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Evaluating the fidelity of downscaled climate data on simulated wheat and maize production in the southeastern US

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Abstract Crop models are one of the most commonly used tools to assess the impact of climate variability and change on crop production. However, before the impact of projected climate changes on crop production can be addressed, a necessary first step is the assessment of the inherent uncertainty and limitations of the forcing data used in these crop models. In this paper, we evaluate the simulated crop production using separate crop models for maize (summer crop) and wheat (winter crop) over six different locations in the Southeastern United States forced with multiple sources of actual and simulated weather data. The paper compares the crop production simulated by a crop model for maize and wheat during a historical period, using daily weather data from three sources: station observations, dynamically downscaled global reanalysis, and dynamically downscaled historical climate model simulations from two global circulation models (GCMs). The same regional climate model is used to downscale the

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global reanalysis and both global circulation models' historical simulation. The average simulated yield derived from bias-corrected downscaled reanalysis or bias-corrected downscaled GCMs were, in most cases, not statistically different from observations. Statistical differences of the average yields, generated from observed or downscaled GCM weather, were found in some locations under rainfed and irrigated scenarios, and more frequently in winter (wheat) than in summer (maize). The inter-annual variance of simulated crop yield using GCM downscaled data was frequently overestimated, especially in summer. An analysis of the bias-corrected climate data showed that despite the agreement between the modeled and the observed means of temperatures, solar radiation, and precipitation, their intra-seasonal variances were often significantly different from observations. Therefore, due to this high intra-seasonal variability, a cautious approach is required when using climate model data for historical yield analysis and future climate change impact assessments.

Keywords Crop simulation models · Climate variability · Global circulation models · Reanalysis · Wheat · Maize

Introduction

Dynamic Crop Simulation Models (CSMs) have become an integral part of agronomic research. Their application in decision support systems for farmers is increasing. The strength of the CSMs is in their ability to extrapolate observed crop growth and yield beyond a single experimental site (Jones et al. 2001).

Climate strongly influences agricultural production. One of the key inputs of CSMs is daily weather data. Simulated crop growth and development depend on the solar radiation, rainfall, and temperature levels experienced by a crop (van Ittersum et al. 2003). Therefore, the soundness of a crop simulation study depends strongly on the quality of daily weather data inputs.

Global circulation models (GCMs) are a common tool for simulating past, and projecting future, climate states and variability and are widely used in climate change impact assessments (Randall et al. 2007). The International Panel for Climate Change (IPCC) has coordinated a large systematic multi-GCM project for the simulation of past and projection of future climate (Randall et al. 2007). The output from such models is generally produced at coarse resolution (on the order of hundreds of km). Before such simulations can be used in local modeling applications, such as crop modeling, downscaling to higher resolution (on the order of tens of km) is required (Mearns et al. 2001). This downscaling can be done using dynamic (i.e., using a regional climate model), statistical, or statistic–dynamic methods (Fowler et al. 2007). However, all downscaling techniques have their pros and cons, which can be critical for the simulation of crop growth and development (Carbone et al. 2003; Challinor et al. 2005; Baigorria et al. 2007). Understanding the consequences of downscaled GCM simulations on modeled crop production in historical climate is an important prerequisite for using such simulations in a projected future climate setting.

Global circulation model climate simulations are different from forecasts or hindcasts. An ideal climate simulation will match the observations only in a statistical sense, that is, in terms of long-term means, variance, etc., but without year-to-year correspondence between model and observations. It is therefore impossible to validate climate simulations using year-specific measures; instead validation using gross statistical measures is commonly adopted.

Prior studies have indicated that the use of GCM data as inputs for CSMs may result in bias in the simulation of crop yields. The GCMs tend to overestimate the number of rainfall events and create unrealistic distributions of dry spells within the crop growing season (Hansen and Jones 2000). In another study, Mavromatis and Jones (1999) used GCM outputs directly as input for a CSM run at regional level to match the GCM spatial resolution to simulate wheat production. They reported that simulated yields at regional level with GCM data as inputs were close to mean yields simulated at such coarse grid using observed weather data, but the yield simulation with GCM data did not represent the year-to-year variability correctly.

Downscaling the GCM output provides finer resolution climate data for use in applications, such as CSMs. Mearns et al. (2003) indicate that when a GCM is downscaled using a regional model, the mean climate variables were better simulated. But, both the global and regional models failed to reproduce the spatial patterns of rainfall, especially in spring and summer. Both the spatial scale and the spatial patterns of rainfall can affect the simulations of crop yields (Carbone et al. 2003; Tsvetsinskaya et al. 2003).

Approaches that either directly use the GCM outputs in a crop model or downscale them to a finer resolution carry a certain amount of uncertainty (Olesen et al. 2007). The uncertainty in the inter-annual variability of rainfall and temperature (including their extremes) in the growing season can be significant (Lobell and Burke 2008). Watson and Challinor (2012) found that in dryland regions, where growing season rainfall is critical for the crop, the errors in the inter-annual variability of growing season rainfall and also temperature caused significant bias in simulating crop yields.

GCMs can also be integrated with continuous assimilation of observed weather data, resulting in what is called "reanalysis". Similar to global climate simulations, global reanalysis are generally produced at relatively coarse resolutions (on the order of a 100–250 km; Kalnay et al. 1996; Kanamitsu et al. 2002; Uppala et al. 2005). A reanalysis provides a temporally and spatially consistent representation of the observed weather at a given point in time that is similar (yet non-identical) to gridded station observations. Reanalysis have been used to explore the uncertainties caused by GCMs (Bengtsson and Shukla 1988; Gibson et al. 1997). Challinor et al. (2005) used reanalysis weather data as inputs for a CSM, finding smaller bias in simulated yield compared to simulated yields using GCM data.

Deviations of downscaled GCMs or reanalysis rainfall, temperature, and solar radiation data from observed weather data could have significant impacts on simulated crop production. In this study, we used daily downscaled reanalysis data, two downscaled GCMs, and observed weather data from the National Climatic Data Center as input to CSMs to compare their impact on simulations of crop production. The objective of this study is to evaluate the fidelity of the dynamically downscaled historical climate simulations and dynamically downscaled reanalysis data. This is done by comparing the simulated growth and yield of a summer (maize) and a winter (wheat) crop forced from these downscaled weather data with corresponding weather observations across six locations in the southeastern United States.

