PREDICTING CROP YIELDS USING AN ENSEMBLE OF FORECASTS FROM A REGIONAL CLIMATE MODEL

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ABSTRACT

Global/Regional Circulation Models (GCMs) better predict interannual climate variability than they predict the absolute values of meteorological variables, usually overestimating number of rainfall events and amount of rain. Statistical bias correction methods increase the quality of daily model predictions of incoming solar radiation, maximum and minimum temperatures, and rainfall frequency and amount. However when bias corrected data are used as inputs to dynamic crop simulation models, dry spell distributions within the cropping season create large variations among crop yield ensemble members. In this study we used twenty ensemble members of 18-year periods provided by the Florida State University/Center for Ocean-Atmospheric Prediction Studies (FSU/COAPS) that were outputs from a regional spectral model coupled to the National Center for Atmospheric Research Community Land Model (CLM2). After bias correcting daily weather outputs, we estimated annual simulated crop yields by using principal components obtained from crop yield ensemble members. For three locations in Florida, Alabama, and Georgia, statistically significant correlations were found between the cross-validated crop yield estimations based on principal components and the simulated crop yields using observed meteorological data. From 37 to 71% of interannual crop yield variability was explained by one principal component, and estimated yields were in the correct tercile by margins of 30 to 50% beyond chance. No differences were found between the convective schemes used by the GCM. Predictability of corn yield using principal components was improved relative to the use of bias-corrected daily hindcasts produced by GCMs and directly used as inputs to the CERES-Maize model. Bias corrections of incoming solar radiation, maximum and minimum temperatures, and rainfall increased their predictability compared with bias correction applied only to rainfall.

Key words: Bias correction, crop model, crop yield forecast, global circulation model, principal components, statistical downscaling.

INTRODUCTION

Agricultural management has been improved in several regions of the world using seasonal climate predictions of based on El Niño-Southern Oscillation (ENSO) phase (Nnaji, 2001; O'Brien et al., 1999; Petersen and Fraser, 2001; Podestá et al., 2002; Solow et al., 1998; Stahle and Cleaveland, 1992). Typically, these studies use seasonal forecasts based on the identification of analogues from ENSO categories. Unfortunately, in many regions ENSO signals are seasonal, are not clear, or do not exist, which severely limits their use for forecasts (Hansen et al., 1999; Phillips et al., 1998).

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Useful alternatives for producing seasonal climate forecasts are Global/Regional Circulation Models (GCMs), which have been more successful in reproducing the interannual variation in large-scale atmospheric circulations (Martin et al., 2000; Sperber and Palmer, 1996; Shin et al., 2006). These simulated circulation patterns may be used directly for predicting crop yields as empirical relationships (Baigorria et al., 2006a; Challinor et al., 2003). However, direct use of forecast meteorological values deal with imperfect model specification and spatial averaging within GCM grid cells (Carter et al., 1994; Goddard et al., 2001; Mearns et al., 1995). These numerical models overestimate the number of rainfall events, creating an unrealistic distribution of dry spells during the cropping season (Shin et al., 2006). These frequent rainfall events lead to high yields and decreased interannual variability of predicted yields in rainfed agricultural systems (Dubrovský, 2000). To overcome such inaccuracies in forecasts, different statistical correction methods have been developed. Some methods are applied to monthly GCM ensemble members or their mean. These corrected GCM outputs are used to feed weather generators that produce daily weather inputs to crop models (Cantelaube and Terres, 2005; Feddersen and Andersen, 2005; Marletto et al., 2005). Other methodologies are applied to daily GCM outputs, for direct use by crop models (Baigorria et al., 2006c; Challinor, et al., 2005; Ines and Hansen, 2006).

Simulating crop yields using the mean of seasonal climate hindcast ensembles results in smaller interannual variability than simulations that use observed data (Feddersen and Andersen, 2005). On the other hand, simulating crop yields using each individual hindcast ensemble member generates a large range of possibilities, often without an apparent trend. This variability among the ensemble members is the result of dynamic crop model sensitivity to dry spell distribution during the cropping season (Baigorria et al., 2006c). Some ensemble members perform better than others; however, because all members have equal probability of occurrence there is no physical basis to select the best ones and to use them. Cantelaube and Terres (2005) handle this within-ensemble variability by using probability density functions and using the distributions to assess probabilities of occurrences for yield anomalies. However this approach is restricted by the number of available ensemble members.

