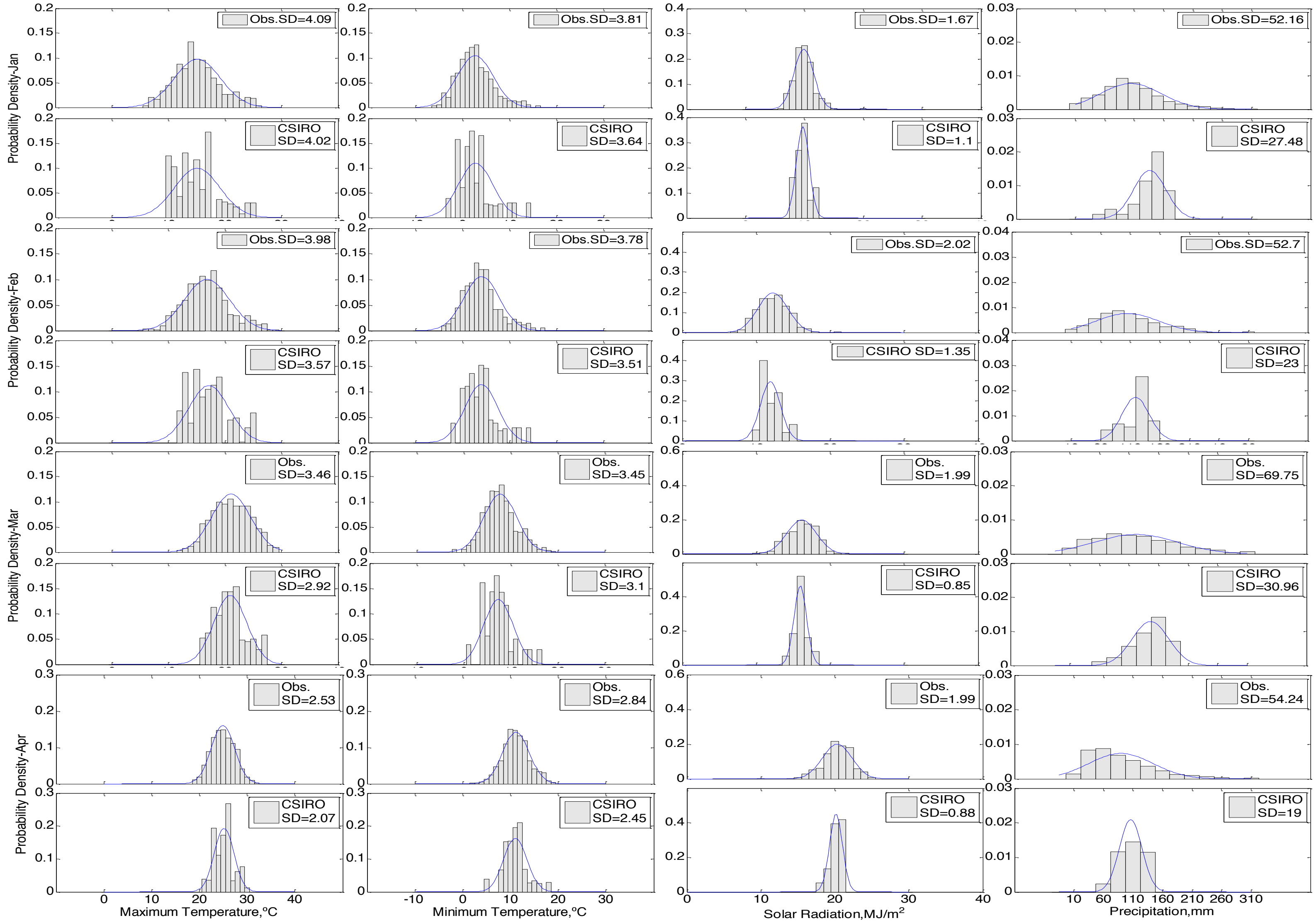
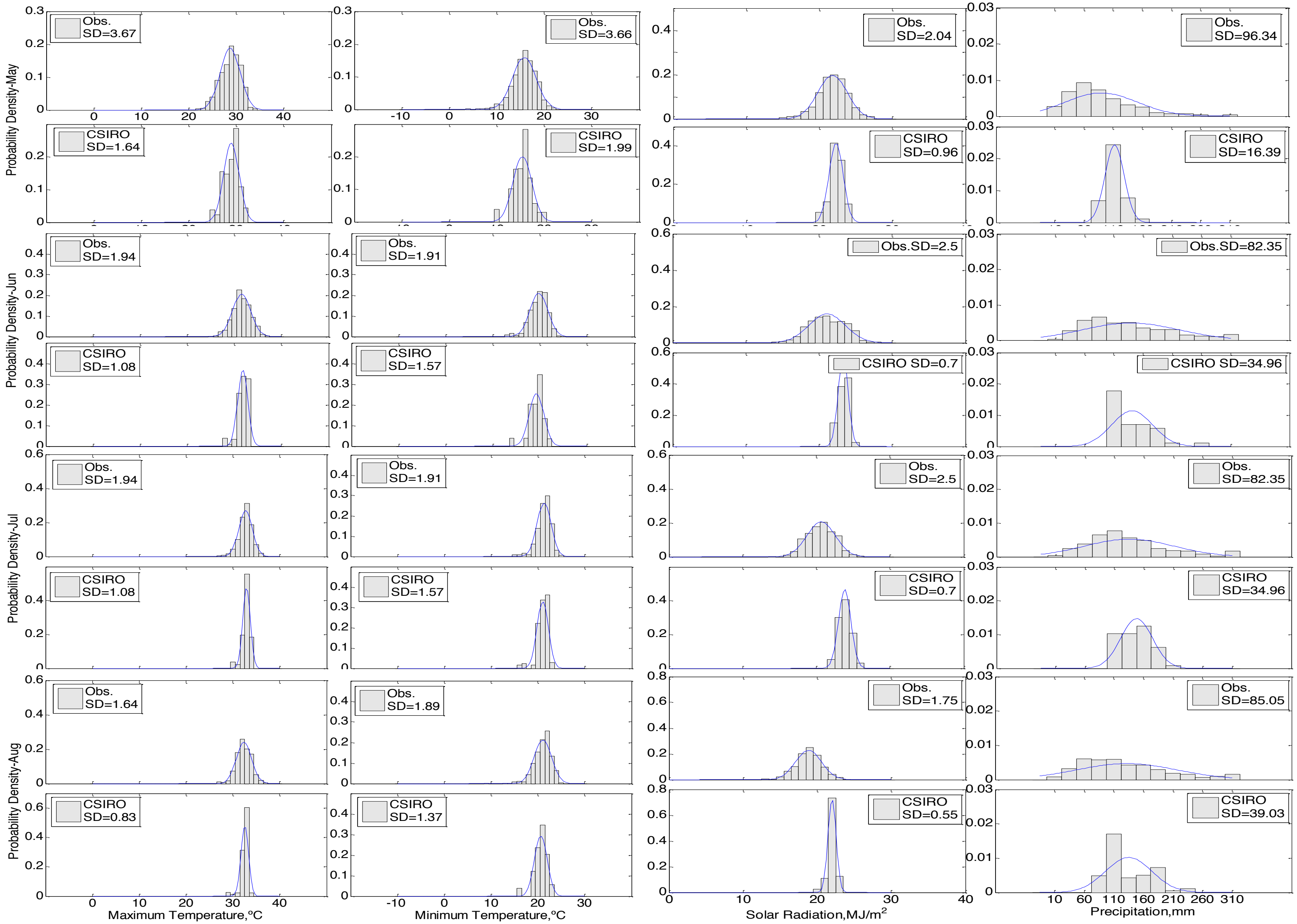


Figure 4.5: Time series for monthly maximum and minimum temperature, monthly precipitation, and monthly solar radiation for Blairsville and Attapulgus, Georgia from 1993 to 2012, and Lake Alfred, Florida from 1998 to 2012.


Obs.SD=4.09
Obs.SD=3.81
Obs.SD=1.67
Obs.SD=52.16
CSIRO SD=4.02
CSIRO SD=3.64
CSIRO SD=1.1
CSIRO SD=27.48
Obs.SD=3.98
Obs.SD=3.78
Obs.SD=2.02
Obs.SD=52.7
CSIRO SD=3.57
CSIRO SD=3.51
CSIRO SD=1.35
CSIRO SD=23
Obs. SD=3.46
Obs. SD=3.45
Obs. SD=1.99
Obs. SD=69.75
CSIRO SD=2.92
CSIRO SD=3.1
CSIRO SD=0.85
CSIRO SD=30.96
Obs. SD=2.53
Obs. SD=2.84
Obs. SD=1.99
Obs. SD=54.24
CSIRO SD=2.07
CSIRO SD=2.45
CSIRO SD=0.88
CSIRO SD=19
Probability Density-Jan
Probability Density-Feb
Probability Density-Mar
Probability Density-Apr
Maximum Temperature,°C
Minimum Temperature,°C
Solar Radiation,MJ/m²
Precipitation,mm


Obs.
SD=3.67
Obs.
SD=3.66
Obs.
SD=2.04
Obs.
SD=96.34
CSIRO
SD=1.64
CSIRO
SD=1.99
CSIRO
SD=0.96
CSIRO
SD=16.39
Probability Density-May
Obs.
SD=1.94
Obs.
SD=1.91
Obs.SD=2.5
Obs.SD=82.35
CSIRO
SD=1.08
CSIRO
SD=1.57
CSIRO SD=0.7
CSIRO SD=34.96
Probability Density-Jun
Obs.
SD=1.94
Obs.
SD=1.91
Obs.
SD=2.5
Obs.
SD=82.35
CSIRO
SD=1.08
CSIRO
SD=1.57
CSIRO
SD=0.7
CSIRO
SD=34.96
Probability Density-Jul
Obs.
SD=1.64
Obs.
SD=1.89
Obs.
SD=1.75
Obs.
SD=85.05
CSIRO
SD=0.83
CSIRO
SD=1.37
CSIRO
SD=0.55
CSIRO
SD=39.03
Probability Density-Aug
Maximum Temperature,°C
Minimum Temperature,°C
Solar Radiation,MJ/m²
Precipitation,mm

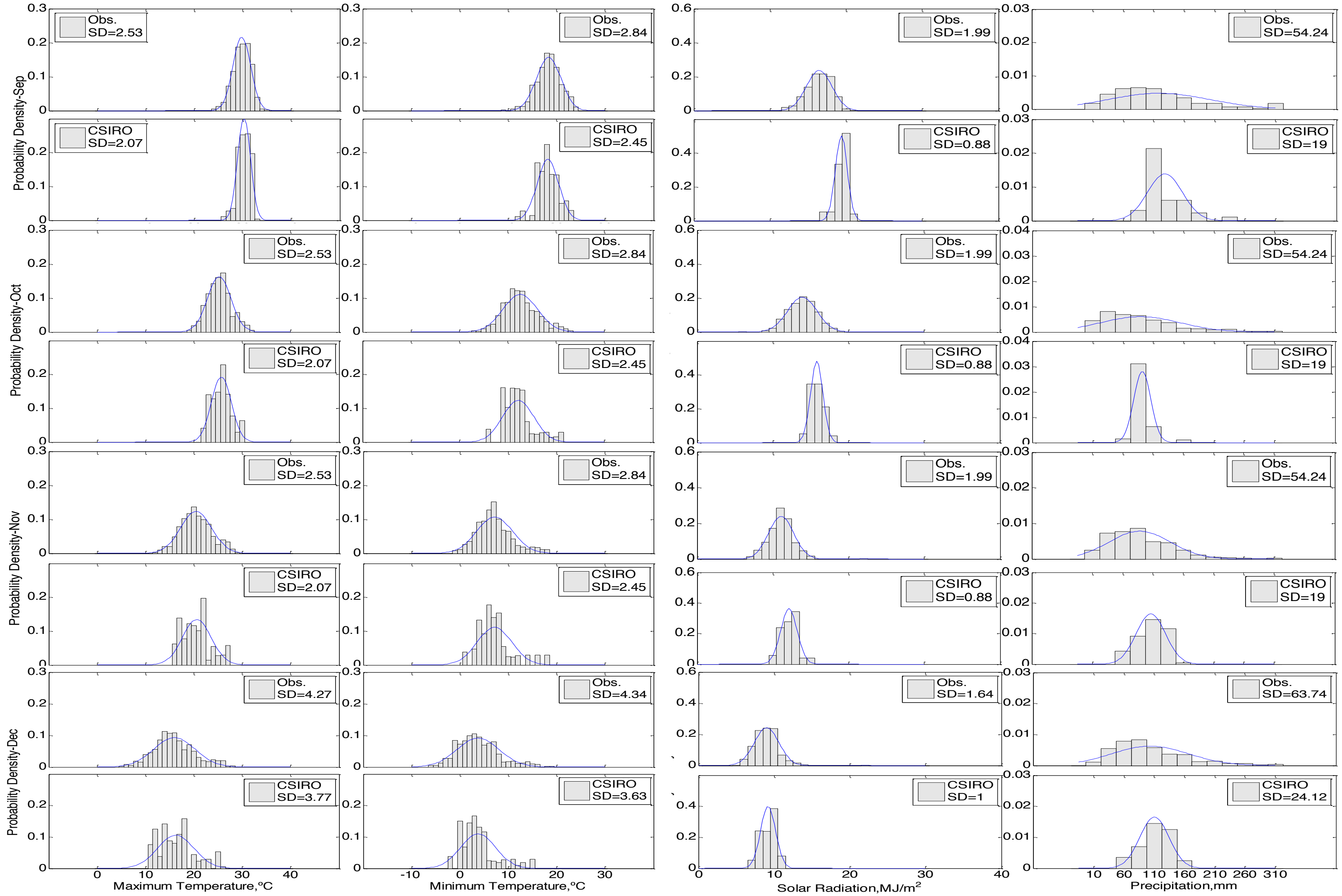


Figure 4.6: Probability density function for the observed and projected monthly maximum and minimum temperature, monthly precipitation, and monthly solar radiation for each month for the southeastern USA based on the data from the 34 selected locations.