Materials and methods

A detailed description of the historical weather data used, bias correction, crop simulation model, and statistical analysis is reported in Online Resources 1. Historical observed daily weather data were obtained from the National Climatic Data Center (NCDC). The data consist of daily maximum temperature ($T_{\max}$), minimum temperature ($T_{\min}$), rainfall (Rfl), and solar radiation (Srad) for the period 1979–1999.

The corresponding meteorological data sets from the regional climate models for the same time period were obtained from http://floridaclimateinstitute.org/resources/data-sets/regional-downscaling. A bias correction was applied to rainfall, $T_{\max}$, and $T_{\min}$ (details of bias correction are explained in Online Resources 1.2).

The crop simulation models used in this study were the DSSAT 4.5 CERES-Maize model (Jones and Kiniry 1986; Decision Support System for Agrotechnology Transfer) (Hoogenboom et al. 2010) and the N-Wheat model (APSIM-Nwheat version 1.55 s; Asseng 2004). Further details about model calibration, evaluation, and management are reported in the Online Resources 1.3. The locations selected for crop model simulations within the Southeast US were as follows: northern and southern Georgia (N-GA, S-GA), northern and southern Alabama (N-AL, S-AL), North Carolina (N-NC), and Florida (N-FL) (Online Resources 4).

Results

The multi-year average values of the relevant climate variables and the results of the statistical significance tests for the summer (1 March–1 August) and winter (1 October–1 June) growing season are shown in Table 1. It is not surprising to note that the multi-year average growing season $T_{\min}$ and $T_{\max}$ of the observations match those of the downscaled reanalysis and the downscaled climate models (Table 1) given that the downscaled products have been bias-corrected. Similarly, the means of the solar radiation (computed from $T_{\min}$ and $T_{\max}$ using the method described in Hargreaves and Samani 1982) are also very close to observations. The multi-year averages of the downscaled reanalysis and climate model rainfall are slightly, but not significantly, different from the observed station data because the precipitation bias correction was done using a gridded observational data set. The intra-seasonal variability of downscaled reanalysis and downscaled climate model was significantly different from that of observations, especially for $T_{\min}$ and rainfall. But the observed and modeled intra-seasonal variability of solar radiation and $T_{\max}$ were found to be significantly different in only some locations.

On average, the number of days with $T_{\min}$ lower than 0 °C (for wheat) was significantly different between the regional climate model generated data and the observed weather (Table 2). For the summer crop (maize), the temperature data had no significant difference in the number of days in which $T_{\min} < 8$ °C, except for the HadCM3 in N-NC (Table 2). On the other hand, the number of days of $T_{\max} > 34$ °C (maize) was significantly different for the CCSM model (Table 2). For both crops, the number of days with rainfall higher than 30 mm was generally underestimated by the downscaled GCMs and downscaled reanalysis and therefore significantly different (Table 2). The average number of dry days at flowering (anthesis) was significantly underpredicted by the climate models for summer (maize), while for winter (wheat), the ERA40 and the HadCM3 showed some significant differences with the observed weather (Table 2). The CCSM model did not have any dry days around flowering for summer in S-GA, N-AL, S-AL, and N-FL (Table 2). However, the growing season rainfall variability (from sowing to harvest), assessed through the frequency distribution of growing total rainfall amounts (Figs. 1a, 3a), showed a variability in terms of rainfall frequency between the different sources with the two GCMs (CCSM and

Table 1 Twenty-year means of solar radiation (Srad), maximum ($T_{\max}$) and minimum ($T_{\min}$) daily temperatures, and rainfall (Rfl) and of the intra-seasonal standard deviation of solar radiation (S_srad), maximum temperatures (S_$t_{\max}$), minimum temperatures (S_$t_{\min}$), and rainfall (S_rfl) for the winter (1 October–1 June) and summer (1 March–1 August) growing seasons for north Georgia (N-GA), south Georgia (S-GA), north Alabama (N-AL), south Alabama (S-AL), North Carolina (N-NC), and Florida (N-FL)