This study is based on the capabilities of GCMs to predict climate interannual variability and not the absolute values of meteorological variables. In this approach, the hypothesis is that the crop yield ensemble should also inherit this ability to predict interannual yield variability better than it predicts absolute values. Therefore, part of the total variance among the ensemble members must be due to the interannual climate variability. Principal Component (PC) analysis was used to summarize the simulated crop yield ensemble in orthogonal linear transformations. Then, these PCs were used to predict the simulated crop yields obtained by using observed weather data.

A number of questions arose as we were considering how to predict crop yields by linking GCM and dynamic crop models. For example, is it possible to predict crop yields based on the use of observed weather data with hindcast crop yields? Is there a PC obtained from the hindcast crop yield ensemble that represents the interannual variability of the observed crop yields? Do bias correction methods applied to all the meteorological variables used by the crop model increase predictability compared to its application only to rainfall? Are there differences between the convective schemes used by the FSU/COAPS regional spectral model? How many hindcast ensemble members do we need? This study was conducted to help answer these questions and to guide us in analyzing the possibility to develop practical crop yield forecasts in the southeast USA. Objectives of this study were: 1) to summarize the hindcast crop yield ensemble by using PCs to predict the interannual variability of simulated maize using observed weather in three locations of the southeast USA; and 2) to quantify the improvements of bias corrections to the daily hindcasts of incoming solar radiation, maximum and minimum temperatures, and rainfall.

METHODS AND PROCEDURES

Study area

The study area is in the states of Alabama, Georgia, and Florida in the southeast USA between 35°23' N, 88°59' W and 24°57' N, 79°26' W. This region has some of the warmest conditions in the USA and is characterized by widespread but discontinuous cooling periods of 1 to 2° C over most of the region (Karl et al., 1993). Annual rainfall ranges from 1100 to 1400 mm, with the highest amounts occurring along the Gulf of Mexico coast and in south Florida (USGS, 2006). Additional detailed information of rainfall in the study area is found at Baigorria et al. (2006b).

Three counties where corn has been consistently cultivated during the last 18 years were selected for the current study and are mapped by Baigorria et al. (2006c). The counties were Alachua, FL (29°41' N latitude, 82°20' W longitude), Crossville, AL (34°28' N latitude, 85°46' W longitude), and Tift, GA (31°28' N latitude, 83°31' W longitude).

Ensemble of hindcast yield simulations

One weather station located in each of the selected counties was used in this study. Daily data of maximum and minimum temperatures and rainfall from these weather stations were obtained from the National Oceanic and Atmospheric Administration - National Climate Data Center [http://ncdc.noaa.gov/?home.shtml]. Incoming solar radiation was estimated using the technique of Richardson and Wright (1984). These data were used to build the observed weather database with two goals: (*i*) to perform the bias corrections on daily GCM model outputs (Baigorria et al., 2006c; Ines and Hansen, 2006); and (*ii*) to serve as inputs for simulations using the CERES-Maize model (Ritchie et al., 1998) for the same period for which GCM outputs were available (1987-2004).

Also, daily hindcasts of incoming solar radiation, maximum and minimum temperatures, and rainfall were taken from the realizations of the FSU/COAPS regional spectral model (Cocke and LaRow, 2000; Shin et al., 2005, 2006). Hindcast outputs corresponded to the 18-year period from 1987 to 2004, from April to September each year. A set of 20 ensemble members was generated by the FSU/COAPS regional spectral model, and each of these ensemble members were used in the analyses. Differences between the ensemble members were: (*i*) the convective schemes; and (*ii*) the initial date of simulation. Convective schemes used were the Simplified Arakawa-Shubert scheme (SAS; Pan and Wu 1994) and the Relaxed Arakawa-Shubert scheme (RAS; Rosmond, 1992). Both convection schemes had 10 different, but consecutives initial dates of simulation beginning from 10- to 1-day before the hindcasts. From the daily hindcasts of each meteorological variable, values corresponding to the location of each weather station were extracted to build the corresponding databases.