APPENDIX I

Table S4.1: The General Circulation Models that were evaluated in this study.

Acronym	Source	Country	Resolution
BCCR-BCM2	Bjerknes Centre for Climate Research, University of Bergen, Norway	Norway	1.9º × 1.9º
CCCMA-31	Canadian Centre for Climate Modeling & Analysis	Canada	2.8º × 2.8º
CNRM-CM3	Me´te´o-France/Centre National de Recherches Me´te´orologiques	France	1.9º × 1.9º
CSIRO-30	CSIRO Atmospheric Research	Australia	1.9º × 1.9º
ECHO-G	Meteorological Institute of the University of Bonn, Meteorological Research Institute of KMA	Germany, Korea	3.9º × 3.9º
GFDLCM20	NOAA/Geophysical Fluid Dynamics Laboratory	USA	2.0º × 2.5º
GFDLCM21	NOAA/Geophysical Fluid Dynamics Laboratory	USA	2.0º × 2.5º
GISS-ER	NASA/Goddard Institute for Space Studies	USA	4º × 5º
INMCM-30	Institute for Numerical Mathematics	Russia	4º × 5º
IPSL-CM4	Institute Pierre Simon Laplace	France	2.5º × 3.75º
MIROCMED	Center for Climate System Research, National Institute for Environmental Studies, and Frontier Research Center for Global Change	Japan	2.8º × 2.8º
MPIECH-5	Max Planck Institute for Meteorology	Germany	1.9º × 1.9º
MRI-232A	Meteorological Research Institute	Japan	2.8º × 2.8º
NCARPCM1	National Center for Atmospheric Research	USA	2.8º × 2.8º
UKHADCM3	Hadley Centre for Climate Prediction and Research/Met Office	UK	2.75º × 3.75º

CHAPTER 5

CLIMATE CHANGE IMPACT ON MAIZE YIELD AT LOCAL LEVEL SOUTHEASTERN USA FOR 2050 AND 2070 BASED ON THE ANALYSIS OF TWO CROP SIMULATION MODELS[1]

[1] Bao, Y., Hoogenboom, G., Seymour, L., McClendon, R.W., Vellidis, G., Ortiz, B. and Mote, T. to be submitted to Climate Research

5.1. INTRODUCTION

The availability, stability, utilization, and access to food determine the well-being of human-beings (Schmidhuber & Tubiello 2007). The foundation of the human food supply is cereal production, including maize (*Zea mays L.*), wheat (*Triticum aestivum L.*), rice (*Oryza sativa* L.), which contribute most of the calories that humans directly or indirectly consume (Cassman 1999). Climate is one of the most important factors to control the future of our food supply and overwhelming evidence already has shown that climate change is already exerting a considerable drag on crop yield (Gosling et al. 2011, Lobell et al. 2011). A significant impact of climate on maize has been found based on both historical data and impact studies (Tsvetsinskaya et al. 2003, Lobell & Field 2007, Eckersten et al. 2010, Lobell et al. 2011, Rowhani et al. 2011).

Meteorological observations have shown that the global average temperatures has increased by about 0.1 °C per decade (Hartmann 2013). In comparison to changes in average temperature and precipitation, more adverse impact on crop production can be expected from changes in extreme weather events. The frequency, intensity, and duration of extreme climate events, e.g., heat waves, droughts, floods, warm nights has increased since 1950 (Hartmann 2013) and are expected to keep increasing (Ainsworth & Ort 2010, Hatfield et al. 2011).

Studies based on field experiments and crop simulations models have provided understanding of biophysical and biological processes of maize response to warmer growing seasons, reduced water supply, and increased carbon dioxide (Bunce 2004, Rotter et al. 2011, Wang et al. 2011). In general, a negative response to rising temperatures has been found for maize production (Kurek et al. 2007, Lobell & Field 2007, Butler & Huybers 2013). Precipitation is also an important driver that affects the inter-annual variability of maize yield. However, under climate change conditions the effect of temperature can be larger than for precipitation for many situations (Burke et al. 2009, Lobell et al. 2011, Asseng et al. 2013). CO_2 enrichment is generally believed to be able to offsite some of the negative effects from high temperature extremes on maize (Challinor & Wheeler 2008). However, some studies also concluded that maize does not directly benefit an increase in CO_2 concentration (Long et al. 2006, Gosling et al. 2011). Therefore, uncertainties still exists whether maize growth and development is affected by CO_2 concentration.

The United Nations Food and Agriculture Organization (UNFAO) recently stated that a 70% increase in agricultural productivity will be required by 2050 to meet the growing food demand (Petherick 2011). Fortunately, some studies have shown that the adaptation of agriculture could result in an increase in yield of cereal crops under a warming climate (Ainsworth & Ort 2010). In general, adaptation is the adjustment of agronomic practices, agricultural processes, and capital investments in response to climate change threats. It could especially increase maize yield for mid- to high-latitude region to take advantage of positive aspects of climate change for those environments (Solomon et al. 2007).

Commonly used approaches to assess the impact of climate change on agriculture and to provide adaptation strategies include agroclimatic indices and Geographic Information Systems (GIS) (Carter & Saarikko 1996), statistical models and yield functions (Parry et al. 2004, Lobell et al. 2011, Altinsoy et al. 2013), and crop simulation models (White et al. 2011) . However, crop simulation models are the most popular method to analyze the climate change impact on crop production and to determine up-to-date adaptation information for policy and decision-makers because of the ability to analyze the sensitivity of crop yield and management to climate change Climate models are usually applied to generate future weather inputs for crop simulation models.

Uncertainties, therefore, are introduced by both generation of future climate and crop simulation models (Mearns (2010), Knutti et al. (2008), and Bao et al. (2014)).

Previous studies have concluded that the uncertainties about future climate were "the natural internal variability of the climate system, the trajectories of future emissions of greenhouse gases and aerosols, the response of the global climate system to any given set of future emission/concentrations, and the application of downscaling methods yields higher resolution projections but presents another source of uncertainty" (Cox & Stephenson 2007, Tebaldi & Knutti 2007, Knutti et al. 2008, Mearns 2010). Although progress has been made on characterizing and analyzing uncertainties (Christensen et al. 2007), it is not likely that they can be mitigated on the short-term (Knutti 2010). Given the uncertainties of the climate scenarios, a good approach is to use several scenarios as inputs for the crop models to provide a range of possibilities for impact analysis (Iglesias 2006). Climate projections based on multiple general circulation models (GCMs) or regional climate models (RCMs) ensembles can also address the uncertainties from climate models (Tebaldi & Knutti 2007, Knutti 2010, Asseng et al. 2013). Furthermore, uncertainties from gas emission scenarios can also be decreased by using plausible projected emission scenarios (Moss et al. 2010).

The uncertainty is also an issue for applying crop simulation model in climate change impact studies. Until recently most climate impact studies have used single crop models for the analysis. Although the complex interaction of crop-climate-soil cannot be simulated at an extreme detailed level (Rotter et al. 2011), it has been shown that a single crop model can accurately simulate crop yield for a range of environments, especially if the input information is sufficient (Soler et al. 2007, Asseng et al. 2013). However, a wide divergence in crop models has been found since they represent crop development and growth differently (Palosuo et al. 2011, Rotter et al. 2011, Carter 2013). Several studies have shown that a greater proportion of the uncertainty in climate change impact projections was due to the variation among crop models than due to the variation among downscaled GCMs (Malcolm et al. 2012, Asseng et al. 2013). However, an the ensemble of multiple crop models can offer a more robust basis for projecting future crop yields and their uncertainties than relying on individual model simulations (Semenov & Stratonovitch 2010, Palosuo et al. 2011, Rötter et al. 2012, Asseng et al. 2013, Carter 2013).

The National Corn Growers Association (NCGA, http://www.ncga.com) reported that 32.1% of the world's maize is produced by United States and 2% of the US maize is from the southeastern USA. As summarized above, maize production is important and the potential impact of climate change on crop varies by region. Furthermore, although studies concluded that more uncertainties could be introduced to climate change impact studies by crop models, few studies so far have been conducted that have used multiple maize simulation models (Carter 2013). This study therefore dedicated the impact of changing climate in 2050 and 2070 on maize production in the southeastern USA. The objectives were 1) to determine the impact of changing climate in maize grain yield in 2050 and 2070 for the southeastern USA, 2) to determine the possible adaptation strategies for future maize planting in the southeastern USA.

5.2. MATERIALS AND METHODS

5.2.1 HISTORICAL CLIMATE

22 locations that belong different climate divisions were selected for Alabama (AL), Florida (FL), and Georgia (GA) to represent the southeastern USA. The climate patterns were divided as 9 zones for Georgia, 8 zones for Alabama, and 8 zones for Florida (http://www.esrl.noaa.gov/psd/data/usclimdivs/data/map.html). These climate divisions were Northwest (1), North Central (2), Northeast (3), West Central (4), Central (5), East Central (6),

Southwest (7), South Central (8), and Southeast (9) for GA. North Valley (1), Appalachian Mountain (2), Upper Plains (3), Eastern Valley (4), Piedmont Plateau (5), Prairie (6), Coastal Plain (7), and Gulf (8) for AL. Northwest (1), North (2), North Central (3), South Central (4), Everglades (5) and Southwest Coast (6), Lower East Coast (7), and Keys (8) for Florida (Table 5.1). Because the Southwest Coast, Lower East Coast, and Keys in Florida are not suitable for maize production, only the remaining 5 climate divisions for Florida were considered in this study. Weather inputs from 1981 to 2010 with daily minimum temperature (ºC), maximum temperature (ºC), and precipitation (mm) were obtained from the National Climatic Data Center (NCDC) for these 22 locations in order to account for the inherent annual weather variability. The solar radiation (MJ/m^2) was then generated with Weather Generator for Solar Radiation (WGENR), which is based on a multivariate stochastic process using minimum and maximum temperature and precipitation (Garcia y Garcia & Hoogenboom 2005, Garcia y Garcia et al. 2008). The southern locations had higher average values for minimum and maximum temperatures than the northern region, while the average monthly precipitation was very similar for all locations (Table 5.1).

5.2.2 CLIMATE CHANGE SCENARIOS

Daily weather data of reference years (1981 to 2010) were perturbed by SimCLIM to generate daily weather data as inputs for the crop models to represent the climate change projections for 2050 and 2070. SimCLIM was applied to southeastern USA for generating site-specific future climate for Bao et al. (2015), which has been commonly applied in many regions (Kenny et al. 2001, Albertin et al. 2011, Jha 2012). Pattern-scaling was used for statistical downscaling of the global projections of 15 GCMs for the southeastern USA. Based on the study of Bao et al. (2015), the best way to minimize uncertainties that could be introduced into the climate projections is to perturb long-term historical daily weather data. Multiple climate scenarios were generated for both 2050 and 2070 based on 15 GCMs (Table 5.3) and three gas emission scenarios A1B (Medium), A2 (High), and B1 (Low). The modifications for daily weather data based on the delta method

$$Max\ Temperature_{future} = Max\ Temperature_{reference} + \Delta Mean\ Temperature$$

$$Min\ Temperature_{future} = Min\ Temperature_{reference} + \Delta Mean\ Temperature$$

$$Precipitation_{future} = Precipitation_{Reference} \times (1 + \Delta Precipitation\ )$$

$\Delta\mathrm{Mean\ Temperature}$ is the change in monthly mean temperature for 2050 or 2070 from the baseline. $\Delta Precipitation$ is the percentage change in monthly precipitation for 2050 or 2070 from the baseline.

The projected CO_2 concentration for 2050 was 533 ppm for the A1B and A2 scenarios and 487 ppm for the B1 scenarios. A higher CO_2 concentration was projected for 2070, which was 613 ppm for A1B, 627 ppm for A2, and 522 ppm for B1.

5.2.3 CROP MODELS

In order to analyze the effects of climate impact on maize yield in the southeastern USA for 2050 and 2070, the Cropping System Model (CSM)-CERES-Maize and Erosion-Productivity Impact Calculator (EPIC)-Maize were applied to simulate present and future maize yield. The CSM-CERES-Maize is one of the modules of the Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al. 2003, Hoogenboom et al. 2012). The individual plant modules of CSM are designed for simulating different crops, in order to be able to provide an accurate prediction of the development stages of specific cultivar. Each module simulates growth, development, and yield of a specific crop grown on a uniform area of land by considering weather, soil, management and genetics for single or multiple seasons and for crop rotations for any location where the minimum input data for the models are available (Hunt & Boote 1998, Jones et al. 2003). Potential growth depends on photosynthetically active radiation and its interception, where the actual biomass production is constrained by stresses such as temperature, nitrogen, and water. It also considers the sensitivity of crop to CO_2 concentration.

EPIC was designed to estimate soil productivity as affected by erosion throughout the U.S. (Williams et al. 1989). The components of the EPIC model include weather, hydrology, erosion-sedimentation, nutrient cycling, crop growth, tillage, soil temperature, economics, and plant environment control (Jones et al. 1984b, a, Sharpley et al. 1984, Williams et al. 1984, Williams et al. 1989) to simulate multiple crops. The yield is estimated using the harvest index and aboveground biomass. The aboveground biomass in turn is a function of photosynthetically active radiation and leaf area. Leaf area is calculated as a function of heat unit accumulation, crop development states, and crop stresses.