	Winter growing season (1 Oct–1 Jun)							
	Srad (MJ m^{-2} d^{-1})	$T_{\max}$ (°C)	$T_{\min}$ (°C)	Rfl (mm d^{-1})	S_srad (MJ m^{-2} d^{-1})	S_$t_{\max}$ (°C)	S_$t_{\min}$ (°C)	S_rfl (mm d^{-1})
N-GA								
OBS	14.5 (0.5)	18.7 (0.7)	6.6 (0.7)	3.3 (0.9)	5.7 (0.3)	7.3 (0.5)	6.7 (0.6)	8.8 (2.3)
ERA40	14.7 (0.2)	18.7 (0.7)	6.6 (0.8)	3.3 (0.7)	5.4 (0.2)[a]	7.0 (0.5)[c]	7.0 (0.5)[b]	7.5 (1.5)[b]
CCSM	14.7 (0.3)	18.6 (0.7)	6.5 (0.6)	3.2 (0.6)	5.5 (0.3)[c]	7.1 (0.7)	7.2 (0.5)[a]	7.7 (1.4)[c]
HadCM3	14.7 (0.3)	18.6 (1.1)	6.6 (1.0)	3.4 (0.6)	5.3 (0.3)[a]	6.9 (0.7)[c]	7.0 (0.4)[c]	8.0 (1.1)[d]
S-GA								
OBS	15.3 (0.4)	21.3 (0.9)	9.1 (1.0)	3.3 (1.0)	4.9 (0.3)	6.6 (0.5)	6.6 (0.5)	10.2 (3.2)
ERA40	15.3 (0.4)	21.3 (0.8)	9.1 (0.8)	3.3 (0.9)	4.9 (0.3)	6.4 (0.6)	6.8 (0.5)[d]	8.4 (2.3)[b]
CCSM	15.3 (0.5)	21.2 (1.0)	9.0 (0.6)	3.1 (0.7)	5.1 (0.2)[b]	6.7 (0.6)	7.0 (0.4)[a]	8.2 (1.3)[b]
HadCM3	15.3 (0.4)	21.2 (1.0)	9.0 (1.0)	3.1 (0.8)	4.8 (0.3)	6.5 (0.7)	6.8 (0.4)[d]	8.4 (2.2)[b]
N-AL								
OBS	14.3 (0.4)	17.5 (0.8)	5.7 (0.9)	4.3 (1.0)	5.6 (0.3)	7.9 (0.6)	7.3 (0.6)	11.4 (2.7)
ERA40	14.3 (0.3)	17.4 (0.7)	5.7 (0.8)	4.2 (0.8)	5.4 (0.2)[c]	7.5 (0.6)[c]	7.7 (0.6)[b]	9.9 (1.8)[b]
CCSM	14.3 (0.4)	17.4 (0.8)	5.5 (0.7)	4.1 (0.8)	5.6 (0.3)	7.7 (0.7)	7.9 (0.5)[a]	9.5 (2.6)[b]
HadCM3	14.4 (0.3)	12.4 (1.2)	5.6 (1.2)	4.2 (0.7)	5.4 (0.3)[a]	7.5 (0.8)[c]	7.7 (0.6)[b]	10.2 (1.8)[d]
S-AL								
OBS	16.2 (0.7)	21.6 (0.8)	8.0 (1.0)	3.7 (0.8)	5.2 (0.3)	6.8 (0.5)	6.6 (0.6)	11.2 (2.5)
ERA40	16.2 (0.4)	21.5 (0.8)	7.9 (0.8)	3.7 (0.8)	5.2 (0.4)	6.7 (0.5)	6.9 (0.5)[c]	9.4 (1.7)[b]
CCSM	16.2 (0.4)	21.5 (0.9)	7.8 (0.7)	3.7 (0.9)	5.4 (0.3)[c]	6.9 (0.6)	7.1 (0.5)[a]	9.9 (2.8)[d]
HadCM3	16.2 (0.4)	21.5 (1.0)	7.8 (1.0)	3.8 (1.0)	5.1 (0.3)	6.7 (0.7)	6.9 (0.4)[c]	10.1 (2.6)[d]
N-NC								
OBS	15.7 (0.7)	18.9 (0.7)	4.6 (1.4)	2.9 (0.7)	5.8 (0.3)	7.6 (0.5)	6.9 (0.7)	7.9 (1.8)
ERA40	15.9 (0.2)	18.9 (0.7)	4.7 (0.8)	2.9 (0.6)	5.5 (0.2)[a]	7.1 (0.6)[b]	7.1 (0.5)	6.9 (1.2)[b]
CCSM	15.8 (0.3)	18.9 (0.9)	4.6 (0.7)	2.7 (0.5)	5.6 (0.3)[d]	7.4 (0.6)	7.5 (0.5)[a]	6.7 (1.1)[b]
HadCM3	15.9 (0.3)	18.9 (1.2)	4.6 (1.1)	3.1 (0.7)	5.5 (0.3)[a]	7.1 (0.8)[b]	7.2 (0.5)[d]	7.7 (1.4)
N-FL								
OBS	16.2 (0.4)	23.8 (0.7)	10.5 (1.0)	3.4 (1.1)	5.1 (0.4)	5.8 (0.4)	6.4 (0.5)	10.7 (3.2)
ERA40	16.3 (0.4)	23.8 (0.7)	10.4 (0.8)	3.0 (0.8)	5.1 (0.3)	5.9 (0.5)	6.6 (0.5)	8.4 (1.8)[a]
CCSM	16.2 (0.6)	23.7 (0.9)	10.3 (0.8)	2.9 (0.9)[d]	5.3 (0.2)[b]	6.1 (0.6)[b]	6.8 (0.5)[b]	8.1 (2.2)[a]
HadCM3	16.3 (0.4)	23.7 (1.1)	10.4 (1.0)	3.1 (0.9)	5.1 (0.3)	6.0 (0.6)	6.6 (0.4)	8.4 (2.2)[b]

	Summer growing season (1 Mar–1 Aug)							
	Srad (MJ m^{-2} d^{-1})	$T_{\max}$ (°C)	$T_{\min}$ (°C)	Rfl (mm d^{-1})	S_srad (MJ m^{-2} d^{-1})	S_$t_{\max}$ (°C)	S_$t_{\min}$ (°C)	S_rfl (mm d^{-1})
N-GA								
OBS	20.8 (0.7)	26.5 (0.8)	14.2 (0.7)	3.3 (1.0)	4.1 (0.3)	6.7 (0.9)	6.8 (0.5)	8.8 (2.9)
ERA40	20.9 (0.5)	26.5 (0.7)	14.2 (0.7)	3.3 (0.9)	4.0 (0.2)	6.7 (0.7)	7.1 (0.6)[d]	6.8 (1.9)[b]
CCSM	20.8 (0.8)	26.5 (1.0)	14.2 (0.7)	3.4 (1.0)	4.3 (0.3)[b]	6.7 (0.9)	7.4 (0.7)[b]	7.4 (1.8)[c]
HadCM3	20.9 (0.5)	26.5 (0.9)	14.2 (0.8)	3.5 (0.7)	4.0 (0.3)	6.6 (0.9)	7.0 (0.6)	7.5 (1.4)[c]
S-GA								
OBS	20.7 (0.6)	27.7 (0.8)	15.9 (0.8)	3.2 (1.1)	3.1 (0.3)	5.7 (0.8)	6.1 (0.6)	9.1 (3.0)
ERA40	20.6 (0.8)	27.7 (0.9)	15.9 (0.7)	3.4 (0.9)	3.5 (0.2)[a]	5.7 (0.8)	6.2 (0.7)	7.4 (2.0)[b]
CCSM	20.5 (1.0)	27.7 (1.0)	15.9 (0.7)	3.6 (0.9)	4.1 (0.3)[a]	5.8 (1.0)	6.3 (0.7)[d]	7.9 (1.8)[d]
HadCM3	20.6 (0.6)	27.7 (0.9)	15.9 (0.7)	3.5 (0.9)	3.5 (0.3)[a]	5.5 (0.9)	6.1 (0.8)	7.7 (2.3)[c]