To correct daily rainfall amount and frequencies, bias correction was applied to rainfall by using the cumulative probability function of the two-parameter gamma distribution described by Ines and Hansen (2006). To correct daily incoming solar radiation bias corrections were applied using the beta cumulative probability function, and for maximum and minimum temperatures, the Gaussian distributions. All bias corrections were applied daily to each ensemble member and for each month from March to September across the 18-year period. Detailed descriptions of the procedures are found in Baigorria et al. (2006c). Finally, twenty 18-year bias-corrected ensemble members of daily meteorological data were created and formatted for input to the crop model.

The CERES-Maize model (Ritchie et al., 1998) was selected for this study as crop simulator because of the economical importance of corn in the region and because this crop is more sensitive to soil moisture deficit than other crops (Sadras and Calviño, 2001). Thus, impacts of rainfall forecasts on crop yields can be evaluated relative to impacts of total rainfall amount and frequency.

Soil profile characteristics needed for crop simulations were obtain from the Natural Resources Conservation Service [www.nrcs.usda.gov]. The soil in Crossville was characterized by a silt loam soil of 1.8 m depth, in Tift by a loamy sand of 2.0 m depth, and in Alachua by a sandy soil of 2.5 m depth. The highest field capacity was for the Crossville soil (0.244 cm^3 cm^{-3}) followed by Tift (0.183 cm^3 cm^{-3}) and Alachua (0.103 cm^3 cm^{-3}). Soil organic carbon content followed the same trend among locations with 15.3, 11.4 and 5.7 g kg^{-1} respectively. Detailed descriptions of chemical and physical properties from the soil profile used in this study can be found in Baigorria et al. (2006c).

With the exception of planting date, crop management was set according to previous research in Gainesville, FL (Jones et al., 1986). The simulated corn variety was McCurdy 84AA, planted at a density of 7.2 plants m^{-2}. Planting was on same date every year depending on location: 15 May in Alachua and Tift and 1 April in Crossville. Rainfed conditions were simulated with a total amount of 255 kg N ha^{-1} N fertilizer split into 5 applications every 14 days. We did not attempt to evaluate the representativeness of the scenarios, or account for heterogeneity of soils or weather within each county.

The three evaluated bias correction scenarios were: (*i*) bias correction applied to all meteorological variables from the hindcast, (*ii*) rainfall bias-corrected hindcast and raw hindcast of the remaining variables, and (*iii*) rainfall bias-corrected hindcast and climate monthly average of the remaining variables. For each bias correction scenario and each ensemble member yearly simulated crop yields (crop yield ensembles) were correlated with the yearly realizations using observed weather data (observed crop yields).

Summarizing crop yield ensemble by principal components

Considering our hypothesis that part of the total variance among the ensemble members is the result of interannual climate variability, PC analysis was applied to summarize the ensemble members based on their variance. The software used was the Climate Predictability Tool[3] developed by the International Research Institute for Climate Prediction and Society.

<u>*Principal component analysis.*</u> Principal component (PC) analysis is an effective way of summarizing correlated multivariate data. PCs are orthogonal linear transformations of a multivariate data set that successively maximize the residual variance that remains after higher-order PCs are removed. The transformation matrix consists of eigenvectors of the covariance matrix where the sum of the squared annual weights is 1 (Hair et al., 1998; Wilks, 2006).

[3] http://iri.columbia.edu/outreach/software

For each location, PC analysis was applied to summarize the 20 ensemble members of each bias correction scenario in new variables based on explaining most of their total variance. After calculating and removing the first PC from the ensemble, the 20 ensemble members were now constituted by residuals, not by simulated yields. From this ensemble of residuals, a second PC was calculated and removed. This procedure was applied iteratively until the maximum number of PCs was obtained. Each PC was constituted by 18 annual weights, each of these weights representing one year from the 18-year period.

