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Key Points:

- Economically valuable crop production can be assessed better using a set of the regional climate models
- A reanalysis-driven crop yield might not be good for a decision-making process
- The multi-model ensemble method is a very useful tool for delivering improved crop yield estimation

Supporting Information:

- Supporting Information S1

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Assessing crop yield simulations driven by the NARCCAP regional climate models in the southeast United States

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Abstract A set of the North American Regional Climate Change Assessment Program (NARCCAP) regional climate models is used in crop modeling systems to assess economically valuable agricultural production in the southeast United States, where weather/climate exerts strong impact on agriculture. The maize/peanut/cotton yield amounts for the period of 1981–2003 are obtained in a regularly gridded (~20 km) southeast U.S. using (a) observed, (b) a reanalysis, and (c) the NARCCAP Phase I multimodel data set. It is shown that the regional-climate model-driven crop yield amounts are better simulated than the reanalysis-driven ones. Multimodel ensemble methods are then adopted to examine their usefulness in improving the simulation of regional crop yield amounts and are compared to each other. The bias-corrected or weighted composite methods combine the crop yield ensemble members better than the simple composite method. In general, the weighted ensemble crop yield simulations match marginally better with the observed-weather-driven yields compared to those of the other ensemble methods.

1. Introduction

As an initial research step to detect the possible impacts of climate variability and climate change on agricultural production in the southeast United States, this study is performed to evaluate a regional climate multimodel data set in crop yield simulations. Climate models tend to have significant biases. These biases could be due to not resolving fine-scale features, to imperfections in model physics, low resolution, or a number of other reasons [*Shin and Cocke*, 2013]. For detailed crop models, biases in the climate input can have a significant impact, leading to unrealistic results [*Ceglar and Kajfez-Bogataj*, 2012]. Thus, in order to use climate projections for crop model simulations, downscaling and/or bias correction techniques might be a prerequisite step [e.g., *Baigorria et al.*, 2007, 2008; *Shin et al.*, 2010].

To address the above issue, a set of downscaled weather/climate data is utilized. The North American Regional Climate Change Assessment Program (NARCCAP) [*Mearns et al.*, 2009, 2012] Phase I is perhaps the most comprehensive set of regional climate model simulations available over North America. This is a large collaborative effort to downscale the World Climate Research Programme Phase 3 of the Coupled Model Intercomparison Project (CMIP3) [*Meehl et al.*, 2007] climate models by using six participating regional climate models. There is no comprehensive dynamical downscaling effort using the CMIP5 [*Taylor et al.*, 2012] models yet over North America. The confidence in the regional models is mostly based on how well they simulate the regional climate compared to the global counterpart. The NARCCAP Phase I shows a promising result in simulating regional scale climate [*Mearns et al.*, 2012].

What is the distribution of possible outcomes, both for climate and subsequent agriculture production? To answer this question, the multimodel ensemble (MME) concept of using weather/climate models has been adopted in a few agricultural studies [e.g., *Challinor et al.*, 2005; *Rotter et al.*, 2011; *Rosenzweig et al.*, 2014]. Most of these studies, at most, used a simple composite method (i.e., regular ensemble averaging). However, it is expected that some models are superior to others, based on certain metrics applied to historical simulations where observations are available. To take into account differential skill, a weighting method can be used. In this research, the aim is to provide reliable maize (*Zea mays*), peanut (*Arachis hypogaea*), and cotton (*Gossyium L.*) crop yield simulations by using the MME method for use in planning and policies for agriculture, which might maximize crop yields and minimize risk of low yields in the southeast United States. By improving crop yield estimation quantitatively in the region, we will fulfill decision/policy-makers' desire to have a more confident and credible crop yield estimate compared to the existing widespread estimates [*Rotter et al.*, 2011; *Martre et al.*, 2015] for their use. For climate information to benefit society, it must fit into a decision-making process and must affect actions of decision-makers [*Letson et al.*, 2005]. For this to happen, seasonal to decadal climate forecasts should be integrated in the context of a broader information delivery and decision support system [*Letson et al.*, 2005; *McCown et al.*, 2002; *Cash and Buizer*, 2005].

The paper is organized as follows: the data and methods used in the present study are described in section 2. The assessments of crop yield simulations are presented in section 3. The conclusions follow in section 4.

2. Data and Methods

Our system links a global climate reanalysis to downscaling models to dynamic crop models to MME methods. The NARCCAP data (23 years, 1981–2003) are chosen to obtain temporal and spatial scales appropriate to drive the dynamical crop model simulations. An ensemble of crop yield simulations is generated by using six NARCCAP regional climate models. MME methods are then used to produce a better crop yield estimate by narrowing the uncertainty of the simulations.