5.2.4 SOIL AND CROP MANAGEMENT

The soil types (Table 5.1) and profile data for 22 locations were obtained from both the collection of Perkins et al. (1978, 1979, 1982, 1983, 1985, 1986) and the National Cooperative Soil Survey (NCSS, http://ncsslabdatamart.sc.egov.usda.gov). The planting dates that were considered included February 15, March 1 and 15, April 1 and 15, May 1 and 15, and June 1, 15, and 30 to seek for effective adaption strategies for a changing climate. The plant population at seeding was around 6 to 8 plants/m^2, row spacing was 76 cm, and the planting depth was 5 cm, which were the same that were used in the maize performance tests from the University of Georgia (UGA) College of Agricultural & Environmental Science (CAES) Statewide Variety Testing (SWVT) program (Coy et al. 2010). Both rainfed and irrigated management practices were considered. For irrigated maize, both models set automatic irrigation with a threshold of 50%

of available soil moisture. This means that irrigation is “triggered” or applied when 50% of the available soil moisture has been depleted. The previous crop grown in the field was also set as maize for CSM-CERES-Maize.

The hybrids Dyna-Gro V5373VT3, Pioneer 33M57(Hx1/LL/RR2), SS 731CL, Croplan Genetics 851 VT3 PRO, Croplan Genetics 8756 VT3, DeKalb DKC69-71(RR2/YGCB), and Pioneer 31D58 were used to represent the planted hybrids in the three states, which were calibrated and evaluated by Bao et al. 2015 (Table 5.2). We made the assumption that the current range of hybrids might be suitable for future maize production, as they represent a range of different maturities. However, seed companies release new varieties on a regular basis. In addition to the calibrated hybrids, daily observed weather data (minimum temperature, maximum temperature, precipitation, and solar radiation), soil profile data (bulk density, pH in water, soil water content, and clay on each soil layer), and crop management (planting date, population, seed depth, row spacing, and date and amount for irrigation and fertilization) were obtained as input for both models.

5.2.5 STATISTICAL ANALYSIS

The Analysis of Variance (ANOVA) was applied to test the difference among simulated maize yield based on multiple climate scenarios and crop management scenarios: (1) simulated grain yield based on 15 GCMs, (2) simulated grain yield based on three gas emission scenarios, (3) simulated grain yield for the 2050 and 2070 projections, (4) simulated maize yield based on two crop models. The null hypothesis of ANOVA tests was that simulations based on different input combinations provided the same yield predictions. The significance level was 0.05.

5.3 RESULTS

5.3.1 CHANGES IN CLIMATE

The combination of GCMs (15) and gas emission scenarios (3) generated 45 climate scenarios for both 2050 and 2070 for each location. In general, the changes in both monthly temperature and monthly precipitation were larger for 2070 than for 2050 (Table 5.4). In Alabama, the changes in monthly temperature for 2050 showed that the smallest change was 1.3 °C for all locations, while the largest change varied with location ranging from 3 °C to 4.6 °C. For 2070, all locations in Alabama showed at least 1.7 °C of increase in the monthly temperature, while the largest change varied from 4.5 °C to 6.8 °C. Monthly temperature changes in Florida were much smaller than for Alabama. They ranged from 0.8 °C to 2.8 °C for 2050 and from 1.1 °C to 4.2 °C in 2070 for Florida. For Georgia, the changes ranged from 1.1 °C to 3.9 °C for 2050 and from 1.4 °C to 5.8 °C for 2070. The changes in monthly precipitation from the baseline climate data varied significantly for each location in Alabama, with extremes for some locations. Calera, Alabama showed the largest change in monthly precipitation which ranged from -58.7% to 77.5% for 2050 and from -87.6% to 115.7% for 2070. For Montgomery, Alabama the changes ranged from -30.8% to 53.3% for 2050 and from -46% to 79.6% for 2070. For Bankhead, Alabama the changes in precipitation ranged from -19.4% to 42% for 2050 and from -29 to 62.7% for 2070. The other locations showed similar changes in precipitation, ranging from -14.2% to 21.1% for 2050 and from -21.2% to 31.5% for 2070. For Florida, the changes in monthly precipitation ranged from -11.7% to 18.8% for 2050 and from -18.3% to 28.1%, while for Georgia they ranged from -17.4% to 32.6% for 2050 and from -25.9% to 48.7% for 2070.

5.3.2 PREDICTED MAIZE GRAIN YIELD

5.3.2.1 RAINFED YIELD FOR THE REFERENCE YEARS

The analysis for grain yield for the reference years was based on the average values for seven hybrids for 30 years for each of the 10 planting dates, which ranged from February 15 to June 30 (Figure 5.1). Rainfed grain yield that based on the simulations of both crop models showed sensitivity to different planting dates for all locations. For maize planted in February and March, both crop models predicted no yield especially for locations in northern Georgia and Alabama, because low temperatures caused a delay in germination.

For the February 15 planting date, CSM-CERES-Maize predicted about 2321 kg/ha to 4280 kg/ha for Mobile, Alabama and for all locations in Florida except for Chipley. The grain yield for the other locations ranged from 0 to 1383 kg/ha. As planting dates were changed to later dates from March 1 and 15, grain yield increased. Compared to February 15, grain yield increased. Yield for Mobile, Alabama reached 4500 kg/ha for March 1 and 6700 kg/ha for the March 15 planting dates. For the locations in Florida, yield ranged from 3700kg/ha to 5600 kg/ha for March 1 and from 4500 kg/ha to 7500 kg/ha for the March 15 planting date. However, Chipley, Florida had lower yields that were about 1797 kg/ha for March 1 and 2541 kg/ha for March 15. Grain yields for Colquitt, Georgia and Tifton, Georgia were about 3000 kg/ha for March 1 and 3800 kg/ha for March 15. The other locations had grain yield that ranged from 7 kg/ha to 2707 kg/ha. Grain yields continued to increase as planted dates were moved to April and May, and then slightly decreased when planted in June. Blairsville, Georgia showed the largest change with the change in planting dates; simulated yield reached 7237 kg/ha on May 15 and then dropped to 1708 kg/ha for the June 30 planting date. For Mobile, Alabama and Chipley, Florida yield continued to increase until the latest planting date of June 30. The grain yield for

Bankhead, Calera, and Mobile in Alabama and Ocala in Florida ranged from 6000 kg/ha to 8000 kg/ha for planting between April and June. Naples, Florida and Griffin, Georgia showed a relatively higher grain yield that ranged from 7913 kg/ha to 10615 kg/ha. The remaining locations had yield that ranged from 3200 kg/ha to 7571 kg/ha.

Simulated rainfed grain yield based on EPIC showed similar trends compared to the simulations based on the CSM-CERES-Maize model (Figure 5.1). Even lower yield were simulated because of some temperature limitations. For maize planted on February 15 and March 1, only Avon, Naples, and Ocala in Florida had yields that ranged from 4862 kg/ha to 6474 kg/ha, while the other locations had had a simulated yield that was less than 2657 kg/ha. For the March 15 planting date the southern locations had a simulated yield that ranged from 5414 kg/ha to 9655 kg/ha, while yield for the other locations ranged from 161 kg/ha to 4724 kg/ha. The simulated yield for maize that planted during April and June ranged from 4512 kg/ha 9931 kg/ha, while the simulated yield for the late June 30 planting decreased by about 500 kg/ha to 1000 kg/ha compared to the June 15 planting.

5.3.2.2 IRRIGATED YIELD FOR THE REFERENCE YEARS

Irrigated yield for most of the locations was higher compared to rainfed yield because there was no water limitation (Figure 5.1). However, there was still a temperature limitation for February 15 and March 1 planting dates, especially for the northern areas of the region and simulated yield decreased for the later planting dates in June based on both crop models. Simulated yield of the CSM-CERES-Maize model February 15 and March 1 ranged from 0 to 5344 kg/ha for most locations in Alabama, Florida, and Georgia. Mobile in Alabama had yields from 4690 kg/ha to 7159 kg/ha. For Naples, Florida yield was 12458 kg/ha and 12344 kg/ha for the February 15 and March 1 planting dates, respectively. For the March 15 to June 30 planting dates, Heflin, Montgomery, and Scottsboro in Alabama, Chipley in Florida, and Colquitt and Savannah in Georgia had a simulated yield that was less than 6300 kg/ha. Yields at the other locations ranged from 6900 kg/ha to 12655 kg/ha. When planted on June 15 and June 30, simulated yield at Belle Mina in Alabama, Avon in Florida, Blairsville, Elbert, and Rome in Georgia dropped to a range of 1787 kg/ha to 5560 kg/ha.

Irrigated grain yield based on the simulations with EPIC had a very similar trend when compared to the simulations based on the CSM-CERES-Maize model. Low temperatures on February 15, March 1 and Mar 15 resulted in a low yield for locations that were north than Calera in Alabama, which had yield that was less than 2715 kg/ha. The other locations generally had a simulated yield that was less than 3481 kg/ha for maize planted on February 15 and March 1 and a yield of 5126 kg/ha to 8885 kg/ha for maize planted on March 15. However, Avon, Naples, and Ocala in FL were not limited by low temperature and as a result yield ranged from 4713 kg/ha to 8986 kg/ha for maize planted in February and March. Grain yield increased for all locations when planting date was moved to April to June 15, with yield ranging from 7047 kg/ha to 11133 kg/ha. For planting on June 15 yield decreased to 4922 kg/ha to 9039 kg/ha.

5.3.2.3 STATISTICAL ANALYSIS FOR MAIZE YIELD UNDER FUTURE CLIMATE

Grain yield for multiple hybrids was simulated based on a wide range of climate scenarios in this study. In order to be able to analyze the predictions, ANOVA tests were conducted to identify whether significant differences exist among simulated yield for each hybrid based on 15 GCMs, three gas emission scenarios, and two crop models for the projections for 2050 and 2070 (Table 5.5). For yield simulated with the CSM-CERES-Maize model, significant differences were found for rainfed production for 2050 based on 15 GCMs and also for three gas emission scenarios. The p-value of those ANOVA tests was 0. However, simulated yield for irrigated production for 2050 did not show significant differences among the GCMs or gas emission scenarios. The p-value for GCMs was 1 and ranged from 0.065 to 0.638 for gas emission scenarios. For 2070, the 15 GCMs (p-value was 1) did not show a significantly different effect on rainfed production, but there was a significant difference among the three gas emissions (p-value was 0). For irrigated production for 2070, the 15 GCMs (p-value was 0) did show a significantly different effect on yields. The three gas emission scenarios showed a significantly different effect for irrigated production for 2070 for the hybrids Pioneer 33M57(Hx1/LL/RR2), SS 731CL, Croplan Genetics 851 VT3 PRO, DeKalb DKC69-71(RR2/YGCB), and Pioneer 31D58, but not for the hybrids Dyna-Gro V5373VT3 (p-value was 0.116) and Croplan Genetics 8756 VT3 (p-value was 0.259). Significant differences were found among the GCMs and gas emission scenarios for both the 2050 and 2070 projections for all hybrids for both rainfed and irrigated production based on yield simulated with the EPIC model, which p-value of all tests was 0.

5.3.2.4 CHANGES IN YIELD FOR 2050 BASED ON CSM-CERES-MAIZE MODEL

Both the rainfed and irrigated grain yield for the 2050 projection was analyzed based on the differences from baseline yields (Figure 5.2). The commonly used gas emission scenario A1B was selected for this analysis. For the February 15 planting date, the changes in rainfed maize yield varied with location and also climate scenario. The baseline rainfed grain yields for February 15 was zero for Blairsville and Elberton in Georgia and Belle Mina in Alabama, which caused the changes in percentage as infinite. There was a variation for the changes for all locations. The median changes ranged from 0 to 50% based on all climate scenarios. The northern locations generally showed a larger variation than the southern locations. The largest increase in yield was 510% more than the baseline yield for Rome, Georgia, due to its northern location and relatively low yield for early planting dates. However, decreases in yield reached 100% under some climate scenarios at Rome, Georgia. The changes in yield ranged from -100% to 200% for Midville and Griffin in Georgia. The negative value means a decrease from baseline yields. Grain yields at the other locations changed from -100% to 150% from baseline.

Grain yield for rainfed production for on the March 1 planting date for 2050 still showed that the northern locations were more sensitive to an increase in temperature than the southern locations (Figure 5.2). The baseline yield for Blairsville, Georgia was still zero similar to the February 15 planting date. The largest changes were found for Rome, Georgia, with yield changes that ranged from -100% to 1150%. Griffin and Savannah, Georgia showed changes in yield that ranged from 5% to 170%. Bankhead, Belle Mina, and Heflin in Alabama and Midville, Milledgeville, and Tifton in Georgia showed changes in yield from -100% to 270%. Grain yields at the other locations generally showed increases in yields, which were about 2% to 30%. The changes for rainfed yield for the March 15 planting date still showed similar trend as for March 1. However, large changes that ranged from -110% to 700% were found at the locations in Georgia but not for Blairsville and Colquitt, Georgia. The rest locations have relatively smaller changes that ranged from -43% to 32%. The changes for rainfed grain yield for the other planting dates for April, May, and June were much less than the earlier planted maize. Some locations in Georgia still showed large changes that ranged from -120% to 210%. However, for the other locations the changes ranged from -10% to 60%.

For irrigated maize the increase in temperature for 2050 benefited the early planting dates for many locations (Figure 5.2). For the February 15 planting date, large changes in yield that ranged from -28% to 800% for Calera and Heflin in Alabama and Griffin and Milledgeville in Georgia. Tifton, Georgia had changes that ranged from -95% to 50%. Changes for the other locations ranged from -7% to 60%. The changes in yield for the March 1 and March 15 planting date were similar to the February 15 planting date, but with lower values. The changes ranged from -43% to 307% for March 1 and from -35% to 291% for March 15 for all locations. Irrigated maize also did not show too many changes for the other planting dates from April 1 through June 15, which ranged from -55% to 186%. For Blairsville, Georgia yield for the June 30 planting date increased from 84% to 1150%, while the changes for the other locations ranged from -50% to 210%.