Table 1 continued

	Summer growing season (1 Mar–1 Aug)							
	Srad ($MJ\ m^{-2}\ d^{-1}$)	T_{max} (°C)	T_{min} (°C)	Rfl ($mm\ d^{-1}$)	S_srad ($MJ\ m^{-2}\ d^{-1}$)	S_t_{max} (°C)	S_t_{min} (°C)	S_rfl ($mm\ d^{-1}$)
N-AL								
OBS	20.6 (0.6)	25.7 (0.8)	13.6 (0.7)	4.0 (1.1)	3.9 (0.3)	6.9 (0.8)	7.1 (0.5)	10.6 (3.0)
ERA40	20.5 (0.6)	25.7 (0.6)	13.6 (0.7)	4.0 (0.9)	4.4 (0.3)[a]	7.0 (0.7)	7.6 (0.5)[b]	8.7 (1.8)[b]
CCSM	20.5 (0.8)	25.7 (1.1)	13.6 (0.8)	4.1 (1.1)	4.6 (0.4)[a]	6.7 (1.0)	7.8 (0.7)[a]	8.6 (2.3)[b]
HadCM3	20.5 (0.5)	25.7 (0.9)	13.6 (0.9)	4.1 (0.9)	4.4 (0.4)[a]	7.0 (1.0)	7.4 (0.8)	9.4 (2.3)[d]
S-AL								
OBS	22.0 (1.1)	28.3 (0.7)	14.9 (1.0)	3.9 (1.3)	3.2 (0.3)	5.7 (0.9)	6.0 (0.6)	10.9 (3.6)
ERA40	21.9 (0.8)	28.3 (0.8)	14.9 (0.7)	4.0 (1.1)	3.8 (0.2)[a]	5.8 (0.8)	6.2 (0.7)	8.6 (2.4)[b]
CCSM	21.9 (1.0)	28.3 (1.0)	14.9 (0.7)	4.3 (1.1)	4.3 (0.4)[a]	5.9 (0.9)	6.3 (0.7)[d]	10.0 (3.5)
HadCM3	22.0 (0.6)	28.3 (0.8)	14.9 (0.7)	4.1 (1.0)	3.8 (0.3)[a]	5.8 (0.9)	6.1 (0.7)	9.7 (3.1)
N-NC								
OBS	22.1 (1.1)	26.4 (0.7)	12.5 (1.3)	3.4 (0.9)	3.8 (0.4)	6.7 (0.8)	7.4 (0.5)	9.2 (2.0)
ERA40	22.2 (0.5)	26.4 (0.8)	12.5 (0.7)	3.5 (0.5)	3.5 (0.2)[a]	6.4 (0.7)[d]	7.5 (0.5)	7.1 (1.0)[a]
CCSM	22.1 (1.0)	26.4 (1.0)	12.5 (0.7)	3.5 (0.8)	4.1 (0.4)[a]	6.6 (1.0)	7.8 (0.7)[b]	7.4 (1.4)[a]
HadCM3	22.2 (0.5)	26.4 (0.9)	12.5 (0.9)	3.6 (0.6)	3.5 (0.3)[b]	6.2 (0.9)[c]	7.4 (0.6)	7.7 (1.1)[a]
N-FL								
OBS	21.7 (0.7)	29.4 (0.7)	16.3 (0.8)	4.0 (1.1)	3.0 (0.2)	4.7 (0.6)	5.7 (0.7)	10.9 (2.9)
ERA40	21.6 (0.7)	29.4 (0.8)	16.3 (0.7)	4.0 (0.9)	3.7 (0.2)[a]	5.0 (0.7)[d]	5.8 (0.7)	8.4 (2.2)[a]
CCSM	21.5 (1.0)	29.4 (0.9)	16.3 (0.7)	3.8 (1.0)	4.3 (0.3)[a]	5.1 (0.8)[b]	5.9 (0.7)	7.9 (2.1)[a]
HadCM3	21.6 (0.6)	29.4 (0.8)	16.3 (0.7)	3.9 (1.2)	3.8 (0.3)[a]	4.9 (0.8)	5.7 (0.7)	8.4 (3.0)[a]

Differences with observations significant above the 99 % significance level are indicated with [a], above 95 % with [b], above 90 % with [c], and above 80 % with [d]

HadCM3) having different seasonal rainfall frequency distribution compared to the observations (Fig. 1). The average growing season temperature did not statistically differ between the observed and any of the downscaled climate model outputs. But the variability around the mean was significantly different from the observations at N-AL, S-AL, N-NC, and N-FL (Figs. 1b, 3b; Table 1).

For maize, the yield was significantly different (at $P > 95$ % significance level) for N-AL under irrigated maize and both soil types (Online Resources 6). The irrigated maize yields were not different between the two soil types because the cumulative amount of rainfall, plus the irrigation canceled out the soil effects. The variability around the average yield depends on location, soil type, and irrigation management (Fig. 2). Sandy soils showed higher variability in simulated maize yield for any of the input weather data used, while clay soils and irrigation showed lower variability (Fig. 2, Online Resources 6). In addition, the impact of the weather data sources was different for summer (Fig. 2, Online Resources 6) and winter crops (Fig. 3c, Online Resources 6). In N-AL, the winter wheat yield was different at 99 % significance level for crop simulation made using CCSM and different at 80 % significance level for the ERA40. Winter wheat yields were not significantly different between the two soil and the two irrigations because the amount of cumulative rainfall that fell during the growing season was already sufficient for the simulated crop to not cause a water deficit (Fig. 3a). The numbers of days above 32 °C, which are statistically different (Table 2), show a high year-to-year variability between the CCSM and the observed weather data (Fig. 3d). Crop simulations using CCSM showed different maturity dates which in turn will affect the final yield (Online Resources 7). In addition, the number of dry days at flowering (which on average were not statistically different as shown in Table 2) and number of days below 0 °C showed high variability when the yearly values between observed weather and CCSM were compared (Online Resources 7).