2.1. Observed Weather/Climate Data

The Cooperative Observer Network (COOP)-based observed weather/climate data for Alabama, Georgia, and Florida are provided by the Florida Climate Center—Office of the State Climatologist. The daily weather data consist of maximum and minimum temperatures, and precipitation on a regularly gridded mesh (~20 × 20 km, see Figure 1). The 20 km horizontal resolution is chosen because it is roughly resolving the county scale in the southeast United States. Daily values of incoming solar radiation are estimated by using the method published by *Bristow and Campbell* [1984], because these data are not in the COOP data. Data are available for 1171 grid points across the three states. These data are the baseline data used in the corn, peanut, and cotton models to simulate observed-weather-driven crop yield amounts.

2.2. NARCCAP

NARCCAP engages six regional climate models (RCMs) that are run at a 50 km horizontal resolution and driven by the National Centers for Environmental Prediction (NCEP)–Department of Energy Reanalysis II (R2) [*Kanamitsu et al.*, 2002] and four CMIP3 models forced with the Special Report on Emission Scenarios A2 scenario [*Nakicenovic et al.*, 2000]. Downscaling is necessary to adjust coarse resolution output of climate reanalysis or model simulations to provide more detailed spatial representation of weather systems, which can have significant influence on yield simulations of dynamic crop models.

An advantage of dynamical downscaling is that the atmospheric variables are physically consistent with each other. However, the computational costs of running the RCM are significant. In this study, the Phase I data set (wherein six RCMs use boundary conditions from the R2) is collected and statistically further interpolated to ~20 km (roughly resolving the county scale) over the southeast United States for use in crop model simulations. Table 1 provides information on the NARCCAP data used in this study.

2.3. Crop System Modeling—Decision Support System for Agrotechnology Transfer

The Crop System Modeling—Decision Support System for Agrotechnology Transfer (CSM-DSSAT) model [*Jones et al.*, 2003; *Hoogenboom et al.*, 2004] version 4.6 is used to simulate the potential effects of weather/climate on crops in the southeast United States. Three economically important crops are selected: peanut, cotton, and corn. The specific models within the DSSAT include the CERES-Maize for corn and the CROPGRO for peanut and cotton [*Jones et al.*, 2003]. These three models take into account the lower CO_2 responsiveness and new information on temperature sensitivities, which was presented in *Hatfield et al.* [2008], as derived from publications such as *Alagarswamy et al.* [2006] and *Boote et al.* [2010]. CSM-DSSAT integrates the effects of crop genotype, soil profiles, weather data, and management options into a crop model. The crop model uses maximum and minimum surface temperature, rainfall, and incoming solar radiation from season-long daily weather records. It simulates plant growth and development processes on a daily basis in a specific location, from planting data to maturity date.

The crop models described above are developed for single-point locations. A fine horizontal resolution grid, in the order of 20 km, is set up over the southeast United States that specifies the crop locations. For testing

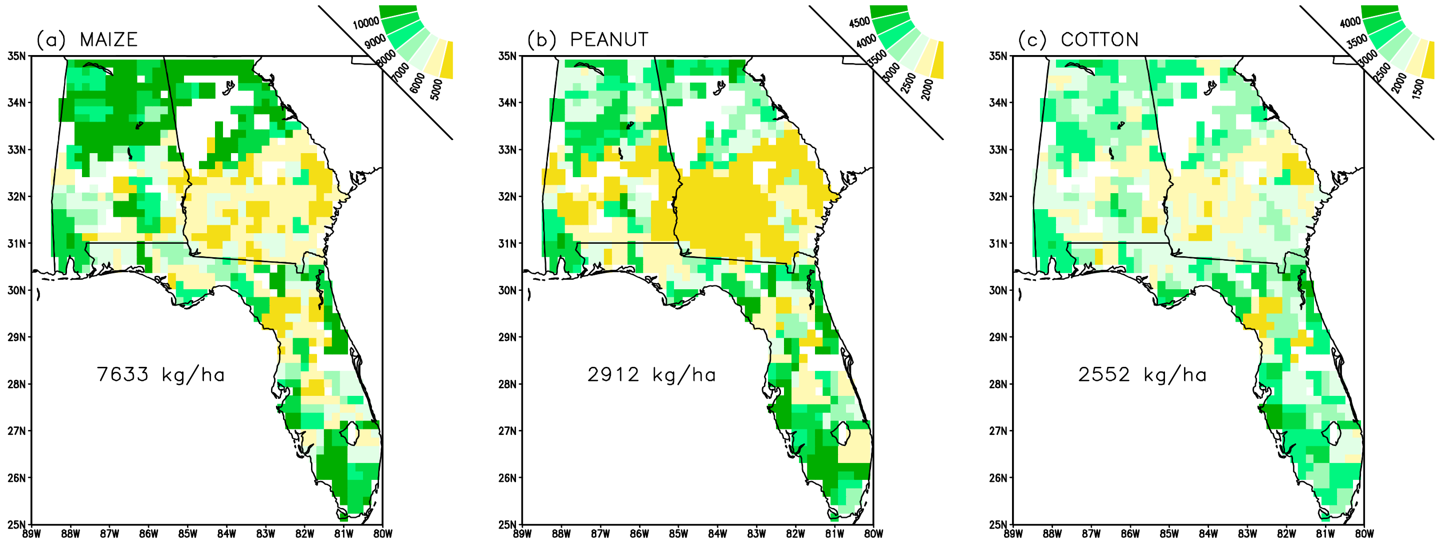

Figure 1. Simulated observed-weather-driven (a) maize, (b) peanut, and (c) cotton dry matter yields (23 year average, 1981–2003) under rainfed conditions. Unit is of kg ha^{-1}. Area averaged yield values are shown in the map.