Linear regression analyzes were performed between annual weight of each PC and annual observed crop yields. Only one PC, the one which gave the best predictability for each location, was selected as predictor. Cross-validation analyzes (Efron and Tibshirani, 1993) were performed leaving three years out from the 18-year period and performing a linear regression analysis with the remaining years. Next, the three removed years were estimated by the linear model using the annual weights of the other years as predictors. This procedure was performed iteratively after all the years were simulated. This procedure tested the ability of using this approach to predict crop yields using independent data.

Predictability analyses. Two types of measures were used to analyze predictability between PC-predicted yields and observed crop yields. Measures based on continuous predictands were Pearson's correlation (r), statistical significance level, Spearman's correlation (r_{rank}), and root mean square error (RMSE). Measures based on categorical predictands were the hit score and hit skill score based on terciles (Murphy, 1993). The hit score was defined as the percentage of times the forecast tercile category corresponded with the observed tercile category (Equation 1). The hit score can be interpreted as the probability of forecasting terciles. The hit skill score was defined as the percentage of times, beyond that expected by chance, the forecast tercile category corresponded with the observed tercile category (Equation 2).

$$\text{Hit score} = \frac{\#\,\text{correct forecasts}}{\#\,\text{number of forecasts}} \times 100\% \qquad [1]$$

$$\text{Hit skill score} = \frac{\#\,\text{correct} - \#\,\text{expected correct}}{\#\,\text{forecasts} - \#\,\text{expected correct}} \times 100\% \qquad [2]$$

Hit scores range from 0 to 100% and are directly related to the predictability skill. Hit skill scores range from -100% (total lack of predictability beyond chance) to 100% (maximum predictability).

Predictability analyses were compared among the cross-validated PC-predicted crop yields from the three bias correction scenarios at each evaluated place.

Convection schemes. To address the question whether there were differences in crop yield predictability between convection schemes (SAS and RAS), the ensemble of the best bias correction scenario was split into two sub-ensembles of ten ensemble members each. The split was based on the convection schemes. The same continuous and categorical predictability measures described in section 2.3.2 were applied to each 10-member sub-ensemble to compare the convection schemes.

Minimum number of ensemble members. To address the question of how many ensemble members were needed to predict crop yields, several sub-ensembles containing different number of ensemble members were generated from the best bias correction scenario. Each sub-ensemble had an equal number of ensemble members from each convection scheme.

Because initial dates in the original ensembles were chosen in a logical manner, we constrained the sub-ensembles to only possible logical combinations of these initial dates based on: (*i*) consecutive dates with a total number of ensemble members less than or equal to 10 and more than or equal to 4; and (*ii*) initial dates of beginning the simulations ranging from 10- to 1-day before the hindcasts. The largest number of ensemble members was established according to the maximum number of available realizations for each convection scheme. The minimum number of ensemble members was established to have a sample size large enough for the cross-validation analyzes.

PCs were computed for each sub-ensemble, and omit-one cross-validation analyzes were performed between the observed crop yields and each crop yield sub-ensemble. From each set of sub-ensembles containing the same number of ensemble members, the sub-ensemble with the smallest predictability skills was selected. Predictability values of this sub-ensemble represented the predictability baseline obtained from different sub-ensembles randomly selected by a GCM operator.

RESULTS AND DISCUSSION

Predicting observed yields

Table 1 shows Pearson's correlations between observed crop yields and each of the crop yield ensemble members using the bias correction method applied to all meteorological variables. Few ensemble members showed significant correlations, and according to results shown in Figure 1, there was no apparent trend among the ensemble members. All ensemble members equally predicted corn yields in the three locations and there was neither physical- nor physiological-based reasons to select any particular member for use as predictors.

Table 2 shows the predictability measures after selecting the PC that best predicted observed corn yields. These cross-validated results were performed for the three locations and for the three bias correction scenarios. According to the results, bias correction applied to all variables explained more variability than the other two scenarios. The use of raw hindcast values of incoming solar radiation, and maximum and minimum temperatures, was better than using the monthly climatology combined with bias-corrected rainfall. Bias correction applied to all variables was always statistically significant. Spearman's correlation showed that the Pearson correlations were not due to outliers in the cross-validated PC-predicted yields. For the best bias correction scenario, PC 10 was used for predicted yields in Crossville, PC 12 for Tift and PC 4 for Alachua.