Discussion

Overall, there was little impact in terms of average simulated crop yield when using the dynamically downscaled historical climate simulations or the dynamically

Table 2 Average and standard deviation (in brackets) of dry days (10 days before and 10 days after anthesis date), rainfall above 30 mm, maximum temperature >32 °C, minimum temperature <8 °C for maize and <0 °C for wheat for north Georgia (N-GA), south Georgia (S-GA), north Alabama (N-AL), south Alabama (S-AL), North Carolina (N-NC), and Florida (N-FL) calculated from the observed weather data (Observed), reanalysis (ERA40), and two GCMs (CCSM and HadCM)

	Maize				Wheat			
	Observed	ERA40	CCSM	HadCM	Observed	ERA40	CCSM	HadCM
	Average # of dry days at anthesis				*Average # of dry days at anthesis*			
N-GA	14.3 (3.6)	10.2 (3.8)^{a}	14.5 (3.3)	12.1 (3.5)^{b}	15.7 (1.8)	12.9 (2.4)^{a}	15.0 (3.5)	13.4 (2.9)^{a}
S-GA	13.8 (3.0)	9.2 (3.4)^{a}	0.0 (0.0)^{a}	10.9 (4.4)^{a}	16.7 (2.4)	14.1 (2.7)^{a}	15.4 (3.5)	14.3 (3.2)^{b}
N-AL	15.2 (2.8)	10.4 (3.8)^{a}	0.0 (0.0)^{a}	11.8 (3.3)^{a}	15.2 (2.7)	12.1 (3.0)^{a}	14.6 (3.3)	12.5 (3.4)^{a}
S-AL	14.0 (2.9)	8.8 (3.8)^{a}	0.0 (0.0)^{a}	10.7 (3.8)^{a}	16.3 (2.8)	13.5 (2.9)^{a}	16.0 (2.7)	13.5 (2.9)^{a}
N-NC	14.8 (3.1)	9.8 (3.1)^{a}	13.3 (2.7)	11.6 (3.5)^{a}	15.3 (2.4)	12.9 (2.7)^{a}	14.4 (2.9)	12.8 (3.4)^{b}
N-FL	13.4 (2.5)	8.3 (3.0)^{a}	0.0 (0.0)^{a}	9.2 (3.7)^{a}	17.5 (1.9)	14.4 (2.7)^{a}	16.2 (2.9)^{d}	14.4 (2.3)^{a}
	Average # of days >30 mm				*Average # of days >30 mm*			
N-GA	4.4 (2.6)	2.3 (1.6)^{a}	2.5 (1.9)^{a}	2.6 (1.3)^{a}	6.6 (3.3)	4.5 (2.5)^{b}	4.4 (2.4)^{b}	5.1 (2.6)^{c}
S-GA	3.8 (1.9)	2.5 (1.9)^{a}	3.5 (1.8)	2.8 (1.8)^{c}	7.2 (3.5)	5.4 (3.3)^{c}	5.6 (2.4)^{c}	5.2 (2.5)^{b}
N-AL	5.6 (2.4)	4.0 (2.3)^{b}	4.0 (2.2)^{b}	4.2 (1.8)^{b}	9.5 (3.4)	7.4 (2.3)^{b}	7.0 (2.2)^{a}	7.8 (2.8)^{c}
S-AL	5.2 (2.4)	3.2 (1.9)^{a}	4.1 (2.1)^{d}	3.7 (1.6)^{b}	8.3 (2.7)	6.9 (3.3)	7.5 (3.3)	7.4 (3.4)
N-NC	4.0 (2.0)	2.6 (1.2)^{b}	3.2 (1.7)^{d}	3.3 (1.8)	4.6 (2.5)	3.5 (1.8)^{c}	3.3 (1.8)^{c}	4.4 (2.1)
N-FL	5.5 (2.2)	3.5 (1.9)^{a}	2.9 (2.2)^{a}	3.6 (2.7)^{b}	8.2 (4.2)	5.8 (2.7)^{b}	5.6 (3.4)^{b}	6.3 (3.0)^{c}
	Average # days with T_{min} <8 °C				*Average # days with T_{min} <0 °C*			
N-GA	33.7 (5.6)	33.4 (5.1)	32.6 (6.6)	31.6 (7.5)	39.1 (9.6)	51.3 (11.9)^{a}	54.7 (12.7)^{a}	51.6 (13.6)^{a}
S-GA	19.8 (5.9)	19.5 (6.1)	21.1 (5.8)	19.4 (6.7)	21.8 (10.8)	30.0 (10.2)^{b}	32.8 (9.0)^{a}	30.5 (9.5)^{a}
N-AL	36.3 (5.8)	36.5 (5.8)	37.3 (6.0)	34.3 (7.3)	54.7 (12.5)	66.5 (9.4)^{a}	69.5 (11.7)^{a}	64.4 (15.3)^{b}
S-AL	24.3 (6.5)	23.9 (6.1)	24.8 (5.6)	23.1 (7.2)	29.7 (11.7)	38.2 (10.0)^{b}	42.3 (10.6)^{a}	39.1 (11.9)^{b}
N-NC	45.0 (7.5)	42.5 (5.2)	42.5 (6.4)	40.1 (7.7)^{b}	65.8 (19.1)	71.7 (10.5)	79.6 (10.6)^{b}	74.6 (16.4)^{d}
N-FL	15.2 (5.7)	16.3 (6.5)	16.9 (6.2)	15.9 (6.5)	15.6 (8.1)	22.6 (9.8)^{b}	22.0 (7.9)^{b}	20.9 (8.2)^{c}
	Average # days with $T_{\max}$ >34 °C				*Average # days with T_{max} >32 °C*			
N-GA	15.8 (10.9)	17.4 (7.3)	18.7 (9.2)	15.9 (8.6)	3.4 (3.3)	3.4 (3.7)	4.5 (4.3)^{c}	3.0 (2.5)
S-GA	13.9 (10.0)	18.4 (11.2)^{d}	19.9 (10.2)^{c}	15.7 (8.5)	6.5 (6.0)	6.2 (4.4)	8.5 (5.7)	5.6 (3.4)
N-AL	10.1 (7.4)	13.0 (5.4)^{d}	13.9 (10.1)^{d}	13.6 (7.3)^{d}	1.9 (3.2)	2.2 (1.8)	3.4 (3.8)^{d}	1.8 (1.8)
S-AL	19.7 (13.2)	24.3 (13.2)	24.0 (10.2)	21.9 (10.1)	8.7 (5.7)	10.7 (6.2)	11.5 (6.0)^{d}	9.9 (4.3)
N-NC	12.6 (7.7)	14.0 (7.7)	17.1 (10.2)^{d}	11.9 (8.0)	4.7 (3.1)	3.3 (2.7)^{d}	4.9 (4.2)	2.3 (2.1)^{a}
N-FL	19.5 (12.6)	24.7 (10.7)^{d}	24.7 (10.4)^{d}	21.5 (8.6)	13.1 (7.2)	13.7 (7.4)	16.9 (8.3)^{d}	13.1 (6.2)