and evaluation, the current study uses hypothetical crop coverage on the grid and adopts representative crop management practices that reflect current agricultural land use by farmers. Soil profiles for the dominant agricultural soils are based on published Soil Surveys for Georgia, Alabama, and Florida at county level [*U.S. Department of Agriculture-National Resources Conservation Service*, 2015]. Fixed fertilizer applications are assumed in management conditions. Identical initial soil moisture conditions are also used in all simulations; however, simulations are initiated at least 2 months prior to planting to let the soil modules of crop model to stabilize the soil moisture at the time of emergence according to the environmental conditions. The planting date for each year is 1 April for maize and cotton, and 25 April for peanut. These dates correspond to the middle of the range of planting dates reported by *USDA-National Agricultrual Statistics Service* (NASS) [2010]. Therefore, the weather/climate input is the only parameter that can change crop yields in a given year at a given location. The crop simulations make use of existing soil, historical climate, and management databases in addition to climate scenarios data provided by the NARCCAP. This study builds on the considerable experience in using these models for simulating effects of climate on cotton, peanut, and corn in the three States [e.g., *Southeast Regional Assessment Team*, 2002; *Jagtap et al.*, 2002; *Irmak et al.*, 2005; *Garcia y Garcia et al.*, 2006; *Paz et al.*, 2007].

Although the Southeast Climate Consortium has soil data for almost every county in Alabama, Florida, and Georgia, our analysis indicates that revisions are needed for use in the crop models. Therefore, the soil profile descriptions obtained from the Soil Surveys at each county and the use of revised algorithms to create derived soil properties [*Romero et al.*, 2012] are used to complete the soil profile descriptions (e.g., hydraulic properties such as wilting point, field capacity, and saturation). These additional soil parameters are required by the crop models and used as inputs to simulate crop yields in all 1171 grid points.

Table 1. NARCCAP Phase I Models and Their Available Periods

	Full Name	Reference	Available Period
CRCM	Canadian Regional Climate Model	*Caya and LaPrise* [1999]	1.1.1979 to 30.11.2003
ECP2	Scripps Experimental Climate Prediction Center Regional Spectral Model	*Juang et al.* [1997]	1.1.1979 to 31.12.2004
HRM3	Met Office Hadley Centre's RCM version 3	*Jones et al.* [2003]	1.1.1981 to 31.12.2004
MM5I	Fifth-generation Pennsylvania State University–National Center for Atmospheric Research (NCAR) Mesoscale Model	*Grell et al.* [1993]	1.1.1979 to 30.11.2004
RCM3	Regional Climate Model version 3 (RegCM3)	*Giorgi et al.* [1993]	1.1.1979 to 31.10.2004
WRFG	Weather Research and Forecasting model	*Skamarock et al.* [2005]	1.1.1981 to 30.12.2004

2.4. Multimodel Ensemble

The NARCCAP multimodel data set can produce many different realizations of regional climate over the southeast United States. The uncertainties of the climate can be reduced by proper combination/filtering techniques. The multimodel ensemble (MME) methods have become a predominant approach to extract skillful prediction from the available climate data. A wide variety of weighted multimodel ensembles have been used in seasonal prediction studies [e.g., *Shin and Krishnamurti*, 2003; *Palmer et al.*, 2004; *Kar et al.*, 2006; *Shin et al.*, 2008]. In all these previous studies, a simple composite method or a weighted ensemble method performed better in resolving the mean climate than any individual model in the MME framework.

Three ensemble average methods are used and compared in the NARCCAP MME configurations.

a Regular ensemble (RE)

$$\mathrm{RE} = \sum_{i=1}^{N} \frac{1}{N}(F_i) \tag{1}$$

b Bias-corrected ensemble (BCE)

$$\mathrm{BCE} = \overline{O} + \sum_{i=1}^{N} \frac{1}{N}\left(F_i - \overline{F_i}\right) \tag{2}$$

c Weighted ensemble (WE)

$$\mathrm{WE} = \overline{O} + \sum_{i=1}^{N} w_i\left(F_i - \overline{F_i}\right) \tag{3}$$

where N is the number of ensemble members, F_i is a simulation by model i, $\bar{O}$ is a time average of the observed state, w_i is a weighting function for model i, and $\overline{F_i}$ is a time average of the forecast by model i. The ensemble calculations in equations 1–3 are done for each gridbox individually. The weighting function (w_i) is computed by using the dynamical linear model method [*Shin and Krishnamurti*, 2003]. The weights are varying spatially; that is, the different members have varying relative contributions to the weights depending on the spatial location of the point in question. The WE differs from the RE in that different members are weighed by sets of a priori statistics obtained during a training period before the forecast phase. Unlike the WE, the BCE simply replaces forecast means with observed means. Due to the short data length (23 years), the weights are computed with a cross-validation procedure. In other words, 22 years (except for the one being projected) are used to obtain the weights during the training period. Hence, the weights in equation (3) are different for each year.