The probability of predicting the terciles was larger than 53%, and the probability of a prediction in comparison to the climatology ranged from 30% in Crossville to 50% greater in Alachua. Figure 2 shows cross-validated PC-predicted yields versus the observed crop yields across years. In some locations the methodology performed better than others; however there was a tendency to predict crop yields better in locations where ENSO signals were strong. These results were compared to the predictions completely based on ENSO-phase made by Hansen et al. (1999), who found statistically non significant differences in maize during the summer season in Florida.

Table 1. Pearson's correlation (?) between simulated yields using observed weather data versus simulated yields of each ensemble member using bias-corrected hindcasts of all variables. Largest and smallest ? for each location are bold.

Ensemble member	Crossville	Tift	Alachua
1	-0.2072	-0.0236	0.1103
2	0.0462	0.2127	0.2652
3	-0.2598	-0.2318	**0.5466**
4	**-0.4669**	-0.1162	0.1270
5	0.0047	-0.0768	0.0783
6	-0.1555	-0.1036	**-0.6093**
7	0.1780	0.0900	-0.1667
8	0.0906	**-0.5512**	0.3734
9	0.1491	0.1108	0.2140
10	-0.3480	-0.0506	-0.0200
11	0.0189	0.2827	0.1936
12	-0.0598	**0.6784**	-0.0684
13	0.1408	0.5102	0.5168
14	**-0.3971**	0.2328	-0.3061
15	0.3598	0.2804	0.4254
16	0.4036	-0.2443	0.5610
17	-0.1625	0.2191	0.0689
18	-0.1059	0.0558	-0.0026
19	0.3740	-0.3798	-0.0333
20	-0.0944	0.5165	-0.3411
$\overline{X}$	-0.0649	0.2275	0.3206

$\overline{X}$ = dry matter averaged from the 20 ensemble members.

Predicted yields were increased using more than one PC. PCs are orthogonal, so predictability would not be overestimated if using more than one PC. However, we did not attempt to find the optimal set of these PCs for each location and to avoid complications, these results were not presented.

Effect of convection schemes

According to results in Table 3, correlations were statistically non-significant between the convections schemes. The only exception was the SAS convection scheme applied in Crossville. In general terms SAS, performed better than RAS in the continuous measures of predictability whereas the opposite occurred in the categorical measures of predictability. However none of them performed better than both schemes used together (Table 2). In Tift, Pearson's correlation was significantly higher than Spearman's correlation, which is due to one outlier in the values.