Differences with observations significant above the 99 % level are indicated with ^{a}, above 95 % with ^{b}, above 90 % with ^{c}, and above 80 % with ^{d}

downscaled reanalysis. The intra-seasonal standard deviation of climate variables ($T_{\max}$, $T_{\min}$, solar radiation, rainfall) show that 36 % of them are not different from the observed weather, with the intra-seasonal variability of $T_{\max}$ and $T_{\min}$ being less different between the observed and the downscaled climate models, especially in summer (Table 1). This lower variability in summer than in winter means that simulated maize yields were less different than when downscaled models were used to simulated wheat.

There were, however, situations in which the average simulated yield using downscaled weather data was significantly different from the one simulated with observed weather data. This was due to a combination of several factors. Firstly, the quality of the observations used for rainfall bias correction of climate models can be a source of error. Problems of data quality control, homogeneity, and completeness have to be taken into account because they can affect the bias correction of climate models (Easterling et al. 1999). The observed rainfall data used for rain bias correction come from gridded observations (as opposed to station data), and it is likely to result in a reduction in magnitude of intense precipitation events. Secondly, the intra-seasonal variability of the temperatures, below and above the crop optimum, of the climate models compared to the observed weather data affects the year-to-year crop simulation resulting in statistically different simulated average yields. For example, the simulated wheat yields using observed weather data and CCSM in

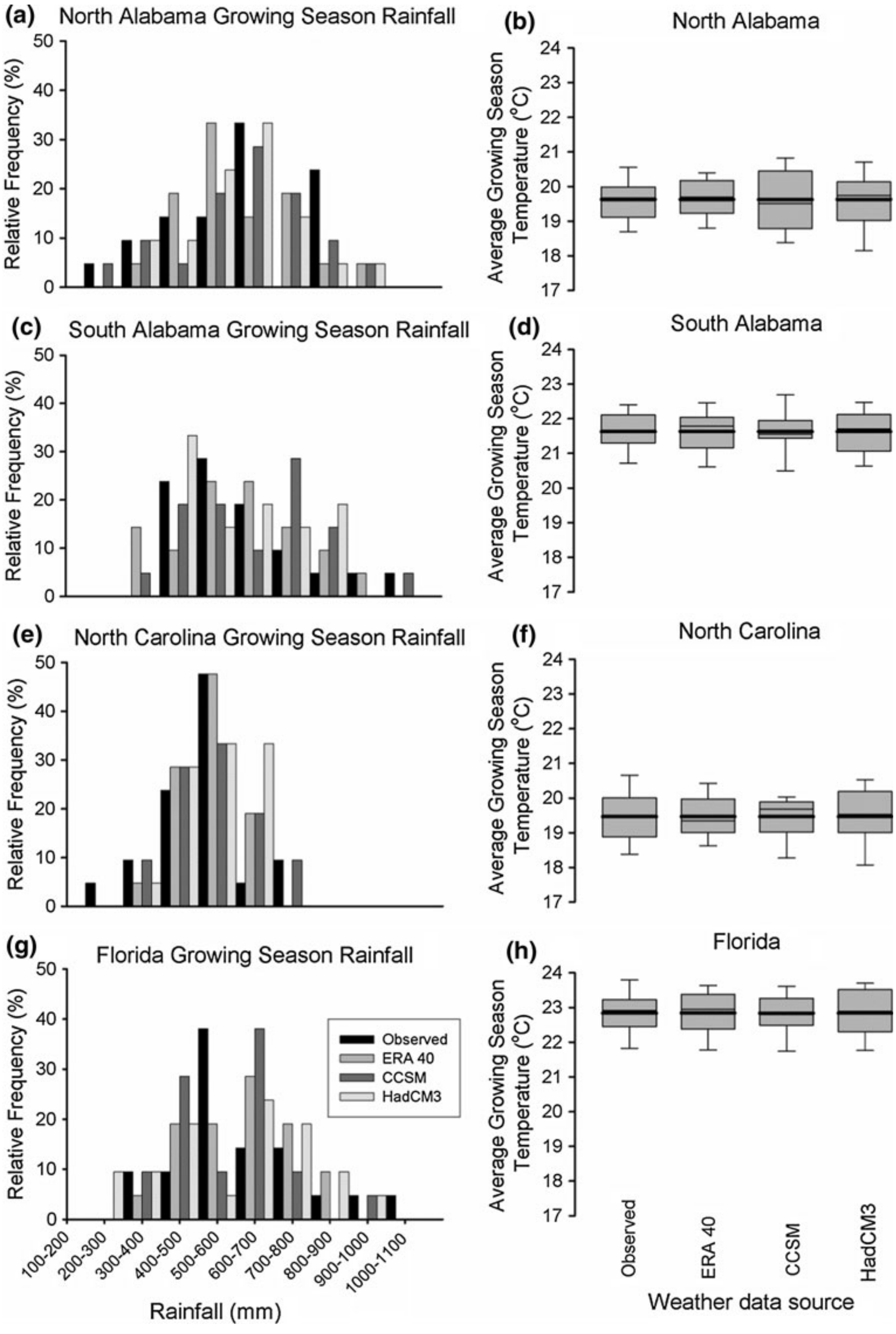

Fig. 1 Growing season rainfall and growing season average temperature (GST) for maize for **a**, **b** north Alabama (N-AL), **c**, **d** south Alabama (S-AL), **e**, **f** for North Carolina (N-NC), **g**, **h** Florida (N-FL) for historical weather from National Climatic Data Center (*Observed*), reanalysis (ERA40), and two GCMs (CCSM and HadCM3) for the same period. *Lower side of box* = 25 %-tile, *upper-hand side of box* = 75 %-tile, *thick horizontal line in box* = average, *thin horizontal line in box* = median, *lower error bar* = 10 %-tile, and *upper error bar* = 90 %-tile of the growing season temperatures