3. Results

The credibility of the DSSAT crop model has been intensively assessed in many previous studies [e.g., *Dubrovský et al.*, 2000; *Garcia y Garcia et al.*, 2006; *Boote et al.*, 2010]. When the model was driven by the "observed" weather/climate data, it has been shown that the crop yields were reasonably reproduced [*Baigorria et al.*, 2008]. It is assumed, in this study, that all crops could potentially be sowed and grown at our defined grid point locations (20 by 20 km, see Figure 1) in Alabama, Florida, ad Georgia. However, as expected, we find that the crops cannot grow well in some areas such as cities or lakes.

The observed weather/climate data are first used to drive the DSSAT maize, peanut, and cotton crop models. Figure 1 shows 23 year averaged (1981–2003) crop yields under rainfed condition. The average yield dry matters are 7633 kg ha^{-1} for maize, 2912 kg ha^{-1} for peanut, and 2552 kg ha^{-1} for cotton, respectively. Crop yield amounts are relatively low in southern GA for all three crops, although this area is currently the primary peanut production zone in the southeast U.S. according to NASS. This might be due to the soil types around this area. This area correspond to the Coastal Plain in Georgia, where soils are not very fertile because of their high content of sand and highly meteorized clay minerals, as well as for their poor drainage conditions. No yields

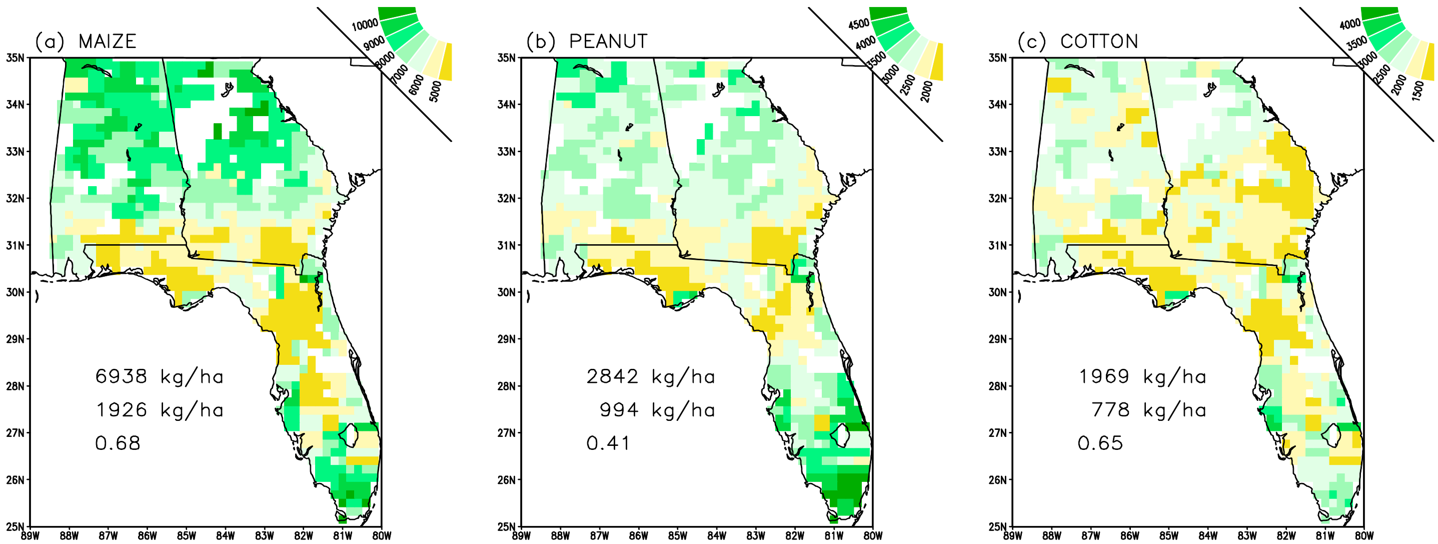

Figure 2. Same as Figure 1 but for the NCEP R2. In each panel, the first value is the area averaged dry matter yield amount, the second one RMSE, and the third one spatial correlation with the observed yields (Figure 1).

are found around the metropolitan areas (e.g., around Atlanta). Although these hypothetical crop yield distributions cannot be verified with any existing observed crop yield data (such as NASS), the authors assume, in this study, that these observed-weather-driven crop yields can be used as good proxies for the observed counterparts.