5.3.2.5 CHANGES IN MAIZE YIELD FOR 2050 BASED ON THE EPIC MODEL

Simulations based on EPIC also showed that increasing temperature will benefit the early planted maize at northern locations (Figure 5.3). For all locations in Alabama and Georgia and for Chipley and Glen St Mary in Florida there was an increase in yield for the February 15 planting date that ranged from 0 to 1800%. However, Avon, Naples, and Ocala in Florida there was a decrease in yield that ranged from -50% to -6%. For the March 1 planting date, most climate scenarios showed an increase in yield that ranged from 0 to 2800% for Andalusia and Calera in Alabama and Griffin, Midville, Milledgeville, and Savannah in Georgia The increase in yield for Glen St Mary in Florida, Mobile and Montgomery in Alabama and Colquitt and Tifton in Georgia were less than 600%. There were also decrease in yield ranging from -60% to -2% for Avon, Naples, and Ocala in Florida. Grain yield for the northern locations increased for the March 15 planting date with values ranging from 2000% to 3000% for Blairsville, GA, and 200% to 1800% for Belle Mina, Alabama and Rome, Georgia. Grain yield for Calera, Heflin, and Scottsboro in Alabama and Elberton in Georgia had an increase that ranged from 0 to 800%. For the later planting dates from April to June, grain yield for all locations changed from about -50% to 10%.

For the February 15 planting date Avon, Naples and Ocala in Florida had a decrease in irrigated yield that ranged from -70% to -20%, while all other locations showed an increase in irrigated yield for almost all climate scenarios that ranged from 0 to 2000% (Figure 5.3). For the March 1 planting date, the changes in yield ranged from -150% to 3200%. For maize planted on March 15 and April 1, grain yield for the northern locations increased, while it decreased for the southern locations. The largest increase was found for Blairsville, Georgia, which ranged from 800% to 3100%. For maize planted from April to June, the changes were almost negative ranging from -70% to 2%. The only exception was Blairsville, Georgia were yield for the June 30 planting showed an increase that ranged from 10% to 71%.

5.3.2.6 CHANGES IN MAIZE YIELD FOR 2070 BASED ON THE CSM-CERES-MAIZE MODEL

For the 2070 projections, the changes in rainfed yield compared to the base line based on CSM-CERES-Maize generally ranged from -100% to 300% for all locations (Figure 5.4). The changes rainfed maize planted from April 1 to June 30, which ranged from -15% to 45%.

For irrigated grain yield, large increases were found for many northern locations when planted on February 15 (Figure 5.4). For Calera, Alabama the increase was 1600%, while for Heflin, Alabama and Griffin and Milledgeville at Georgia the increase was 800%. The other locations showed a change in yield that ranged from -10% to 120% of changes. For planting date March 1, the changes for locations in Alabama and Georgia were about 5% to 35% and the changes for Florida were about -9% to 27%. For the March 15 planting data Blairsville in Georgia also showed the largest increases in yield, ranging from 200% to 650%. Belle Mina, Alabama and Elbert and Rome in Georgia had an increase that ranged from 50% to 160%, while for the other locations the change in yield ranged from -20% to 70%. For maize planted from

April 1 to June 1 yield changes varied from -27% to 51% for almost all locations. However, for Blairsville, Georgia the increase in yield was higher for these planting dates and ranged from 70% to 105%. The changes in grain yield for maize planted on Jun 15 were similar to maize planted on June 1, except again for Blairsville, Georgia where the change in yield varied from 25% to 235%. For the June 30 planting date, the changes in yield ranged from -23% to 146% for all locations, except for Blairsville, Georgia where the yield changes ranged from 125% to 1300%.

5.3.2.7 CHANGES IN MAIZE YIELD FOR 2070 BASED ON THE EPIC MODEL

For February 15 planting date the changes in rainfed yield for the 2070 projections based on EPIC model showed large increases that reached 1800% (Figure 5.5). However, for Avon, Naples, and Ocala in Florida there was a decrease in yield that ranged from -79% to -20%. For the March 1 planting date, the changed in yield ranged -150% to 670% except some locations where there was no baseline yield. For the March 15 planting date the changes in yield ranged from 1800% to 2700% for Blairsville, Georgia, from 200% to 1200% for Belle Mina, Alabama, and 200% to 1500% for Rome, Georgia, and -70% to 353% for the rest locations. For rainfed production planted from April 1 through June 30 the changes in grain yield ranged from -90% to 70%.

For irrigated maize production for the 2070 projections, yield showed an increase from the baseline yield when planted on February 15 and March 1 (Figure 5.5). However, Avon, Naples and Ocala in Florida showed a decrease in grain yield for some climate scenarios, with the changes ranging from -100% to 3300%. For the March 15 and April 1 planting date, grain yields for the northern locations increased, while it decreased for the southern locations. Similar to other planting dates, the largest increase was found fro Blairsville, Georgia which yield changes ranging from 1000% to 3000% For the other locations yield changes ranged from -150%

to 800%. For later planting dates during April, May and June, the changes in yield ranged from -70% to 2% for all locations, except for Blairsville, Georgia for the June 30 planting date, with changes in yield that ranged from 10% to 71%.

5.3.2.8 COMPARISON OF THE CSM-CERES-MAIZE AND EPIC MODELS

The two maize simulation models that were used n this study reported both increases and decreases in grain yield for the 2050 and 2070 projections under multiple climate scenarios compared to the baseline simulations. However, because of the different purpose of each model, the different model structures resulted in differences in the simulations and also showed some different sensitivities to the changing climate factors. Based on the ANOVA test for rainfed and irrigated grain yields based on the simulations with CSM-CERES-Maize and EPIC, significant differences were found for them under the gas emission scenarios A1B, A2, and B1. The ANOVA test for all gas emission scenarios showed p-value as 0.

5.4 DISCUSSION

Compared to previously conducted studies, the application of multiple scenarios for both the climate projections and crop management scenarios that were used in this study was a good approach to search for adaptation strategies under uncertainties. Uncertainties were largely minimized based on that method. The analysis for multiple locations in this study also addressed the spatial variability of climate in the southeastern USA. The use of multiple maize hybrids also provided a wide range of options for future maize production under climate change in the southeastern USA, although in reality the maize hybrids might change more rapidly especially with respect to drought tolerance and heat resistance depending on the interest of the major seed companies

This results from this study showed that changes in maize yields varied with location, planting date, hybrid, climate projection period, climate scenario and GCM. For example, the yield for the northern locations of the study area was more sensitive to planting date. In this study, maize yield simulated with both crop simulation models was mainly affected by the three changing atmospheric factors, including temperature, precipitation, and CO_2 concentration.

So far only a few studies have studied the impact of climate change on maize production in the southeastern USA and none have used multiple crop models. Bassu et al. (2014) conducted a sensitivity study of the response of twenty-three maize crop simulation models to the change in climate factors. The results of our study were consistent compared to the results of the study by Bassu et al. (2014). Normally, an increase in temperature decreases the number of days from planting to maturity and thus decreases grain yields, while an increase in CO_2 concentration will benefit grain yield for certain environments. In our study, the early-planted maize in reference years, such as on February 15 and March 1, was limited due to the low temperature, which caused fail in germination. The days from planting to maturity of the later planted maize (June 15 and 30) were affected by the low temperature near maize maturity date. Increasing temperature in the future will offset some of the restrictions and yield for the northern locations of the southeastern USA. However, the high temperature caused by the climate change projections decreased yield for maize planted in April and May. Finally, the projected increase in precipitation generally benefitted rainfed grain yield, while a projected decrease in precipitation caused a decrease in rainfed grain yield.

For the 2050 and 2070 projections, the predicted increase in temperature was relative larger for the northern than the southern locations. The crop modeling results also showed that the changes in maize grain yields for the northern locations was in general also larger than for the southern locations. In this study we evaluated the combined effects of all these changes in the multiple climate variables on maize yield. However, as concluded by Boote et al. (2010) that temperature is always considered as the main factor because it affects many processes, such as phenological development, growth and biomass partitioning, in crop simulation models.

Although there were differences for simulated grain yield based on the CSM-CERES-Maize and EPIC models, these two crop models still provided similar responses to the projected change in climate conditions. Multiple planting dates from February through June were covered in this study for potential adaptation to a changing climate. In general, the early-planted maize will benefit from an increase in temperature (Abraha & Savage 2006). However, the large percentage increase in maize grain yield for the early planting dates does not mean necessarily a high yield. Because of the low temperature, the baseline grain yield for the early-planted maize was very low or sometimes even zero. In general, maize in Blairsville and Rome in Georgia and Belle Mina, AL cannot plant maize before March 15. Therefore, for the locations in Florida maize can be planted in February in 2050 and 2070 since the yield for the locations in Alabama and Georgia were still low.

Yield for maize planted in April and May decreased for all locations for both rainfed and irrigated conditions. However, irrigated grain yields showed more resistance to an increase in temperature. Maize will not be suitable for planting in Florida during April and May in 2050 and 2070 a because of the high temperature that will require an increase in irrigation demand but also a large decrease in yield. The distribution of maize planting should move to north for planting during April and May in 2050 and 2070 in order to obtain a reasonable yield. Maize planted during June in 2050 and 2070 will be more suitable for the northern region such as Blairsville and Rome in Georgia that the southern regions because the increase in temperature will offset the low temperature risk during the time near crop maturity. Finally, irrigated maize will have a larger increase in yield than rainfed maize for all climate scenarios. It is possible that the shift of maize planting area, planting dates, and irrigation cannot offset the risk from climate extremes in the future. Breeders therefore need to develop new hybrids that are more resistant to changes in local weather conditions.

In summary, for the southern region of the southeastern USA maize should be planted earlier to avoid the increase in temperature projected for 2050 and 2070 that could cause heat stress. For maize planted during April, May, and June, production should be shifted to the northern region. Irrigation could also be an adaptation strategy in order to minimize the negative effects associated with the projected changes in precipitation, especially for regions where there is a decrease in precipitation that could cause water stress.

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Table 5.1: Annual average maximum and minimum temperature and total precipitation for the 22 selected locations in Alabama, Florida, and Georgia.

	Station	Latitude (ºN)	Longitude (ºW)	Elevation (m)	Min Temp (°C)	Max Temp (°C)	Precipitation (mm)	Climate zones	Soil Types
AL	Andalusia	31.1	-86.52	76	10.4	25.1	128	7	Shadygrove Sandy Loam
AL	Bankhead	33.45	-87.35	85	9.8	23.3	124	3	Choccolocco Sandy Loam
AL	Belle Mina	34.68	-86.88	183	8.9	22.0	114	1	Dickson Silty Loam
AL	Calera	33.12	-86.75	162	9.3	23.7	116	4	Hanceville Loam
AL	Heflin	33.65	-85.6	259	8.4	22.5	120	5	Lucedale Loam
AL	Mobile	30.68	-88.25	66	13.9	25.1	137	8	Norfolk Sandy Loam
AL	Montgomery	32.3	-86.4	62	12.0	24.5	109	6	Lucedale Loamy Sand
AL	Scottsboro	34.66	-86.05	186	8.5	22.1	122	2	Hartsells Sandy Loam
FL	Avon Park	27.6	-81.53	47	16.1	28.6	107	4	Immokalee Sand
FL	Chipley	30.78	-85.48	40	12.4	25.6	125	1	Albany Sand
FL	Glen St Mary	30.27	-82.18	39	12.5	26.3	117	2	Blanton Sand
FL	Naples	26.02	-81.72	1.5	17.8	29.1	113	5	Immokalle Fine Sand
FL	Ocala	29.2	-82.08	23	14.9	27.9	109	3	Eureka Loamy Sand
GA	Blairsville	34.83	83.92	590	19.6	5.9	121	2	Hayesville Sandy Loam
GA	Colquitt	31.17	84.77	118	12.4	25.8	114	7	Wahee Sandy Loam
GA	Elberton	34.12	82.87	145	8.1	22.2	104	3	Cecil Sand Loam
GA	Griffin	33.27	84.27	285	10.3	22.2	107	4	Lloyd series
GA	Midville	32.87	82.18	79	11.4	24.4	95	6	Shellbluff Clay Loam
GA	Milledgeville	33.07	83.25	84	9.8	24	100	5	Cecil Sandy Clay Loam
GA	Rome	34.25	85.15	187	8.9	21.9	115	1	Conasauga Silt Loam
GA	Savannah	32.12	81.18	13	13.2	24.9	103	9	Kenansville Loamy Sand
GA	Tifton	31.47	83.52	5	12.5	24.7	100	8	Tifton Sandy Loam

Table 5.2*: Optimized cultivar coefficients for the CSM-CERES-Maize and EPIC models for the selected seven maize hybrids.