N-AL are statistically different because of the high intra-seasonal variability of the number of days above 32 °C (Fig. 3d, Online Resources 6). When 32 °C is reached, development is halted for wheat and the CCSM weather data showed higher number of days above 32 °C for 18 out of 20 growing seasons (Fig. 3d). Since most of the days above 32 °C are around flowering, it will also cause a reduction in grain yield for wheat (Fischer 1979).

In addition, the simple delta approach used for temperature variables in this study does not adjust the variance of temperatures around their bias-corrected mean. Tsvetsinskaya et al. (2003) found that the temperature during vernalization from climate models affects the simulated wheat yields. In this study, we found that the inter-annual variability of the number of days above 32 °C affected final simulated wheat yields (Fig. 3).

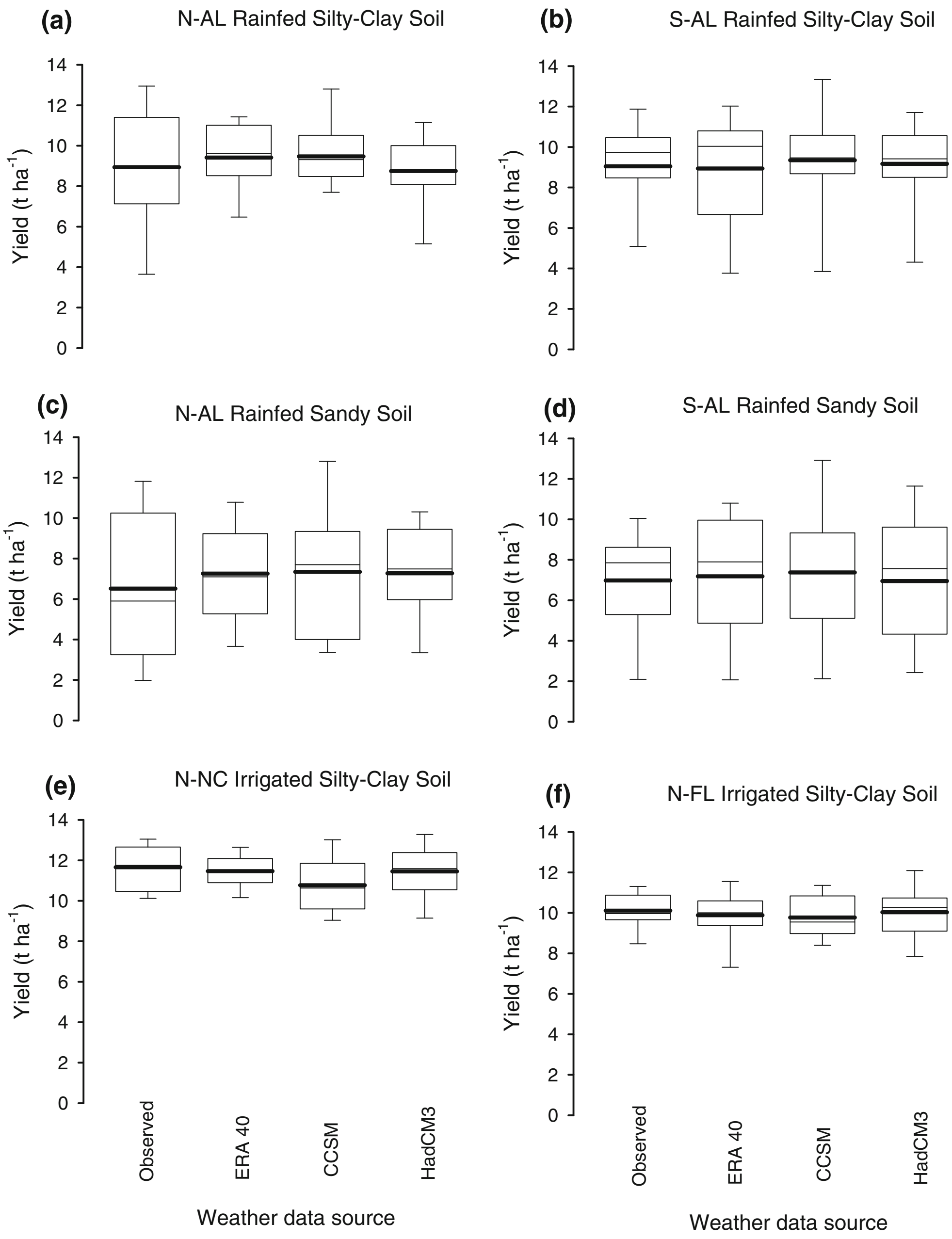

Fig. 2 Simulated yield for **a**–**d** rainfed maize for north Alabama (N-AL) and south Alabama (S-AL) for **a**, **b** silty-clay and **c**, **d** sandy soil, and **e**, **f** irrigated maize for North Carolina (N-NC) and Florida (N-FL) for silty-clay soil for simulations with historical weather from the National Climatic Data Center (*Observed*), reanalysis (ERA40), and two GCMs (CCSM and HadCM3) for the same period. *Lower side of box* = 25 %-tile, *upper-hand side of box* = 75 %-tile, *thick horizontal line in box* = average, *thin horizontal line in box* = median, *lower error bar* = 10 %-tile, and *upper error bar* = 90 %-tile of the simulated yield