A simple bilinear interpolation is employed to statistically downscale the R2 data (~1.875°; maximum and minimum temperatures, rainfall, and radiation) to our 20 km resolution grid. The yearly simulated maize, peanut, and cotton yields are averaged for the period of 1981–2003 (Figure 2). Rainfed conditions are assumed for all simulations. In terms of the area averaged (AL, FL, and GA) yield amount, maize (6938 kg ha^{-1}), peanut (2842 kg ha^{-1}), and cotton (1969 kg ha^{-1}) are all underestimated, compared to the observed-weather-driven yields (Figure 1). While maize and cotton are approximately 600–700 kg ha^{-1} lower, peanut is only 70 kg ha^{-1} lower than the observed counterparts. The 23 year average June-July-August mean precipitation and maximum/minimum temperature bias (R2-observation) maps are shown in Figure S1 in the supporting information. This figure showing climatological averages does not provide in-depth insight as to why the area-averaged crop yields are underestimated by using R2. As demonstrated in *Shin and Cocke* [2013], the subseasonal dynamics may be a major factor in determining the crop yield amount. However, it is notable that the bias of the R2 with respect to observations is substantial. The entire domain has a wet bias, and excess rainfall of up to 5 mm/d in the R2 may affect plant growth through N leaching. This would have a bigger effect on corn and cotton than the legume peanut (Figure 2). Maximum temperature in the R2 is cooler than observations by 3–4°C, but this is probably partially offset by a consistent warm bias in minimum temperature, which results in similar overall mean temperature.

Figure 2 includes root-mean-square error (RMSE) and spatial correlation (SCORR) statistics with the observed yields (Figure 1) for each crop. The RMSEs (SCORRs) are 1926 kg ha^{-1} (0.68) for maize, 994 kg ha^{-1} (0.41) for peanut, and 778 kg ha^{-1} (0.65) for cotton. These simple skill measures indicate that the reanalysis might not be good input data for the crop model as it is. Since many scientists consider a reanalysis as being close to observation, a better performance might be expected, especially with the 23 year averaged statistics. This poor performance could be due to the reanalysis's imperfections, such as missing fine-scale features and having low resolution. It should be, however, noted that the R2 (like most reanalyses) does not assimilate 2 m temperatures, rainfall, or solar radiation. Reanalyses provide good large-scale conditions but are known to have bias in surface conditions.

The corresponding six NARCCAP regional-model-driven maize dry matter yields under rainfed condition are shown in Figure 3. (The corresponding precipitation climatology bias maps are shown in Figure S2.) Although the number of ensemble members is too few (only six) to encompass all possible outcomes in this study,