CSM-CERES-Maize							
Parameter	**Dyna-Gro V5373VT3**	**Pioneer 33M57 (Hx1/LL/RR2)**	**SS 731CL**	**Croplan Genetics 851 VT3 PRO**	**Croplan Genetics 8756 VT3**	**DeKalb DKC69-71(RR2/YGCB)**	**Pioneer 31D58**
P1	310	260	220	310	290	330	270
P2	1.8	1.5	1.2	0.9	1.8	0.9	0.9
P5	900	940	820	820	940	840	900
G2	646.8	646.8	954.8	646.8	677.6	646.8	708.4
G3	12.43	10.94	12.64	12.64	12	12.64	11.79
PHINT	63.9	58.9	53.90	48.9	63.9	48.9	58.9
EPIC							
WA	50	50	50	50	50	50	50
HI	0.45	0.50	0.55	0.45	0.5	0.45	0.5
DLAI	0.95	0.95	0.95	0.95	0.95	0.95	0.95
WSYF	0.01	0.01	0.01	0.01	0.01	0.01	0.01
DMLA	6.0	6.0	6.0	5.0	6.0	6.0	6.0
PHU	1800	1650	1800	1800	1800	1730	1770

P1: Thermal time from seedling emergence to the end of the juvenile phase
P2: Extent to which development is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate
P5: Thermal time from silking to physiological maturity
G2: Maximum possible number of kernels per plant
G3: Kernel filling rate during the linear grain filling state and under optimum conditions
PHINT: The interval in thermal time (degree days) between successive leaf tip appearances
WA: Biomass-Energy ratio
HI: Potential harvest index - ratio of crop yield to above ground biomass
DLAI: Fraction of growing season when leaf area starts declining
WSYF: Water stress factor for adjusting harvest index
DMLA: Maximum LAI potential for a crop
PHU: Potential Heat Units
*: This table was cited from Chapter 2

Table 5.3: General circulation models (GCMs) that were evaluated in this study.

Acronym	Source	Country	Resolution
BCCRBCM2	Bjerknes Centre for Climate Research, University of Bergen, Norway	Norway	1.9º × 1.9º
CCCMA-31	Canadian Centre for Climate Modeling & Analysis	Canada	2.8º × 2.8º
CNRM-CM3	Me´te´o-France/Centre National de Recherches Me´te´orologiques	France	1.9º × 1.9º
CSIRO-30	CSIRO Atmospheric Research	Australia	1.9º × 1.9º
ECHO---G	Meteorological Institute of the University of Bonn, Meteorological Research Institute of KMA	Germany, Korea	3.9º × 3.9º
GFDLCM20	NOAA/Geophysical Fluid Dynamics Laboratory	USA	2.0º × 2.5º
GFDLCM21	NOAA/Geophysical Fluid Dynamics Laboratory	USA	2.0º × 2.5º
GISS--ER	NASA/Goddard Institute for Space Studies	USA	4º × 5º
INMCM-30	Institute for Numerical Mathematics	Russia	4º × 5º
IPSL_CM4	Institute Pierre Simon Laplace	France	2.5º × 3.75º
MIROCMED	Center for Climate System Research, National Institute for Environmental Studies, and Frontier Research Center for Global Change	Japan	2.8º × 2.8º
MPIECH-5	Max Planck Institute for Meteorology	Germany	1.9º × 1.9º
MRI-232A	Meteorological Research Institute	Japan	2.8º × 2.8º
NCARPCM1	National Center for Atmospheric Research	USA	2.8º × 2.8º
UKHADCM3	Hadley Centre for Climate Prediction and Research/Met Office	UK	2.75º × 3.75º

Table 5.4: Average changes in temperature and precipitation for the 2050 and 2070 projections compared to the baseline as implemented by SimCLIM.

ST	Station	2050 (°C)	2070 (°C)	2050 (mm)	2070 (mm)
AL	Andalusia	1.3-3	1.7-4.5	-10.2-16.5	-15.3-24.7
AL	Bankhead	1.3-3.8	1.7-5.7	-19.4-42	-29-62.7
AL	Belle Mina	1.3-4.6	1.8-6.8	-10.6-21.1	-15.9-31.5
AL	Calera	1.3-3.6	1.7-5.4	-58.7-77.5	-87.6-115.7
AL	Heflin	1.3-3.7	1.7-5.5	-13.5-14.3	-20.2-21.4
AL	Mobile	1.3-3	1.7-4.5	-13.1-16	-19.5-23.9
AL	Montgomery	1.3-3.2	1.7-4.8	-30.8-53.3	-46-79.6
AL	Scattsboro	1.3-4.3	1.7-6.3	-14.2-13.6	-21.2-20.3
FL	Avon Park	0.9-2.3	1.2-3.4	-8.8-8.8	-13.1-13.1
FL	Chipley	1.2-2.8	1.6-4.2	-11.5-18.8	-17.2-28.1
FL	Glen St Mary	1-2.7	1.4-4	-9.2-11.1	-13.7-16.6
FL	Naples	0.8-2	1.1-3	-12.3-8.4	-18.3-12.6
FL	Ocala	1-2.5	1.3-3.7	-11.7-15.3	-17.5-22.9
GA	Blairsville	1.3-3.6	1.7-5.4	-8.7-11.3	-13-16.9
GA	Colquitt	1.2-2.8	1.6-4.2	-17.4-32.6	-25.9-48.7
GA	Elberton	1.3-3.2	1.7-4.8	-14.9-19	-22.2-28.3
GA	Griffin	1.2-3.3	1.6-4.9	-11.9-17.6	-17.8-26.3
GA	Midville	1.1-2.8	1.5-4.2	-11.7-24.9	-17.5-37.2
GA	Milledgeville	1.1-2.9	1.5-4.4	-9.6-22.2	-14.4-33.2
GA	Rome	1.3-3.9	1.7-5.8	-11.7-16.3	-17.5-24.3
GA	Savannah	1-2.7	1.4-4.1	-14.1-21.1	-21.1-31.5
GA	Tifton	1.1-2.7	1.5-4.1	-14.1-27.7	-21-41.3

Table 5.5: ANOVA tests for changes in simulated maize yield for the seven cultivars with multiple planting dates and locations. The p-values are shown. A value that is near 0 means that at least one of sample means is different from the others. Otherwise, there is no difference among samples.

	DSSAT							
	Rainfed				Irrigated			
	2050		2070		2050		2070	
	GCMs	Scenarios	GCMs	Scenarios	GCMs	Scenarios	GCMs	Scenarios
Dyna-Gro V5373VT3	0	0	1	0	1	0.4194	0	0.1161
Pioneer 33M57(Hx1/LL/RR2)	0	0	1	0	1	0.1114	0	0
SS 731CL	0	0	1	0	1	0.3295	0	0
Croplan Genetics 851 VT3 PRO	0	0	1	0	1	0.0646	0	0
Croplan Genetics 8756 VT3	0	0	1	0	1	0.261	0	0.2593
DeKalb DKC69-71(RR2/YGCB)	0	0	1	0	1	0.3105	0	0
Pioneer 31D58	0	0	1	0	1	0.638	0	0
	EPIC							
Dyna-Gro V5373VT3	0	0	0	0	0	0	0	0
Pioneer 33M57(Hx1/LL/RR2)	0	0	0	0	0	0	0	0
SS 731CL	0	0	0	0	0	0	0	0
Croplan Genetics 851 VT3 PRO	0	0	0	0	0	0	0	0
Croplan Genetics 8756 VT3	0	0	0	0	0	0	0	0
DeKalb DKC69-71(RR2/YGCB)	0	0	0	0	0	0	0	0
Pioneer 31D58	0	0	0	0	0	0	0	0

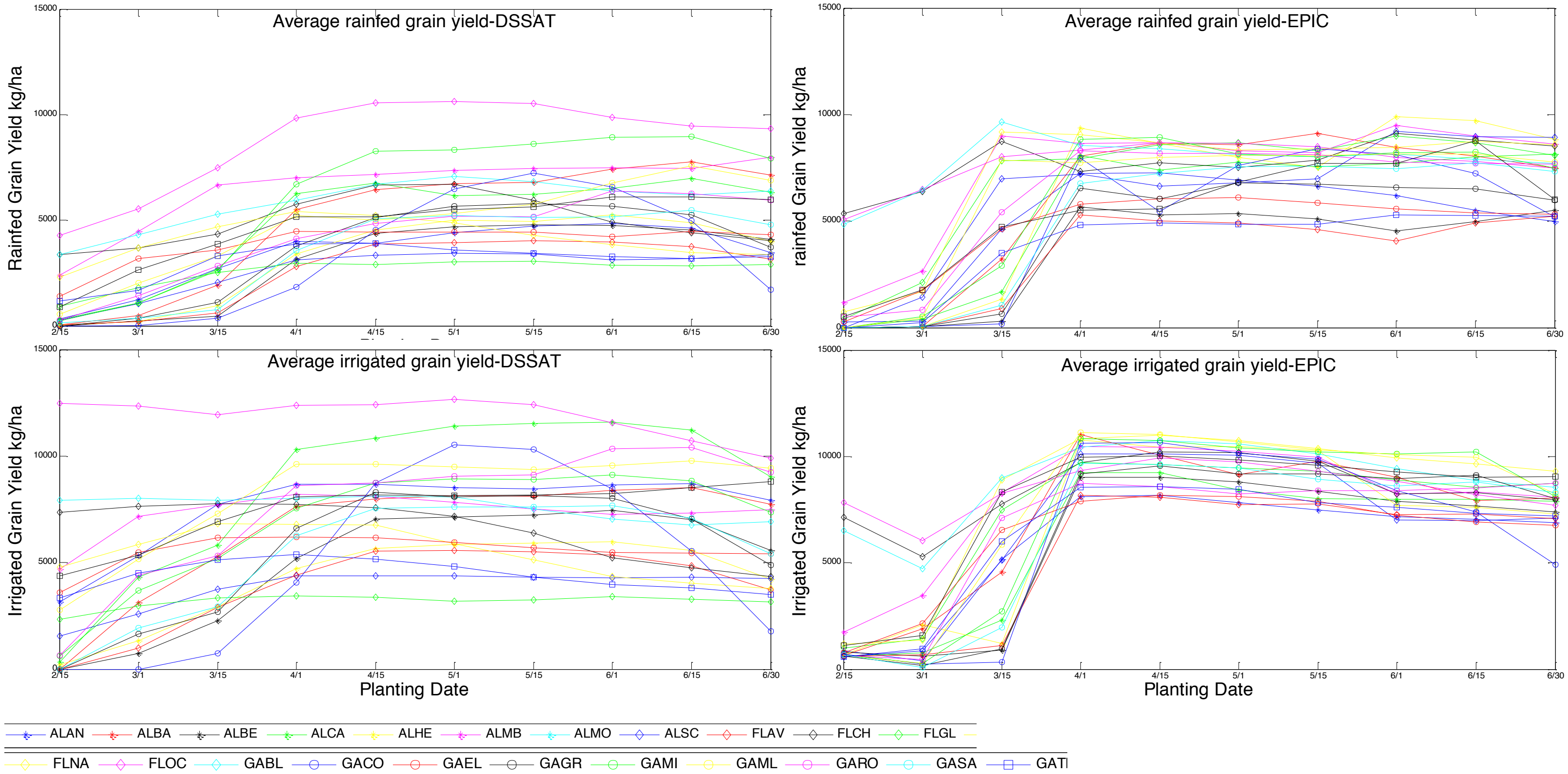
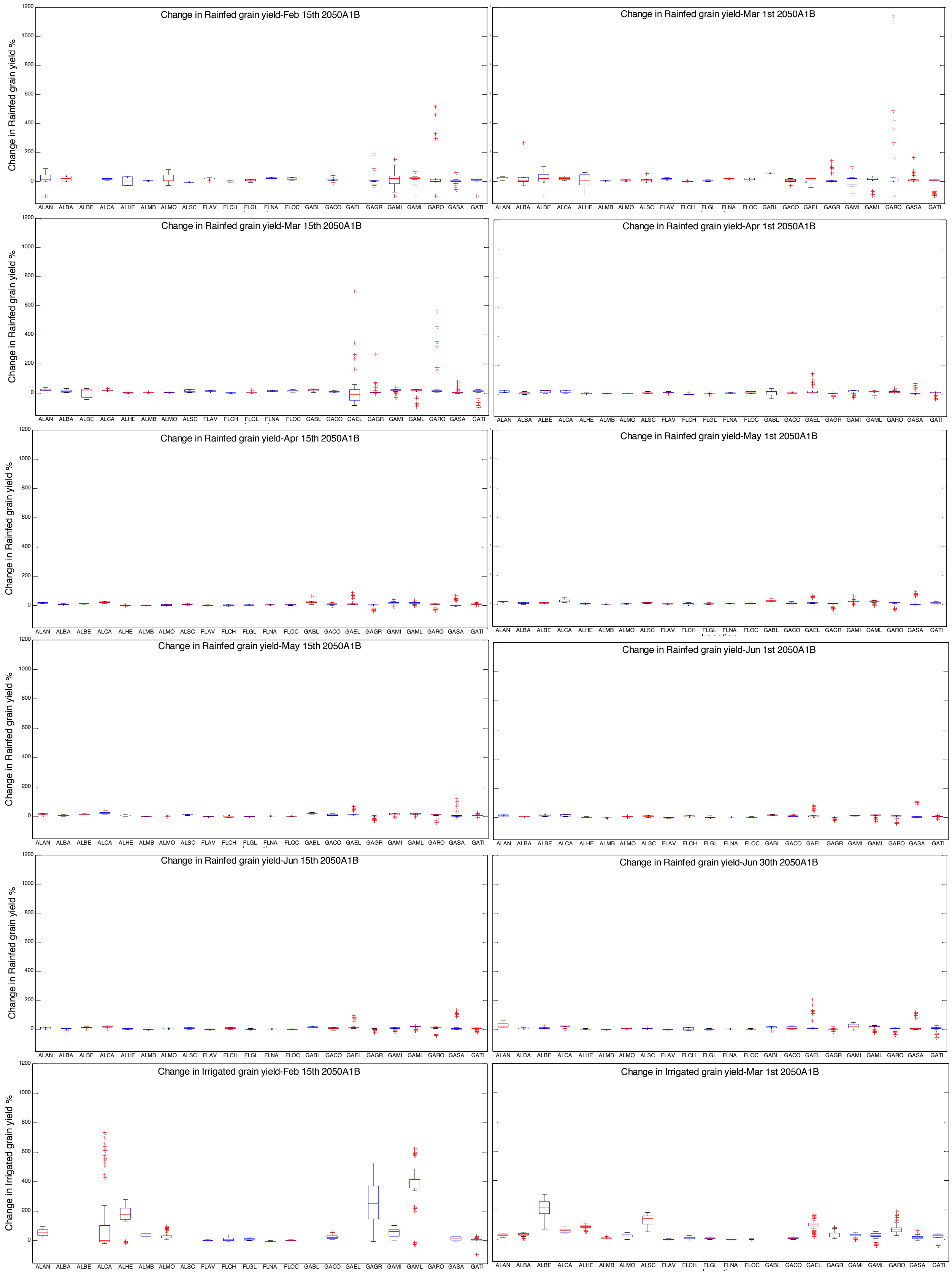


Figure 5.1: Average baseline maize yield simulated by the CSM-CERES-Maize and EPIC models for the seven cultivars. Averages were based on 30 years of simulations (1981 to 2010).