It should be reminded that from a climatological point of view, when looking at the 20-year time series plots (Fig. 3d, Online Resources 7), a year-to-year matching is not what is expected from GCMs, but an expectation that the GCMs will behave climate-like in a statistical sense (Table 1; Fig. 1). However, when predicting climate change impact on agricultural production, it is not sufficient that they can accurately project the averages of crop growing season rainfall, temperatures, and solar radiation over a certain time frame. It is important that the intra-seasonal and daily distribution of these variables is well simulated in order to better represent the changes in yearly crop production variability under future climate. Crop models simulate crop growth and development as a function of daily data, and therefore, the simulated yield will depend on the quality of the daily weather data inputs. For

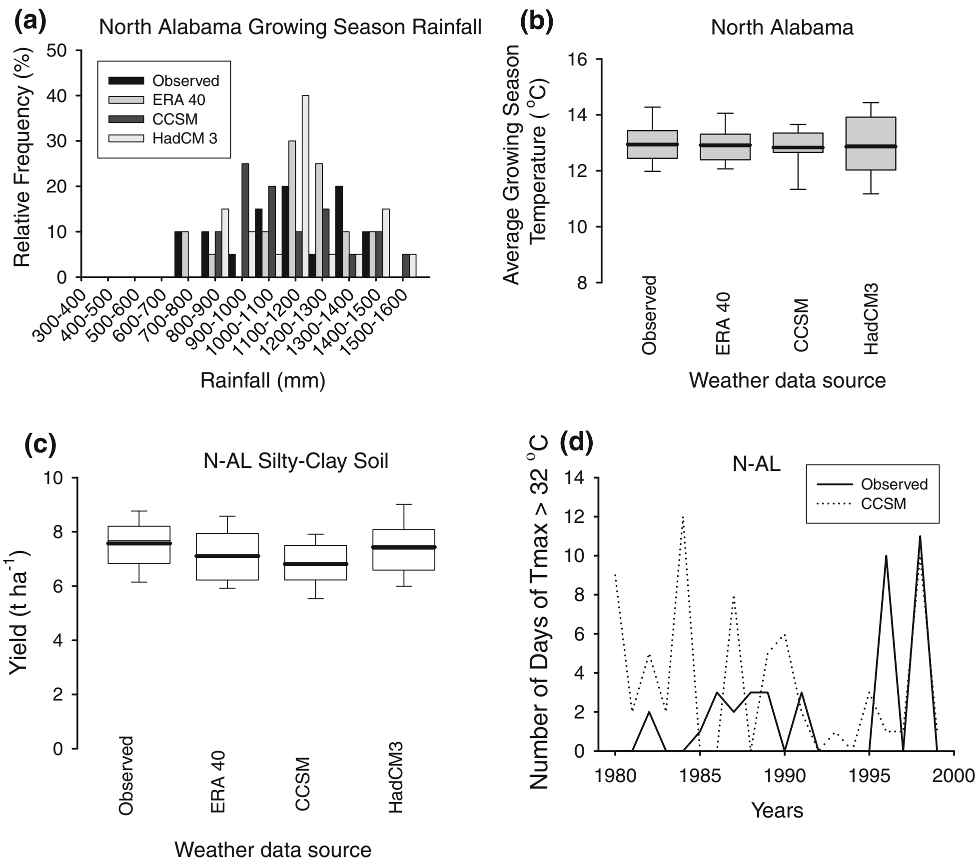

Fig. 3 Growing season rainfall and growing season average temperature (GST) for wheat for **a**, **b** north Alabama (N-AL) and simulated wheat yield **c** for north Alabama (N-AL) for historical weather from National Climatic Data Center (*Observed*), reanalysis (ERA40), and two GCMs (CCSM and HadCM3) for the same period. *Lower side of box* = 25 %-tile, *upper-hand side of box* = 75 %-tile, *thick horizontal line in box* = average, *thin horizontal line in box* = median, *lower error bar* = 10 %-tile, and *upper error bar* = 90 %-tile of the growing season temperatures (*gray boxplots*) and wheat yield (*white boxplots*) and **d** numbers of days with $T_{\max}$ >32 °C for the Observed weather (*full line*) data and the CCSM model (*dotted line*)

example, the different number of days above 32 °C influences the simulated crop evapotranspiration demand, crop water use, and the timing of water availability in soil which affect the simulated yield.

GCMs can be operated with continuous assimilation of weather observations, resulting in reanalysis data. This study agrees with the findings of Challinor et al. (2005) that reanalysis of weather data as inputs for crop model lowers the degree of bias in simulated crop yields as result of the similarities in the intra-seasonal standard deviation of $T_{\max}$ and the better representation of the number of days with $T_{\max}$ and $T_{\min}$ exceeding the upper and lower limits for both crops (Tables 1, 2).

Yield variability is more evident on sandy soils than silty-clay soils but not in irrigated systems because the amount of growing season rainfall plus the additional irrigation was more than enough to make the soil differences unimportant. These results also indicate the importance of cropping systems' components in determining the bias from weather data sources, especially the growing season rainfall (calculated from sowing to harvest). Simulated rainfed maize yields were more susceptible to rainfall distribution and frequency (Table 1; Fig. 1) than wheat because the amount of growing season rainfall for wheat was higher than maize causing less variability in terms of simulated rainfed wheat yield (Figs. 1, 3). Furthermore, wheat was more susceptible to a bias in simulated yields because climate models showed significant differences in the number of days that the upper and lower crop temperature limits were exceeded compared to maize.

Conclusions

In conclusion, this study indicates that the uses of the GCM generated weather into crop simulation models can significantly reproduce the mean instead of the variability of the simulated yield. The GCM weather data are not year-specific and can therefore not be compared day-by-day or year-by-year with observed data. In fact, a comparison must be made using long-term means and gross statistics. However, when high-resolution climate models are used to predict climate change impact on agriculture, it is not sufficient that they can accurately project the averages of crop growing season rainfall, temperatures, and solar radiation. Rather, future research should be aimed to improving the intra-seasonal distribution of these variables from climate models in order to be used as appropriate inputs for crop simulation models in order to reduce the uncertainty of the intra-seasonal simulated yields for studies of climate impacts on agriculture.

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