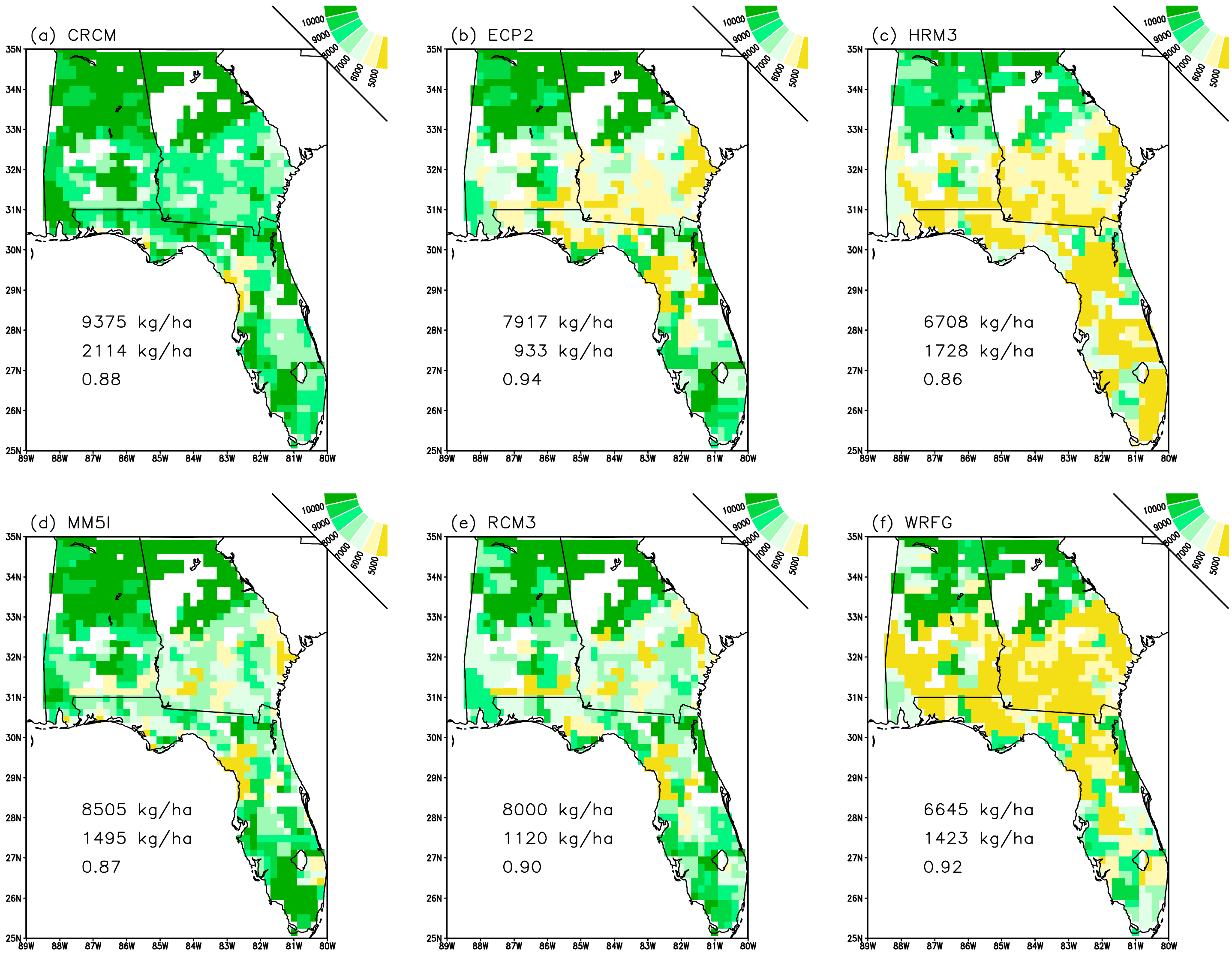

Figure 3. Simulated six NARCCAP regional-model-driven maize dry matter yields (23 year average, 1981–2003) under rainfed conditions. Unit is of kg ha^{-1}. In each panel, the first value is area averaged yield amount, the second one RMSE, and the third one spatial correlation with the observed yields (Figure 1a).

large variability from member-to-member is still visible in crop simulations. The performance of six individual dynamically downscaled models is presented in terms of area averaged yield amount, RMSE, and SCORR. It is not clear whether the regional models improve the yield simulations in terms of area averaged value and RSME. However, the spatial patterns of yields from all regional models match distinctively better with the observed pattern (Figure 1a), compared to the R2 pattern (Figure 2a). The frequency and distribution of rainfall events are likely better in the RCM than the overly drizzling R2. While the SCORR of R2 is 0.68, those of regional models are 0.88 (Canadian Regional Climate Model (CRCM)), 0.94 (ECP2), 0.86 (Met Office Hadley Centre's RCM version 3 (HRM3)), 0.87 (Fifth-generation Pennsylvania State University–National Center for Atmospheric Research (NCAR) Mesoscale Model (MM5I)), 0.90 (Regional Climate Model version 3 (RCM3)), and 0.92 (Weather Research and Forecasting (WRFG)). Hence, it is evident that the dynamical downscaling can capture fine-scale spatial features of weather/climate patterns, which are essential information for the crop yield simulations. Although determining a best model among the regional models is not considered in this study, it is worthwhile to note that a better performance is shown by the ECP2 model (RMSE = 933 kg ha^{-1}, SCORR = 0.94) that uses spectral nudging (a form of bias correction). This result is similar to what *Mearns et al.* [2012] found for some of the atmospheric variables. To show crop model's ability to

Table 2. RMSE and SCORR (Spatial Correlation) for 23 Year Average (1981–2003) Crop Yield Under Rainfed Conditions[a]

	Crop	R2	CRCM	ECP2	HRM3	MM5I	RCM3	WRFG
RMSE	maize	1926	2114	933	1728	1495	1120	1423
	peanut	994	810	678	1336	680	684	1237
	cotton	778	668	456	730	457	407	992
SCORR	maize	0.68	0.88	0.94	0.86	0.87	0.90	0.92
	peanut	0.41	0.81	0.88	0.79	0.85	0.79	0.87
	cotton	0.65	0.73	0.78	0.72	0.74	0.80	0.79

[a]Gray cells denote the best statistics among the analyzed group.

capture the interannual variability, time series correlation maps are presented in Figures S3–S6. The results are mixed depending on crop varieties and/or RCMs used.

The metrics (RSME and SCORR) for peanut and cotton, in addition to maize, are summarized in Table 2. It is clear that downscaling improves the crop yield simulations for all three crops. While the ECP2 performs better than other regional models for maize and peanut, the RCM3 performs better for cotton. This indicates that good downscaled season-long weather data can play a major role in improving the yield simulation performance. The planted crop type is also sensitive to the weather/climate in the crop simulation. Similar to the maize, the spatial patterns of peanut and cotton yields are far better than those of the R2.

Figure 4 shows the 23 year long time series of statistics for the R2, the above six regional-model-based maize yields, and three ensemble averages (RE: regular ensemble, BCE: bias corrected ensemble, and WE: weight ensemble). It is evident that three ensemble average methods perform better than most of the individual models in terms of RMSE (Figure 4a) and SCORR (Figure 4b). Not much distinguishable skill difference can be found among the three ensemble methods in terms of RMSE. However, the spatial pattern statistics show that a rather improved performance can be seen in the BCE and the WE, compared to the RE. In general, individual models have a wide spread interannual variability of metrics. This variability is reduced by all three ensemble methods. Similar results are obtained for peanut and cotton (Figures S9 and S10).