Change in Rainfed grain yield-Feb 15th 2050A1B
Change in Rainfed grain yield-Mar 1st 2050A1B
Change in Rainfed grain yield-Mar 15th 2050A1B
Change in Rainfed grain yield-Apr 1st 2050A1B
Change in Rainfed grain yield-Apr 15th 2050A1B
Change in Rainfed grain yield-May 1st 2050A1B
Change in Rainfed grain yield-May 15th 2050A1B
Change in Rainfed grain yield-Jun 1st 2050A1B
Change in Rainfed grain yield-Jun 15th 2050A1B
Change in Rainfed grain yield-Jun 30th 2050A1B
Change in Irrigated grain yield-Feb 15th 2050A1B
Change in Irrigated grain yield-Mar 1st 2050A1B
Change in Rainfed grain yield %
Change in Irrigated grain yield %
ALAN ALBA ALBE ALCA ALHE ALMB ALMO ALSC FLAV FLCH FLGL FLNA FLOC GABL GACO GAEL GAGR GAMI GAML GARO GASA GATI

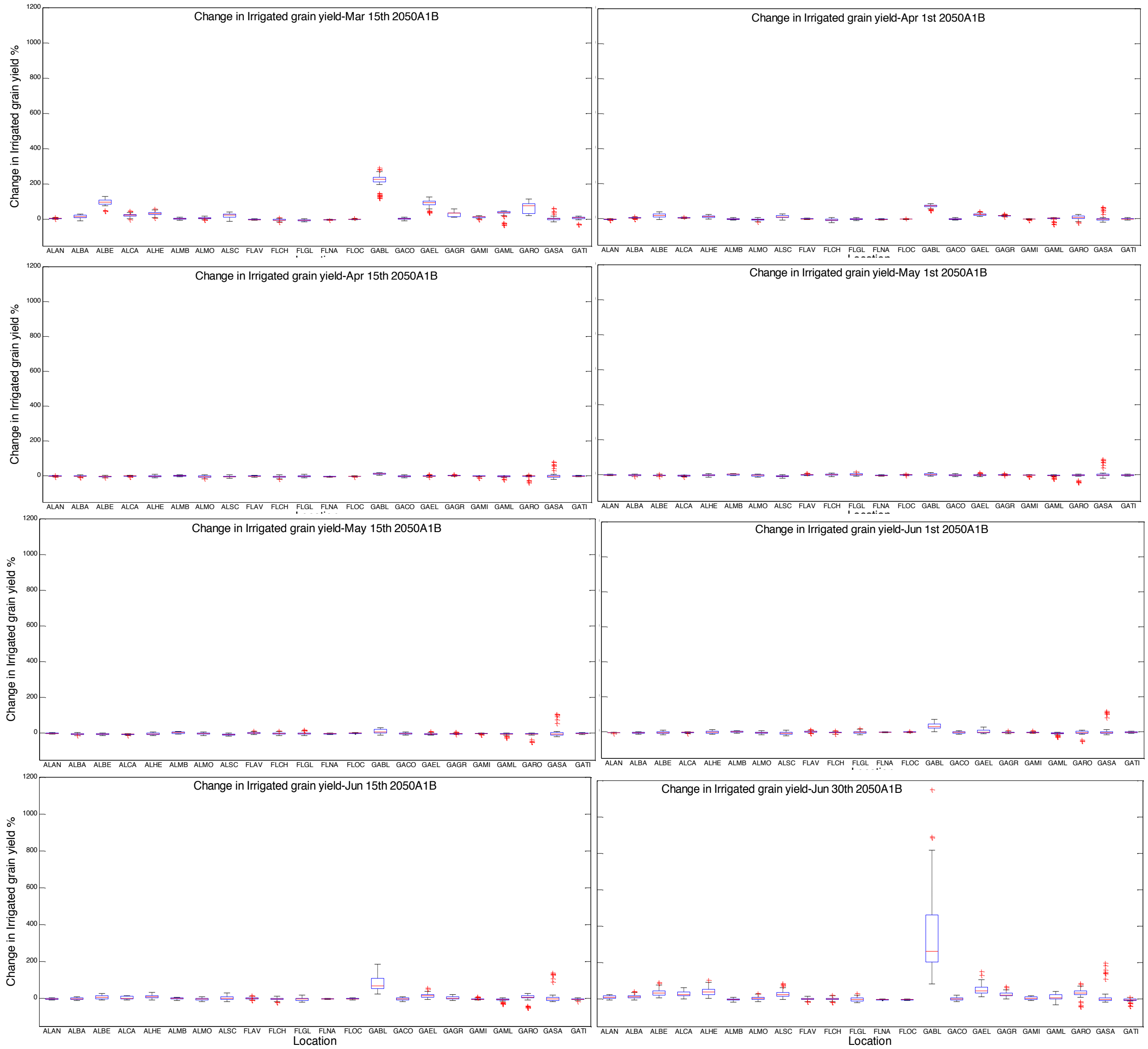
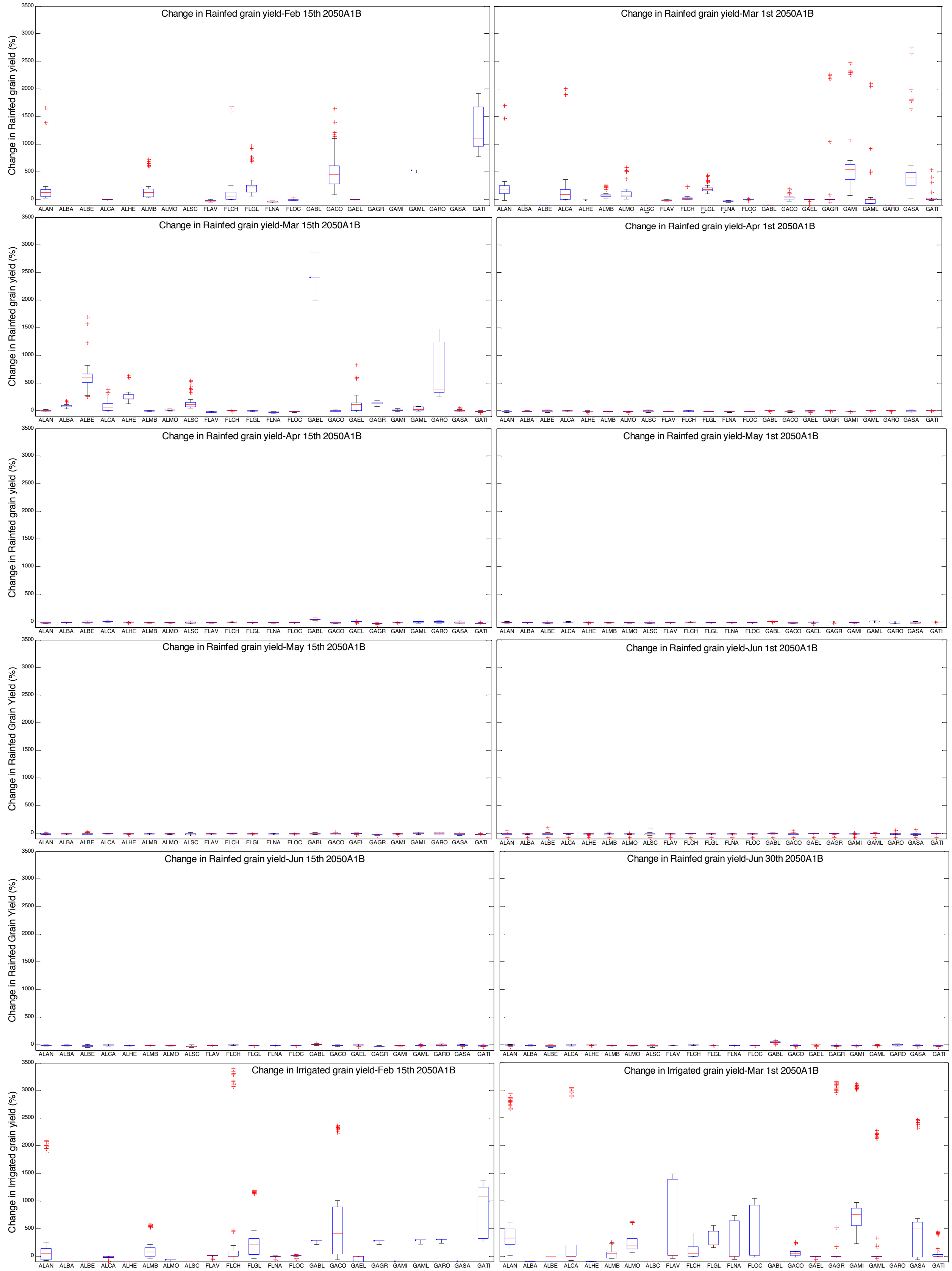


Figure 5.2: Changes in average maize yield predicted by the CSM-CERES-Maize model based on 15 GCMs under scenario A1B for the 2050 projection. The planting dates ranged from February 15 to June 30 for both rainfed and irrigated conditions.



Change in Rainfed grain yield-Feb 15th 2050A1B
Change in Rainfed grain yield-Mar 1st 2050A1B
Change in Rainfed grain yield-Mar 15th 2050A1B
Change in Rainfed grain yield-Apr 1st 2050A1B
Change in Rainfed grain yield-Apr 15th 2050A1B
Change in Rainfed grain yield-May 1st 2050A1B
Change in Rainfed grain yield-May 15th 2050A1B
Change in Rainfed grain yield-Jun 1st 2050A1B
Change in Rainfed grain yield-Jun 15th 2050A1B
Change in Rainfed grain yield-Jun 30th 2050A1B
Change in Irrigated grain yield-Feb 15th 2050A1B
Change in Irrigated grain yield-Mar 1st 2050A1B
Change in Rainfed grain yield (%)
Change in Rainfed Grain Yield (%)
Change in Irrigated grain yield (%)
ALAN ALBA ALBE ALCA ALHE ALMB ALMO ALSC FLAV FLCH FLGL FLNA FLOC GABL GACO GAEL GAGR GAMI GAML GARO GASA GATI

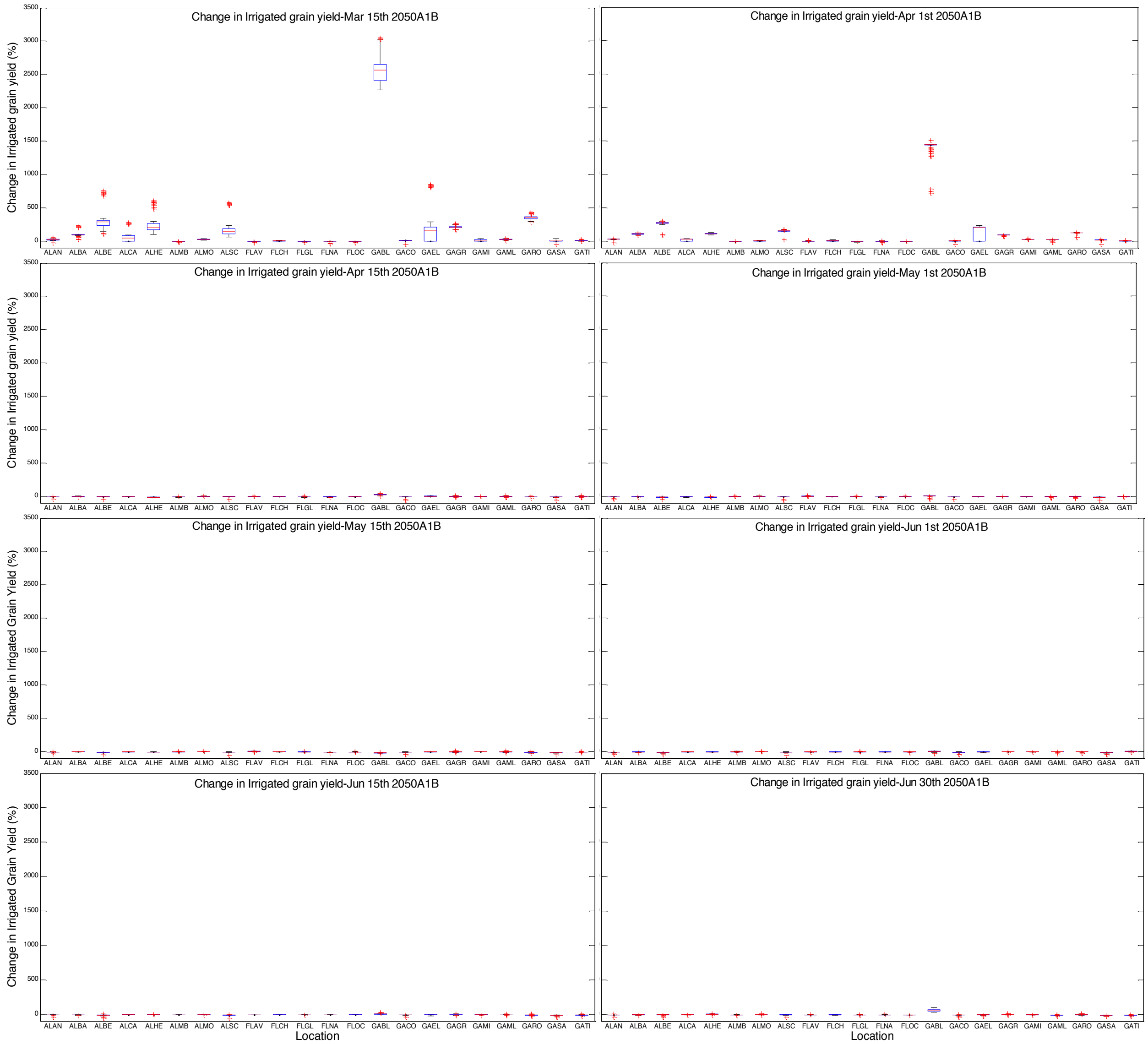


Figure 5.3: Changes in average maize yield predicted by the EPIC model based on 15 GCMs under scenario A1B for the 2050 projection. The planting dates ranged from February 15 to June 30 with both rainfed and irrigated conditions.