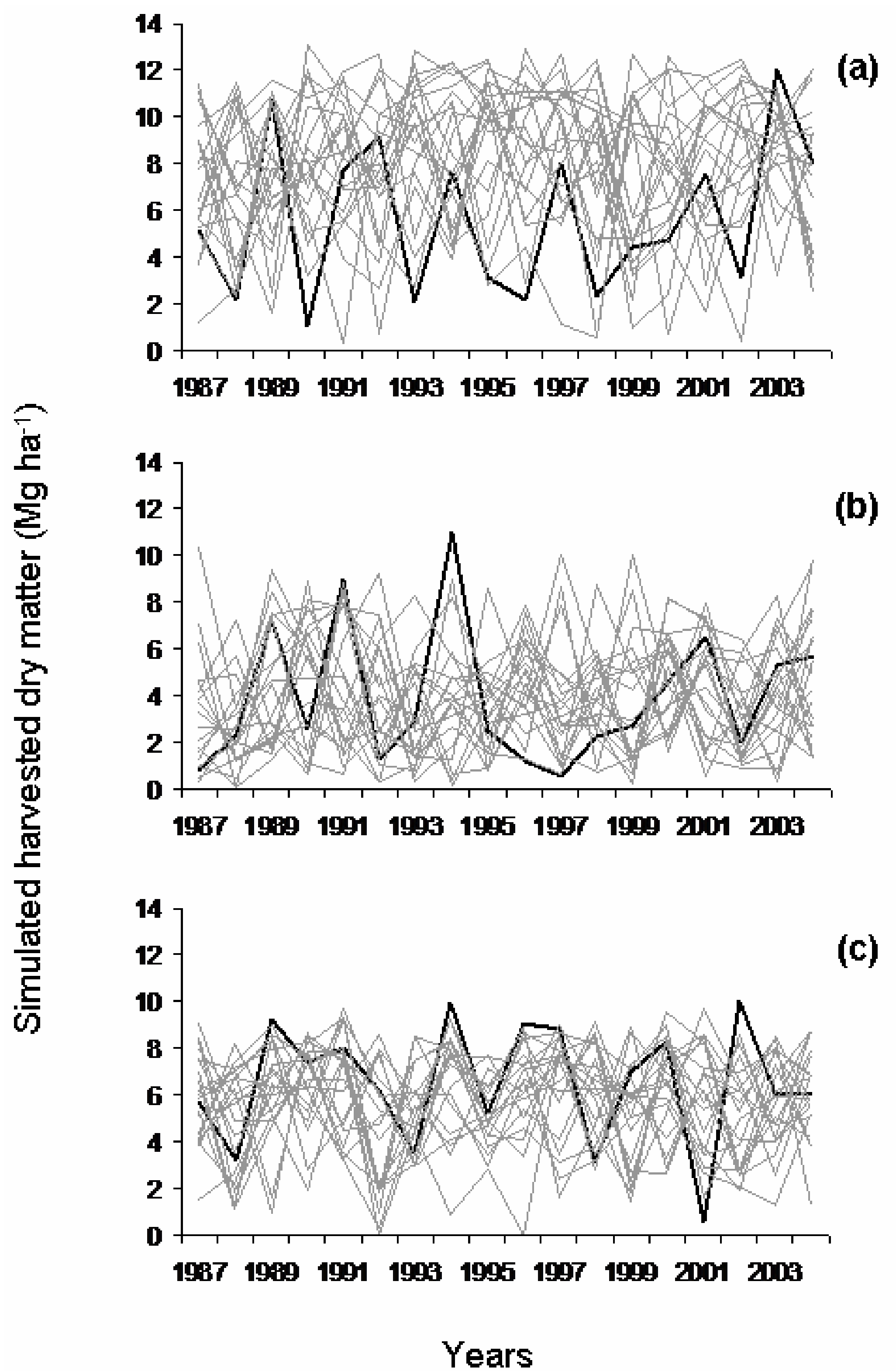

Figure 1. Comparison of the simulated harvested dry matter using observed meteorological variables (bold line) versus simulations using bias-corrected hindcast (thin lines). (a) Crossville, (b) Tift, and (c) Alachua.

Table 2. Pearson’s correlation (*?*), Spearman’s correlation (*?*$_{rank}$), root mean squared error (RMSE), hit score (HS) and hit skill score (HSS) of the PC-predicted crop yields for each location and bias correction scenario.

Location	Bias correction scenario	*?*	*?*$_{rank}$	RMSE (kg ha^{-1})	HS (%)	HSS (%)
Crossville	I	0.6051^{*}	0.6393	2386.2	53.3	30.0
	II	0.3458^{ns}	0.4571	2898.4	66.7	50.0
	III	0.4140^{ns}	0.4179	2934.1	53.3	30.0
Tift	I	0.8451^{***}	0.7893	1752.6	60.0	40.0
	II	0.7442^{**}	0.6571	2071.0	53.3	30.0
	III	0.6148^{*}	0.7036	2422.1	60.0	40.0
Alachua	I	0.8107^{***}	0.7964	1604.8	66.7	50.0
	II	0.7313^{**}	0.8071	1835.0	66.7	50.0
	III	0.6931^{**}	0.7179	1924.8	66.7	50.0

I = Bias-corrected hindcast of all variables.
II = Bias-corrected hindcast of rainfall and raw hindcast of the remaining variables.
III = Bias-corrected hindcast of rainfall and climate monthly average of the remaining variables.
*, **, *** Significant at the 0.05, 0.01, and 0.001 probability level, respectively.
^{ns} Not significant.

Table 3. Pearson’s correlation (*?*), Spearman’s correlation (*?*$_{rank}$), root mean squared error (RMSE), hit score (HS) and hit skill score (HSS) of the PC-predicted crop yields for each location and convection schemes for the best bias correction scenario.