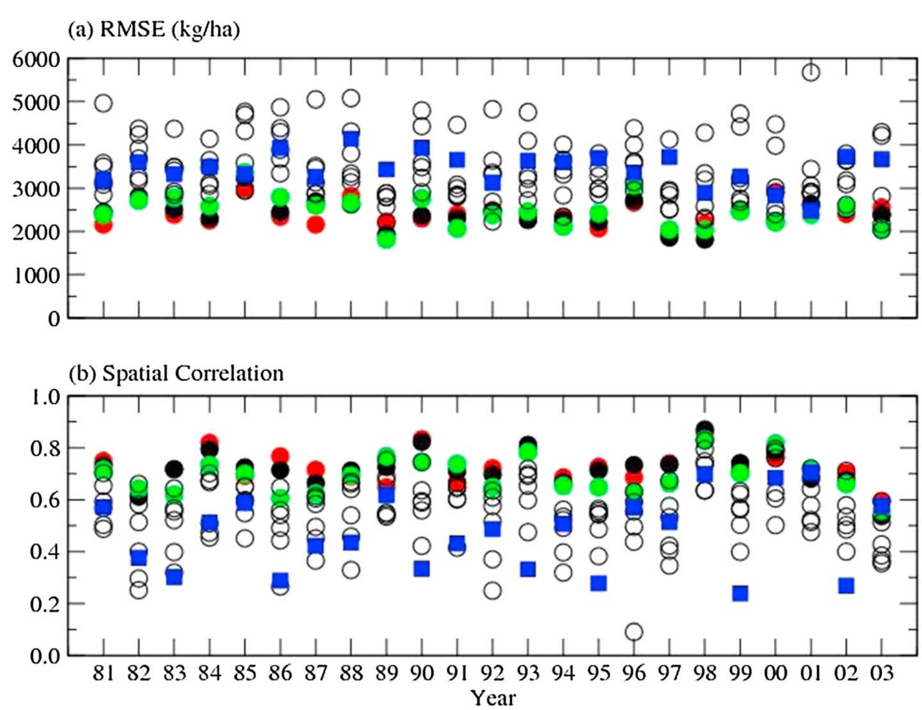

Figure 4. Yearly (1981–2003) (a) RMSE (kg ha^{-1}) and (b) spatial correlation for maize yield. The blue squares represent the R2, the green dots the regular ensemble, the black dots the bias-corrected ensemble, the red dots the weighted ensemble, and the open circles the individual members.