Change in Rainfed grain yield-Feb 15th 2070A1B
Change in Rainfed grain yield-Mar 1st 2070A1B
Change in Rainfed grain yield-Mar 15th 2070A1B
Change in Rainfed grain yield-Apr 1st 2070A1B
Change in Rainfed grain yield-Apr 15th 2070A1B
Change in Rainfed grain yield-May 1st 2070A1B
Change in Rainfed grain yield-May 15th 2070A1B
Change in Rainfed grain yield-Jun 1st 2070A1B
Change in Rainfed grain yield-Jun 15th 2070A1B
Change in Rainfed grain yield-Jun 30th 2070A1B
Change in Irrigated grain yield-Feb 15th 2070A1B
Change in Irrigated grain yield-Mar 1st 2070A1B
Change in Rainfed grain yield %
Change in Irrigated grain yield %
0
200
400
600
800
1000
1200
1400
1600
1800
ALAN ALBA ALBE ALCA ALHE ALMB ALMO ALSC FLAV FLCH FLGL FLNA FLOC GABL GACO GAEL GAGR GAMI GAML GARO GASA GATI

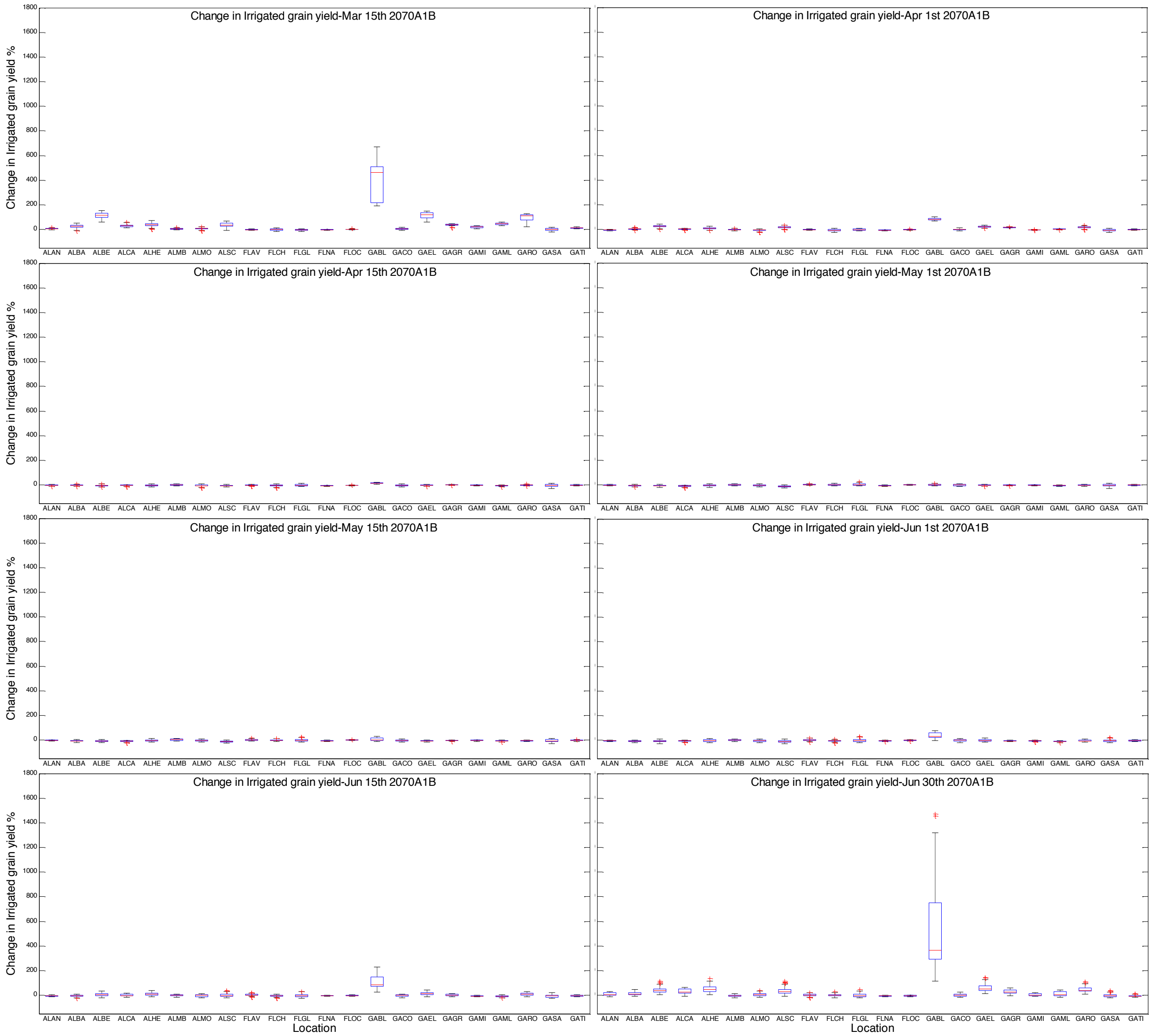
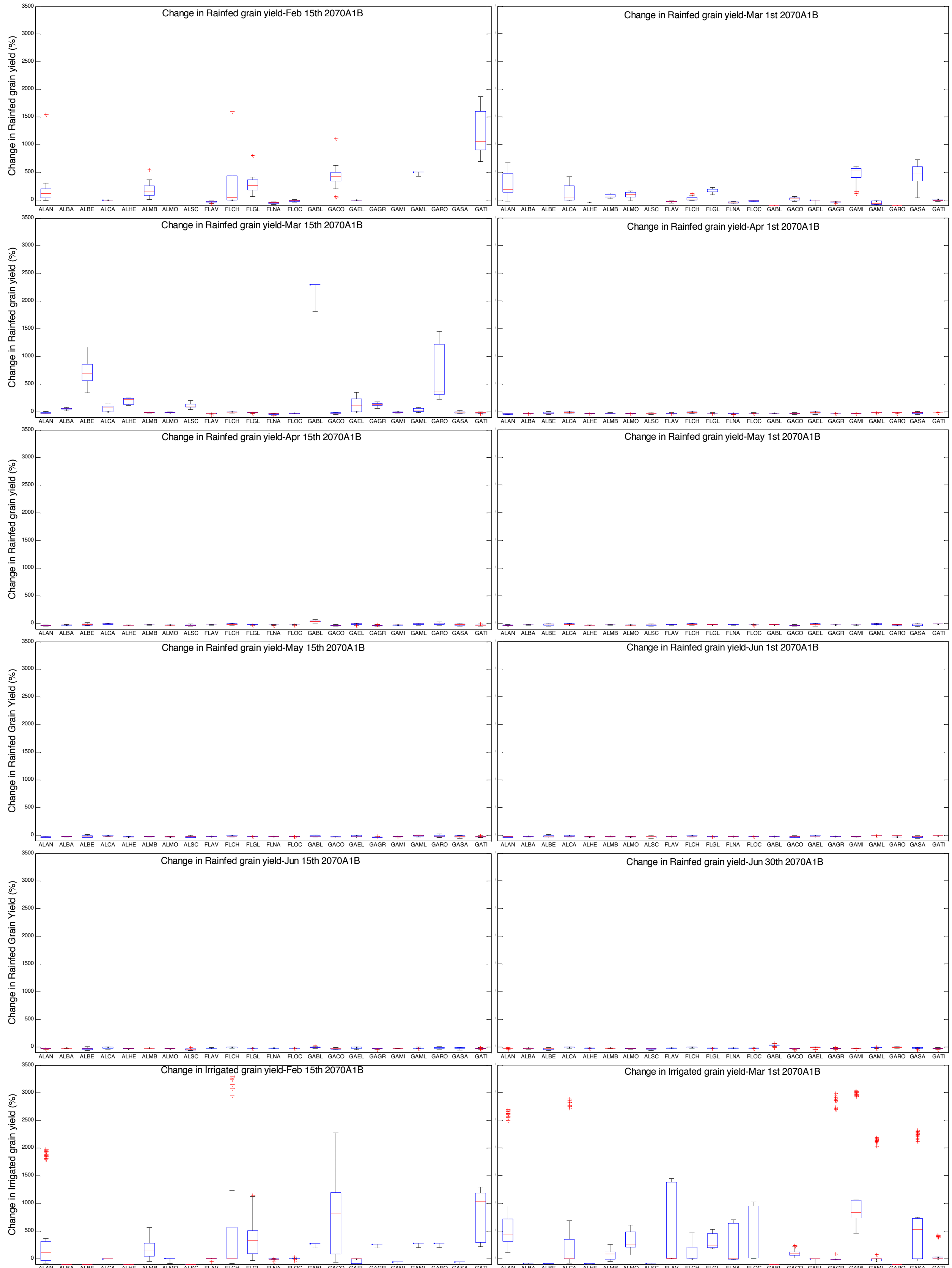


Figure 5.4: Changes in average maize yield predicted by the CSM-CERES-Maize model based on 15 GCMs under scenario A1B for 2070 projection. The planting dates ranged from February 15 to June 30 with both rainfed and irrigated conditions.


Change in Rainfed grain yield-Feb 15th 2070A1B
Change in Rainfed grain yield-Mar 1st 2070A1B
Change in Rainfed grain yield-Mar 15th 2070A1B
Change in Rainfed grain yield-Apr 1st 2070A1B
Change in Rainfed grain yield-Apr 15th 2070A1B
Change in Rainfed grain yield-May 1st 2070A1B
Change in Rainfed grain yield-May 15th 2070A1B
Change in Rainfed grain yield-Jun 1st 2070A1B
Change in Rainfed grain yield-Jun 15th 2070A1B
Change in Rainfed grain yield-Jun 30th 2070A1B
Change in Irrigated grain yield-Feb 15th 2070A1B
Change in Irrigated grain yield-Mar 1st 2070A1B
Change in Rainfed grain yield (%)
Change in Rainfed Grain Yield (%)
Change in Irrigated grain yield (%)
0
500
1000
1500
2000
2500
3000
3500
ALAN ALBA ALBE ALCA ALHE ALMB ALMO ALSC FLAV FLCH FLGL FLNA FLOC GABL GACO GAEL GAGR GAMI GAML GARO GASA GATI

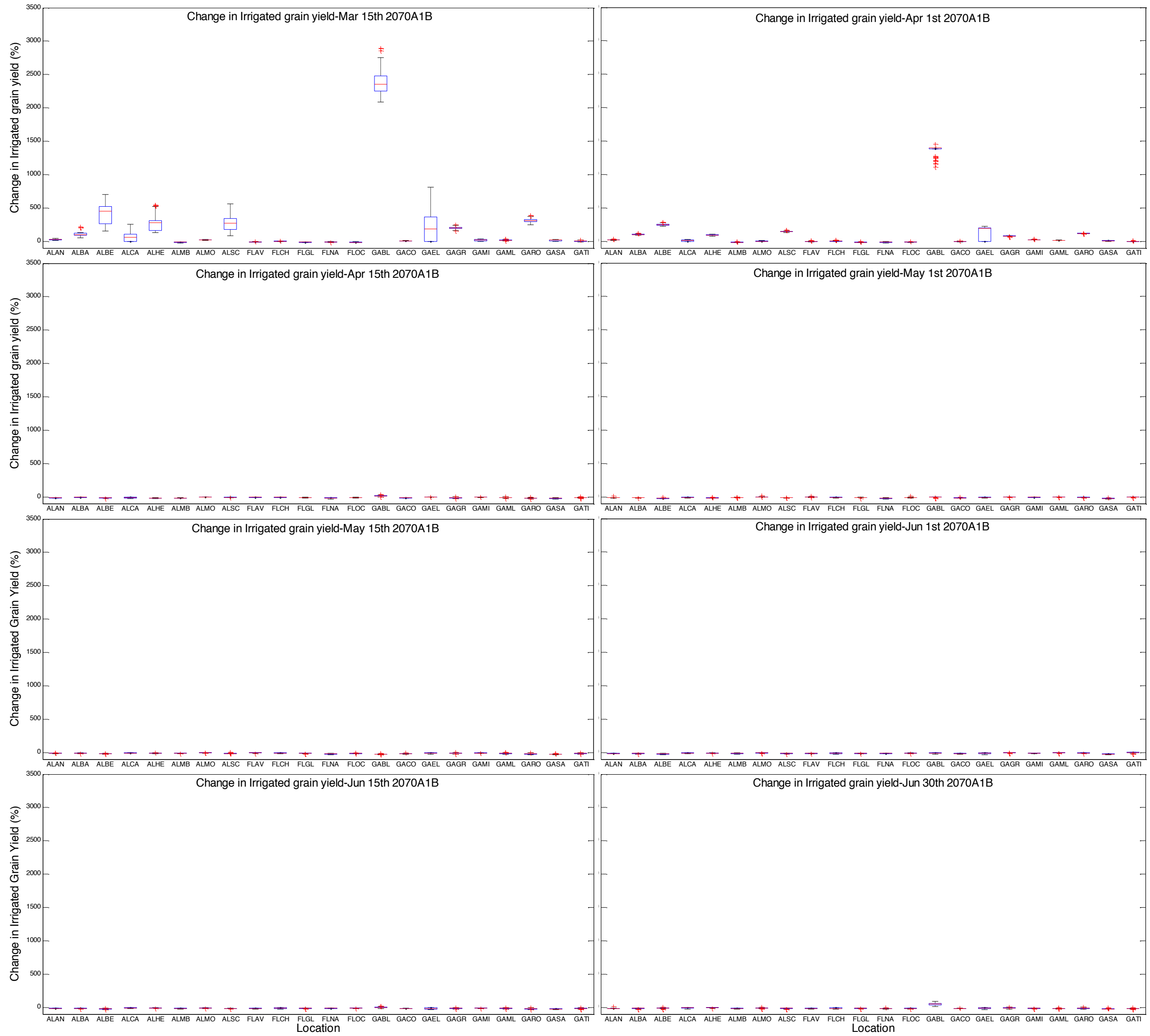


Figure 5.5: Changes in average maize yield predicted by the EPIC model based on 15 GCMs under scenario A1B for the 2070 projection. The planting dates ranged from February 15 to June 30 with both rainfed and irrigated conditions.