Location	Convection Scheme	*?*	*?*$_{rank}$	RMSE (kg ha^{-1})	HS (%)	HSS (%)
Crossville	SAS	0.9040^{**}	0.9286	2765.4	42.9	14.3
	RAS	0.6350^{ns}	0.6071	2906.0	57.1	35.7
Tift	SAS	0.7070^{ns}	0.6429	2170.8	42.9	14.3
	RAS	0.8266^{*}	0.5000	1666.5	71.4	57.1
Alachua	SAS	0.6139^{ns}	0.6429	2684.5	57.1	35.7
	RAS	0.3903^{ns}	0.2857	2743.6	57.1	35.7

SAS = Simplified Arakawa-Schubert scheme.
RAS = Relaxed Arakawa-Schubert scheme.
*, ** Significant at the 0.05, and 0.01 probability levels, respectively.
^{ns} Not significant.

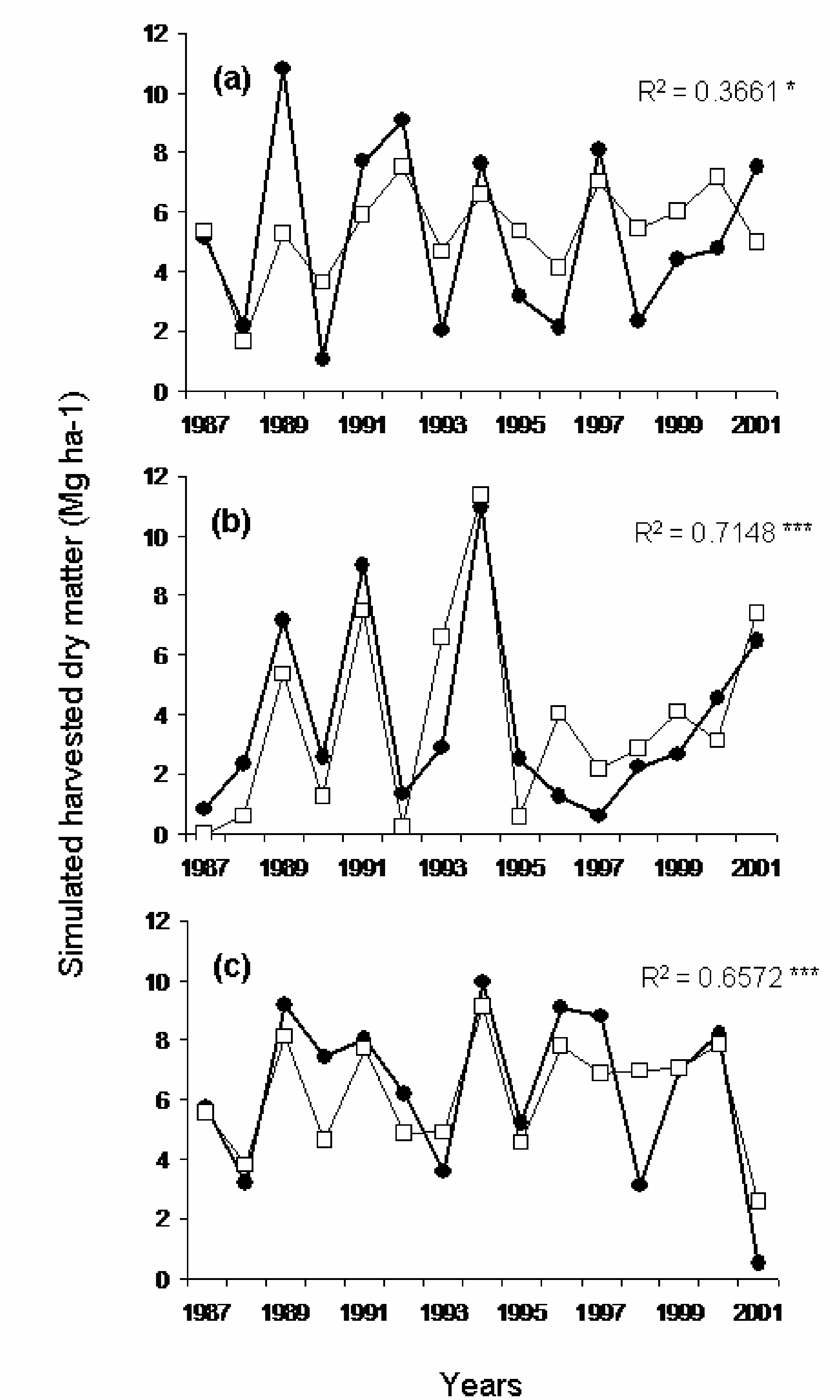

Figure 2. Comparison of the simulated harvested dry matter using observed meteorological variables (bold) and cross-validated predictions using principal component analysis (thin). (a) Crossville, (b) Tift, and (c) Alachua.
*, *** Significant at 0.05, and 0.001 probability level, respectively.

Effect of number of ensemble members

Predictability increased directly as the number of ensemble members increased until a plateau was reached (Figure 3). However, considering RMSE, this plateau was reached first in Alachua using 12 ensemble members, followed by Tift (16 ensemble members) and finally in Crossville (20 ensemble members) A trend was detected related to the strength of ENSO signal in the area. Large number of ensemble members was needed as the influence of the ENSO signal decreased from south (Alachua) to north (Crossville) locations. Some specific combinations of less than twenty ensemble members gave better predictability than that obtained using twenty ensemble members. However, due to the uncertainty created by randomly selecting initial dates of starting simulations, the probability to hit this specific best combination of sub-ensemble members was low.