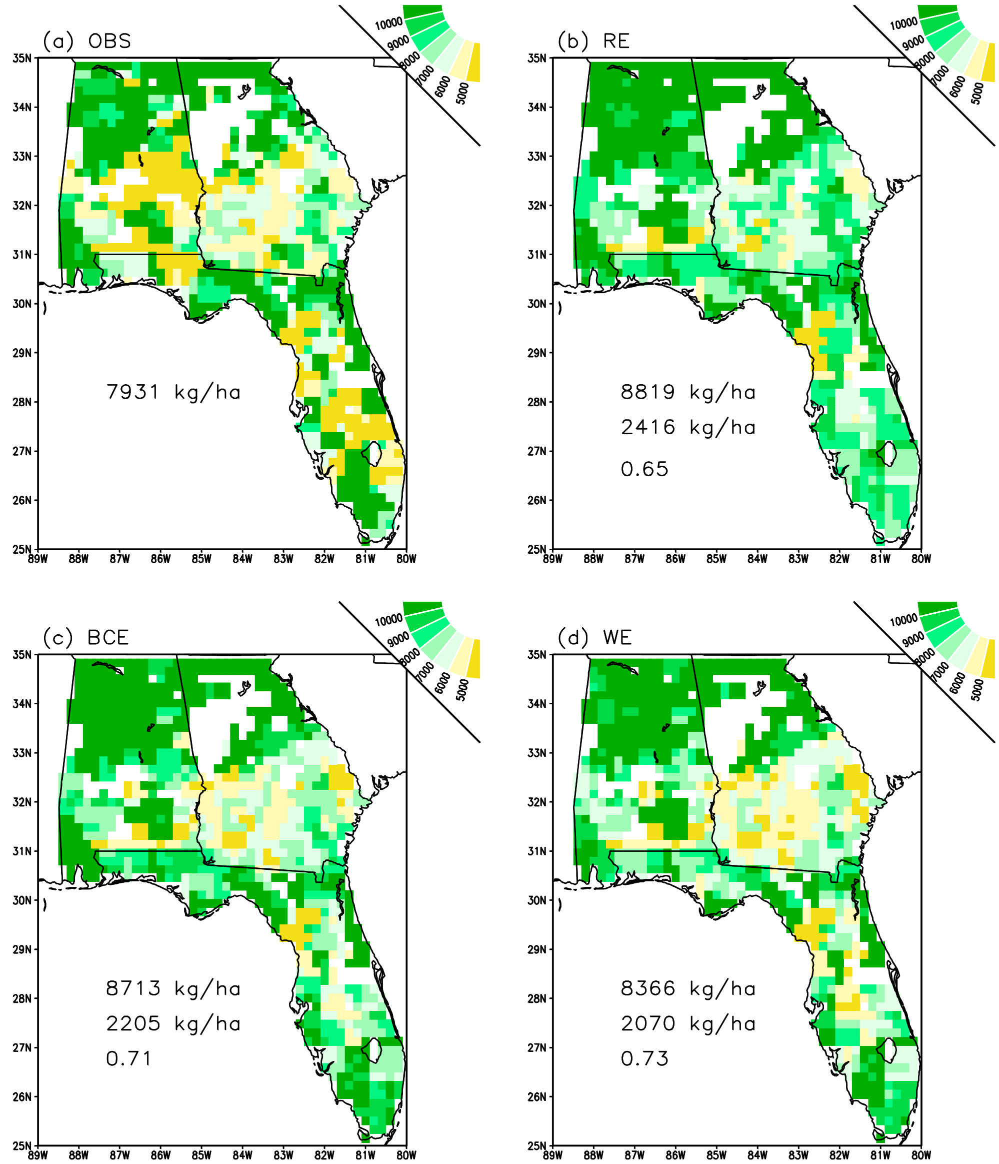

Figure 5. MME maize yield for year 1995 under rainfed conditions; (a) the observed yield, (b) the regular ensemble, (c) the bias-corrected ensemble, and (d) the weighted ensemble. In each panel, the (top) first value is area-averaged yield amount, the (middle) second one is RMSE, and the (bottom) third one is spatial correlation.

The rainfed maize yield maps for year 1995 are shown in Figure 5 to emphasize the differences among the three ensemble methods. Three simple statistics (average, RSME, and SCORR) do not indicate significant differences among the ensemble methods. However, a close visual inspection reveals that the crop yields using the WE or the BCE appears to match better with the observed-weather-driven yields compared to the regular ensemble methods. Similar results are obtained in most of the other years. Due to its performance-based selective nature for assigning weights (i.e., higher number of degrees of freedom), the WE method produces marginally better crop simulations compared to the BCE approach. Hence, it can be concluded that the MME method (BCE or WE) is a very useful tool for delivering improved yield estimation maps to stakeholders for better decision making.

4. Conclusions

This study was performed to improve our understanding of the impacts of weather/climate on agricultural production in the southeast United States. The NARCCAP data set, using a comprehensive dynamical downscaling approach, was employed as a driver in the state-of-art CSM-DSSAT crop model to estimate crop yield amounts which itself is a question of significant interest. The yield amount of three economically important crops (corn, peanut, and cotton) was simulated by using dynamical crop models to assess the impact of using regional climate models for downscaling climate/weather data. Crop-growing-season-long daily weather data from in situ observations, the R2 and the NARCCAP data were used as inputs for the CSM-DSSAT model for the period of 1981–2003 over a regularly gridded pattern (~20 km) over southeast United States. Six ensemble members of the NARCCAP modeling system were used to produce an ensemble of crop yield simulations. It was shown that downscaling is an inevitable step before using coarse scale weather/climate data in dynamical crop models. These yield amount estimations were combined to produce improved crop yield amounts by using bias-corrected or weighted MME methods. The weights in the WE method might be sensitive to sampling over the relatively short training period (22 years) in this study. If much more comprehensive, systematic and longer data sets are used, the WE method might provide more reliable weights to provide an improved crop simulation.

A comprehensive application of NARCCAP outputs would have to include (a) comparing observations to reanalyses, (b) comparing observations to downscaled reanalyses, (c) comparing a and b to understand the benefit of downscaling, (d) comparing observations to downscaled global climate models (GCMs) in the historical period, (e) comparing (b) and (d) to understand the biases of GCMs, and then (f) comparing baseline and future GCM output to understand the signal of climate change. While items (a)–(c) were covered in this paper, items (d)–(f) will be covered in our future study. Hence, the NARCCAP Phase II and CMIP5 data will be used in our future study to demonstrate the capability of the WE method further and to understand the possible impacts of climate variability and change on agricultural production in the southeast United States. Properly designing an ensemble configuration can be a fundamental starting point for successful crop simulations and could be more important than the ensemble averaging methods to produce a usable crop yield simulation by stakeholders.

This study demonstrated the benefit from dynamical downscaling, which is important in the larger debate over the merit of high-resolution climate information [e.g., *Pielke and Wilby*, 2012]. In addition, the current paper shows that the coordinated and centrally distributed RCM simulations by groups like NARCCAP may be cost-effective and have widespread benefits to scientific community for modeling and assessing impact. The current findings are consistent with other recent studies [e.g., *Zhang et al.*, 2015; *Macadam et al.*, 2016] where regional climate models were intensively used in studies of the impacts of climate change on agriculture.

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