CHAPTER 6

SUMMARY AND CONCLUSIONS

The overall goal of this study was to determine the effects of climate change on maize yield in 2050 and 2070 in the southeastern USA and propose adaptation strategies. The specific objectives of this study were 1) to compare the performance of two maize crop simulations models, Cropping System Model (CSM)-CERES-Maize and Erosion-Productivity Impact Calculator (EPIC) for maize, 2) to evaluate the accuracy of an Integrated Assessment Model (IAM)-SimCLIM in projecting future climate for specific locations in the southeastern USA, 3) to determine the maize grain yield in 2050 and 2070 based on two crop models under a wide coverage of climate scenarios, and 4) to develop the adaptation strategies for future maize planting.

In Chapter 2, the feasibility to use limited maize variety trial data for the evaluation of the CSM-CERES-Maize and EPIC models was determined. These two crop models were calibrated only using observed grain yield from variety trials conducted in Blairsville, Calhoun, Griffin, Midville, Plains, and Tifton in Georgia from USA. The software program GenCALC was used to calibrate the yield components coefficients of CSM-CERES-Maize, while the other coefficients were manually adjusted. Several commonly calibrated cultivar coefficients were adjusted for EPIC. The slope of linear regression, R^2, d-stat, and RMSE were the criteria for evaluating the performance of the two crop models. The calibrated crop models were applied to simulate rainfed and irrigated grain yield during 1958 to 2012 for the six locations for model evaluation.

The differences between simulations of CSM-CERES-Maize and observations were no more than 3% for calibration and no more than 8% for evaluation. The differences between simulations of EPIC and observations ranged from 2% to 23% for calibration and evaluation, which was a little bit larger than for the CSM-CERES-Maize model. This analysis showed that calibration of CSM-CERES-Maize was superior than EPIC for some hybrids, but both models can be applied with confidence. The simulated grain yield for long-term period also showed that EPIC was comparable to CSM-CERES-Maize. Although this study only used observed grain yield for calibration and evaluation, the results showed that both calibrated models can provide accurate simulations with confidence.

In Chapter 3, in order to apply SimCLIM in the southeastern USA, the ability of SimCLIM to generate accurate site-specific climate scenarios was evaluated. Tifton, Georgia was taken as an example to determine the good statistical approach to evaluate SimCLIM. The projected monthly maximum and minimum temperature, precipitation, and solar radiation from 1992 to 2012 based on downscaling of 15 GCMs with six gas emission scenarios were statistically compared with the corresponding observations which were obtained from the Georgia Automated Environmental Monitoring Network. Statistics that included box-plot, time-series plot, standard deviation, KS-test, and CDF analyses were used. Biases were found for the projections of maximum and minimum temperature, precipitation, and solar radiation based on 15 GCMs from observations. However, no significant difference was found among the 15 GCMs and among the six gas emission scenarios. The GCM CSIRO-30 was, therefore, selected for a detailed statistical analysis because it had a finer spatial resolution. Although biases between projections and observations were found for all four climate variables based on the analysis of monthly data, it can be concluded that projections captured climate mean and annual variability for maximum and minimum temperature and solar radiation. There was no skill in generating precipitation and monthly variability also could not be regenerated for all four climate variables. Although this evaluation was based on a relatively short period and might be insufficient for detecting long-term climate patterns, it is the most complete and accurate set of observed weather data for all four variables and, therefore, introduces less uncertainty into the evaluation.

In Chapter 4, three states Alabama, Florida, and Georgia represented the southeastern USA. Observations of 34 locations in Alabama, Florida, and Georgia started around 1993-1998 and ended in 2012. Statistical analysis including box-plot, time-series plot, standard deviation, KS-test, and probability histogram were used to quantify SimCLIM's performance. The downscaled projections based on 15 GCMs did not show a significant difference among the 15 GCMs using box-plots for all sites. Further analysis was, therefore, conducted with the GCM CSIRO-30. The projections for monthly maximum and minimum temperature matched the observations well. However, the extreme values for both monthly maximum and minimum temperature were not very well captured. The projected monthly solar radiation captured the mean values of the observed data well, but was unable to project the extreme values very well. Monthly solar radiation projections for Florida showed larger biases than for Georgia. Finally, the projected monthly precipitation did not match the observed values for any of the sites in the three states. The spatial variability among the selected locations was well captured by SimCLIM. In summary, the projections of SimCLIM matched the observed maximum and minimum temperature and solar radiation well. However, SimCLIM was unable to regenerate precipitation compared to the observed values.

In Chapter 5, the potential climate change impact on maize yield in 2050 and 2070 was determined. The approach combined regional climate scenarios with two crop simulation models, CSM-CERES-Maize and EPIC. The climate scenarios were downscaled from 15 GCMs under three gas emissions scenarios using the climate model SimCLIM. Site-specific projections were generated for 22 locations in Alabama, Florida, and Georgia. Seven calibrated maize hybrids were used to represent the maize production under future climate change. Based on the projections of SimCLIM, temperature in the future will increase about 0.9 °C to 6.8 °C, while precipitation will change from -87.6% to 115.7%. Those changes in both temperature and precipitation vary with location. Increasing temperature will benefit the early-planted maize on February 15, March 1, and March 15, which generally will result in a significant increase in yield. Yield changes for maize planted in April, May, and June generally ranged from -100% to 200%. Irrigated maize showed more tolerance to increasing temperature than rainfed maize. The northern locations such as Blairsville in Georgia showed a larger increase in maize yield when planted on June 15th and 30th. In order to adapt to the changing climate, maize in Florida should be planted earlier to avoid the higher temperature that are projected for the future. Maize planted in April, May, and June should shift to the more northern region. Irrigation also could be a method to off set the negative effects, especially from water deficit and high temperature. The adjustment in crop management will not be able to eliminate the agricultural risks. New hybrids with high temperature and drought resistance will also be needed to obtain higher grain yields.

Uncertainties were the most important concerns for climate change impact studies (Kjellström et al. 2010). The application of multiple scenarios in both climate and management in this study was a good approach to search for adaptation strategies under uncertainties.

First of all, GCMs are connected with the uncertainties in generating global climate projections and also introduce the uncertainties into regional climate projections because the driving data for downscaling was obtained from GCMs (Wilby et al. 2004, Hawkins & Sutton

2009, Flato et al. 2013). Previous studies have shown that more uncertainties would be introduced into impact studies if they are only based on a single GCM (Meehl et al. 2007, Murphy et al. 2007). Fortunately, research has shown that the application of multiple climate scenarios can increase the confidence in impact studies (Tebaldi & Knutti 2007, Knutti 2010, Flato et al. 2013). This study generated climate data based on 15 GCMs and three gas emission scenarios, which covered a wide range of climate scenarios and reduced the uncertainties.

Secondly, this study used two calibrated maize simulation models. Research has shown that calibrated crop simulation models and the use of multiple crop simulation models could minimize those uncertainties (Challinor et al. 2009, Thornton et al. 2009, Asseng et al. 2013). CSM-CERES-Maize and EPIC are the two commonly used crop simulation models in USA. The evaluation of these two crop models showed that they can be applied with confidence in simulating grain yield of maize.

Thirdly, the downscaling (SimCLIM) of global climate data from GCMs were also evaluated by comparing with the historical data of the southeastern USA, which also determined the uncertainties that could be introduced into the impact studies. Evaluation showed that SimCLIM model could provide accurate projections in maximum and minimum temperature and solar radiation. However, SimCLIM did not have good skill in the projections of precipitation, which is the same as concluded by the previous studies that showed that it is a challenge to reproduce precipitation in the southeastern USA (Mearns et al. 2003, Stefanova et al. 2012).

Furthermore, the analysis for multiple locations in this study also addressed the spatial variability of the southeastern USA. Multiple maize hybrids also provided wide range of possibilities for the future maize planting in the southeastern USA. Many of crop management scenarios, including planting date, irrigated, and rainfed conditions were also applied to provide possible adaptation strategies.

In this study, the simulations of maize grain yields based on crop models was mainly affected by the three changing climate factors including temperature, precipitation, and CO_2 concentration. Both the CSM-CERES-Maize and EPIC models provided similar responses to changing climate. In general, the early-planted maize will benefit from the increase temperature in future (Abraha & Savage 2006). However, the large percentage of increase for maize grain yield for the early-planted dates does not mean that there is a high yield especially for north locations because the low temperature caused very low or even zero baseline grain yields for early-planted maize. In general, for Blairsville and Rome in Georgia and Belle Mina in Alabama maize cannot be planted before March 15. Only for the locations in Florida maize can be planted in February in 2050 and 2070, as the yield for the locations in Alabama and Georgia were low for the very early planting dates

Maize grain yields that planted in April and May decreased at all locations for both rainfed and irrigated conditions. However, irrigated grain yields showed more resistance for the increasing temperature. Maize will not be suitable for planting in Florida in April and May in 2050 and 2070 anymore because high temperature will cause a higher demand for irrigation but also a large decrease in yield. The distribution of maize planting should move to north if they will be planted in April and May in 2050 and 2070. Maize that planted in June in 2050 and 2070 will be more suitable for northern region such as Blairsville and Rome in Georgia than the southern region because the increasing temperature will offset the low temperature risk during the time near crop maturity. Finally, irrigated maize has a higher increase in yield compared to rainfed maize for all climate scenarios. In order to apply irrigation, water resources must be available and affordable. It is possible that the shift of maize planting area, planting dates, and irrigation cannot offset the all risks from climate extremes in future. In addition, farmers need to use new hybrids with drought- or pest-resistance to adapt to the changing climate.

Although the approach of this study minimized the uncertainties, some uncertainties still cannot be avoided for all current impact studies. It is well known that climate models have been substantially developed and improved, but uncertainties still were caused by our limited knowledge in understanding climate and natural systems and in simulating climate scenarios (Mitchell 1999, Flato et al. 2013). Furthermore, the limited ability in downscaling global climate projections into regional/site-specific climate, which was possibly caused by technical limitation and weather data input sources. In this study, the baseline data for SimCLIM can only be collected from limited locations in the southeastern USA. A finer resolution for collecting baseline data is required. Finally, only climate factors precipitation, mean temperature, and CO_2 concentration were considered. However, the actual projected climate change is much more complex.

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APPENDIX I

GAS EMISSION SCENARIOS

The A1 storyline and scenario family describes a future world of very rapid economic growth, global population that peaks in mid-century and declines thereafter, and the rapid introduction of new and more efficient technologies. Major underlying themes are convergence among regions, capacity building, and increased cultural and social interactions, with a substantial reduction in regional differences in per capita income. The A1 scenario family develops into three groups that describe alternative directions of technological change in the energy system. The three A1 groups are distinguished by their technological emphasis: fossil intensive (A1FI), non-fossil energy sources (A1T), or a balance across all sources (A1B).

The A2 storyline and scenario family describes a very heterogeneous world. The underlying theme is self-reliance and preservation of local identities. Fertility patterns across regions converge very slowly, which results in continuously increasing global population. Economic development is primarily regionally oriented and per capita economic growth and technological change are more fragmented and slower than in other storylines.

The B1 storyline and scenario family describes a convergent world with the same global population that peaks in mid-century and declines thereafter, as in the A1 storyline, but with rapid changes in economic structures toward a service and information economy, with reductions in material intensity, and the introduction of clean and resource-efficient technologies. The emphasis is on global solutions to economic, social, and environmental sustainability, including improved equity, but without additional climate initiatives.

The B2 storyline and scenario family describes a world in which the emphasis is on local solutions to economic, social, and environmental sustainability. It is a world with continuously increasing global population at a rate lower than A2, intermediate levels of economic development, and less rapid and more diverse technological change than in the B1 and A1 storylines. While the scenario is also oriented toward environmental protection and social equity, it focuses on local and regional levels.