CONCLUSIONS

Principal components used with the FSU/COAPS regional spectral model predicted observed maize yield variability with good skill levels in this study. This methodology avoided the problem of highly variable dry-spell within the cropping season, which has led to low skill when linking numerical circulation models to dynamic crop models. The use of bias correction to all meteorological variables used by the CERES-Maize model gave the best results in predicting the observed crop yields. There were no differences in the PC-predicted crop yields between convective schemes. The largest the number of ensemble members needed to predict observed yields varied from 12 to 20 in this study and was related to the ENSO signal strength among these locations. Principal component analysis increased skill of the CERES-Maize model to predict observed crop yields using bias-corrected daily outputs from the FSU/COAPS regional spectral model relative to the use of raw or bias-corrected outputs.

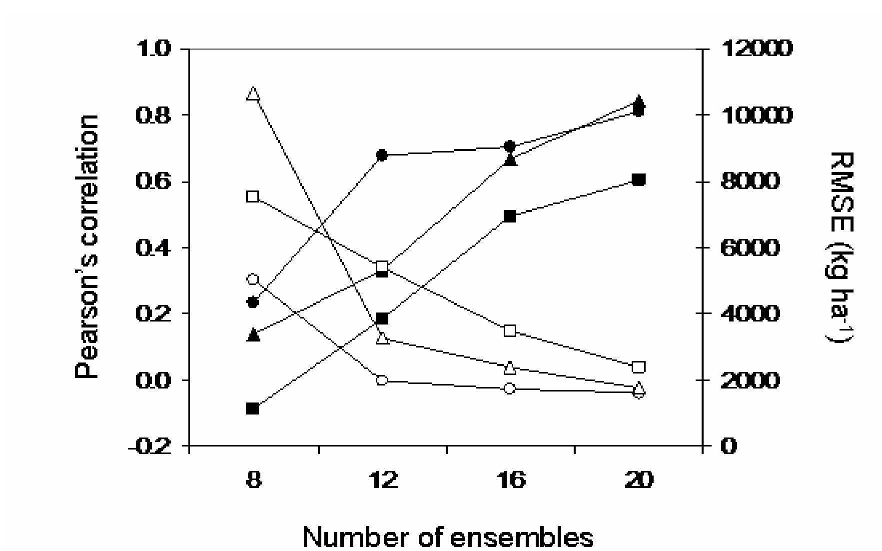

Figure 3. Changes of Pearson's correlation (filled symbols) and RMSE (open symbols) according to the number of ensemble members used in the cross-validated Principal Component regression analysis. Crossville (squares), Tift (triangles), and Alachua (circles).

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